Towards Multi-Device Digital Self-Control Tools

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Abstract. Users can nowadays take advantage of Digital-Self Control Tools (DSCT) to self-regulate their usage of applications and websites by means of interventions like timers and lockout mechanisms. However, DSCTs mainly focus on the interaction between users and a single device at a time, while people typically use more than one device, and in a concurrent way. This motivates the need of exploring tools that can adapt to multi-device settings. We present *FeelHabits*, a DSCT that allows users to set up, through a novel approach, multi-device intentions, i.e., contextual time and launch limits for the simultaneous and/or alternating use of the PC and the smartphone. Stemming from the defined intentions, *FeelHabits* employs different levels of severity to warn the user about a reached limit on the currently used device. A preliminary study on 7 participants suggests that *FeelHabits* might be effective for reducing some multi-device behaviors, and opens the way for further research.

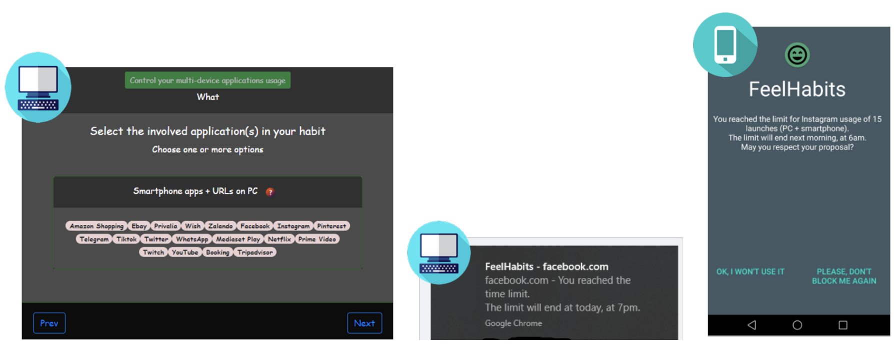
Keywords: Digital Wellbeing · Multi Device · Technology Overuse.

1 Introduction

Nowadays, users interact with a plethora of "smart" devices every day, ranging from personal computers to smartwatches. In this context, a large number of people feel conflicted about the amount of time they spend with digital technologies [17], and researchers now agree that overusing digital devices, e.g., smartphones [7], can lead to negative outcomes, including stress [20] and mental health problems [14]. In response, tech industries and researchers are designing and creating mobile apps and browser extensions for achieving what Google calls "digital wellbeing [4]." Users can take advantage of such Digital-Self Control Tools (DSCTs) to self-regulate their technology-related behaviors. The majority of DSCTs, either commercial or developed as a research artifact, provide users with self-tracking statistics and interventions like access blockers, timers, and launches limits [18], and they mainly targets single devices at a time, e.g., smartphones [21]. As called for by recent work [16,22], however, this single-device conceptualization may fail in capturing all the nuances of people's digital wellbeing, and more effort should be put into designing multi-device and cross-device interactions to enhance digital wellbeing.

In this paper, we present *FeelHabits*, a DSCT that allows users to set up novel interventions that can adapt to different devices in different contextual situations. Such interventions, in particular, are specified by means of user's *intentions*. In the Digital Behavior Change Intervention (DBCI) research area, intentions are defined as concrete if-then behavioral-related goals that are linked to a specific contexts. Recent work [23] describes intentions as one of the most promising strategy for assisting users in changing their behavior through technological support. Such a strategy, in particular, can bridge the intention-behavior gap [25]: through repetition, relevant implementation intentions can become impulses, moving from deliberative processes into automatic processes [9]. In our work, we define an intention as a temporal and/or launch limit for the simultaneous and/or alternate usage of different devices that should be respected in a given contextual situation.

In an initial implementation of *FeelHabits*, composed of a mobile app and a Google Chrome extension, a user can define these intentions by targeting her PC and her smartphone (Figure 1(a)). Intentions can be defined for the overall multi-device usage of the user (*device-level* intentions), or they can be restricted to the usage of specific services available both on the PC and on the smartphone (*app-level* intentions), e.g., a social network that can be accessed through the browser and a dedicated mobile app. Furthermore, intentions can be linked to specific temporal contexts, e.g., the time of the day. *FeelHabits* then monitors the multi-device usage of the user, and it can use different level of severity when intentions are not respected, from simple notifications alerting the user of a reached limit on a given device (Figure 1(b)) to app-blockers (Figure 1(c)).



(a) Definition (b) Notification (c) App-Blocker

Fig. 1. *FeelHabits* is a multi-device DSCT targeting PCs and smartphones. Through a dedicated Google Chrome extension (a), the user can define an *intention*, i.e., a temporal and/or launch limit, for her different devices. When intentions are not respected, *FeelHabits* can send notifications on the device that is currently in use (b), or it can block the access to specific websites or apps (c).

2 Related Work

A growing amount of public [8] and research [15] discussion demonstrates that users may experience negative feelings and severe breakdowns of self-regulation due to an excessive use of technology. Recent topics like digital wellbeing [21] and intentional non-use of technology [24] fostered the development of DSCTs both in the academia and as off-the-shelf products [18]. Kovacs et al. [13], for instance, developed HabitLab, a Google Chrome extension that aims to help people achieve their goals online, e.g., waste less time on Facebook. In the smartphone context, Hiniker et al. [10] proposed MyTime, an app to support people in achieving goals related to smartphone non-use. More complex interventions have been investigated through Lock n' LoL [11] and NUGU [12], two mobile apps leveraging social support to help students focusing on their group activities. Recently, even Google and Apple announced their commitment in designing technology truly helpful for everyone, with the introduction in their mobile operating systems of tools for monitoring, understanding, and limiting technology use [4,5]. Our work stems from the recent need of "designing for self-control," and aims at investigating how to effectively design a DSCT for multi-device scenarios.

Recent reviews on DSCTs [21,18], indeed, highlight that the majority of tools for digital self-control, either commercial or developed as a research artifact, are designed to target single devices at a time, only, e.g., through a mobile app for smartphones [21] *or* a web browser extension for PCs [18]. Contextually, existing literature that can be related to the digital wellbeing context considers (nearly always) one technological source at a time [16], be it a social network [19] or a single device like a smartphone [17]. Such a single-source conceptualization is clearly not sufficient to capture all the nuances of people's digital wellbeing [16]. Indeed, the spread of new devices, from smartwatches to Intelligent Personal Assistants, is now engaging users in a multi-device world. Recent consumer studies reveal that most people own more than one device [2], with multiple devices that are often used in conjunction [1]. To move towards a "multi-device digital wellbeing [22]" conceptualization, this paper presents *FeelHabits*, a DSCT that is able to make sense of data collected from different technological sources, and that allows users to set up interventions that can adapt to them.

3 FeelHabits

FeelHabits is a DSCT that adopts novel interventions that can adapt to different devices. Users can set up these interventions by specifying their multi-device *intentions*, i.e., contextual temporal and/or launch limits for the simultaneous and/or alternate usage of the user's devices that define how much time the user would like to spend on her devices in different contexts.

We implemented a first prototype of *FeelHabits* by targeting computers and smartphones, only. As shown in Figure 2, the system is composed of three main components, i.e., a Google Chrome extension (a), an Android app (b), and a Node.js[1] server hosted on Firebase[2] (c).

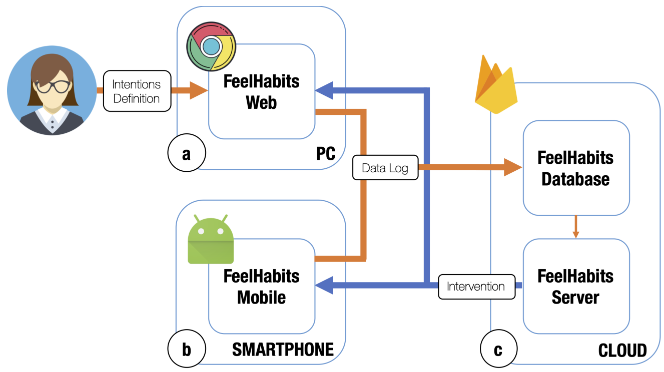


Fig. 2. The architecture of the *FeelHabits* prototype.

Both the smartphone and the PC silently collect usage information like used apps and visited web sites, and update the *FeelHabits* server in real time (*Data Log*). The server analyzes the usage data, and, stemming from the defined *intentions*, it selectively triggers adaptable *interventions* on the user's devices. Intentions can be specified through the dedicated Google Chrome extension (Figure 1(a)). They can be of two different types:

Device-Level Intention. Device-Level intentions refer to the overall multi-device usage of the PC and the smartphone, independently of the visited websites or used mobile apps.

App-Level Intention. App-level intentions refer to a specific service that can be easily accessed both on the PC and on the smartphone. Examples include social networks, e.g., Facebook and Instagram, that are available both as a website on the PC browser and as a dedicated mobile app on the smartphone. The full list of services presented to the user have been extracted by analyzing the most visited websites and used apps in Italy, i.e., the country in which we conducted the preliminary evaluation of *FeelHabits* (see Section 4).

Intentions can be associated to two different temporal contexts, i.e., time of the day (*morning*, *afternoon*, *evening*, or *night*) and period (*working days* or *holidays*). Furthermore, an intention is associated to an *intervention*, composed of the following characteristics:

Intervention Target. An intervention can be defined as a *temporal* or a *launch* limit. For device-level intentions, a temporal limit aggregates the overall time

[1] `https://nodejs.org/en/`, last visited on October 29, 2020
[2] `https://firebase.google.com/`, last visited on October 29, 2020

spent on Google Chrome and on the smartphone, respectively, while for app-level intentions such a limit involves the selected service, only, independently of the adopted device. Similarly, a launch limit in device-level intentions counts for all the occasions in which the user opens Google Chrome or unlocks her smartphone, while a launch limit in app-level intentions is related to how many times the user is opening a given website or the related mobile app.

Interaction Modality. A intervention can be associated to two different interaction modalities, i.e., *simultaneous* or *alternate*. Interventions targeting simultaneous usage are specifically designed for reducing multi-device behaviors like using the smartphone while working on the PC. They are therefore enabled only when the PC and smartphone are actively used together. Interventions targeting alternate usage, instead, are account for situations in which a) the user alternate the usage of the PC and the smartphone during the day, or b) the user primarily uses a single device.

Level of Severity. An intervention can be configured to have two different levels of severity, i.e., *notify* or *block*. The notify level uses simple notifications to alert the user of a reached limit, either temporal or launch-based (see Figure 1(b) for an example of a notification on the PC). When a limit is reached, in particular, a notification is sent to the device that is currently in use. The block level is more restrictive: when a limit is reached, *FeelHabits* blocks the usage of a device or a specific service (see Figure 1(c) for an example of an app-level block on the smartphone).

4 Preliminary Evaluation

We conducted a user study to evaluate *FeelHabits* in a real-world setting. We preliminary investigated how participants defined their intentions, e.g., which type of intentions they preferred, and how they customized the associated interventions. Furthermore, we analyzed the effectiveness of the implemented interventions, by analyzing both quantitative data and qualitative feedback. We recruited 7 participants through convenience and snowball sampling, by sending private messages to our social circles. Participants who accepted to take part in the study (4 male and 3 female) were on average 26 years old ($SD = 4.55$). Four of them were M.S. students, while the remaining 3 were office workers. All the participants declared to regularly use at least an Android smartphone and a laptop or a desktop computer. Before starting the in-the-wild test, we asked them to use the Google Chrome web browser throughout the duration of the study. At the beginning of the study, we sent to the participants an initial questionnaire to collect their demographic data, as well as a consent form to participate in the research study. Then, we sent to them a file with the instructions to install the Android app and the Google Chrome extension, respectively. The file also contained a brief tutorial explaining how to define an intention with the Google Chrome extension. From that moment on, participants were free to use *FeelHabits* for 14 days, without any constraints or restrictions. During the study, we collected data in an anonymous form thanks to the *FeelHabits* database hosted on Firebase. We collected usage data related to participants' smartphone and web browser usage sessions, including the associated contextual information, i.e., time of the day and period. In addition, we kept track of the intentions defined by the participants. In this way, we were able to measure how many times the associated limits were reached, and how many times the interventions were respected or not. At the end of the study, we conducted a debriefing session with each participant to collect their qualitative feedback on their experience with *FeelHabits*. Due to the Covid-19 pandemic [3], interviews were conducted remotely via Zoom [6].

4.1 Results

Intentions Overview During the study, participants defined a total of 28 intentions associated to different temporal contexts, with a preference towards morning and afternoon intentions during working days, and night intentions during holidays. Each participant, in particular, defined 4 intentions on average ($SD = 1.07$). Table 1 reports an overview of the defined intentions and the associated interventions. Results clearly highlight a preference towards app-level intentions: 26 intentions out of 28 (92.86%) were defined to target a specific service, while only 2 intentions were defined at device-level. The most common categories for the targeted services include social networks (e.g., Facebook and Instagram, 46%), communication (e.g., WhatsApp and Telegram, 22%) and video (e.g., YouTube and Amazon Prime Video, 18%). For what concerns the associated interventions, most of them were defined as a time limit (25, 89.29%), while only 3 participants defined a launch limit for specific services, e.g., Netflix and Facebook. Participants defined interventions to mitigate both their simultaneous (12, 42.86%) and alternate (16, 57.14%) interactions with their PCs and smartphones. Furthermore, they selected different level of severity for their interventions, by defining 14 notifications and 14 blockers, respectively.

Table 1. An overview of the 28 intentions, including the associated interventions, defined in the study.

Intentions	**Type**	Device-Level	2
		App-Level	26
Interventions	**Intervention Target**	Time	25
		Launch	3
	Interaction Modality	Simultaneous	12
		Alternate	16
	Level of Severity	Notify	14
		Block	14

Intentions Effectiveness Table 2 is an overview of the effectiveness of the 28 intentions defined during the study. Overall, the intentions generated 125 notifications and 113 blocks, respectively. Participants respected their intention to stop using a given service or device 40 times after receiving a notification (32%). Intentions with a "notify" level of severity were instead not effective in 85 cases (68%). Blocks, instead, were respected 76 times out of 113 (67.26%), while they were ignored in the remaining 37 cases (32.74%). On average, we did not found an influence of the device on which notifications and blockers were delivered and their effectiveness.

By further analyzing the data collected during the study, we found several differences about the relationship between participants and their defined intentions. Some participants, in particular, defined limits that were almost always reached in the associated contexts. The intentions defined by P1, for instance, triggered an intervention, be it a notification or a block, in 75% of cases, while the intentions of P4 triggered an intervention in 80% of cases. Other participants, instead, defined less restrictive limits that were reached a few times, only. Differences also emerged with respect to the users' acceptance of their own intentions. This was particularly evident for intentions with a "block" level of severity. Also in this case, some participants tended to respect block interventions, while others ignored them most of the time. The intentions of P1, for instance, triggered an average of 7 blocks per day that were respected in 92% of cases. On the contrary, P4 skipped 19 out of the 20 blocks she experienced during the study.

Table 2. An overview of the effectiveness of the 28 defined intentions.

	Generated	**Respected**	**Not Respected**
Notifications	125	40	85
Blocks	113	76	37

Qualitative Feedback In the final debriefing session, all the participants shared positive opinions about *FeelHabits*, since it was able to capture the different aspects of their multi-device usage sessions (P4 and P6) and it assisted them in defining their own self-control goals (P3 and P7). *FeelHabits* was described as a particular effective solution for reducing app-related digital interactions. Such a feedback reflects the quantitative data collected during the study. P1, for instance, liked the possibility of defining interventions that reflected her typical usage of a given service on her different devices. To reduce her Netflix usage during working days, in particular, she defined an alternate time limit and a simultaneous launch limit, with 2 separate blockers. P1 stated that the first block was intended to avoid watching films and TV series during lunch, either with her laptop or her smartphone, while the second block was defined to mitigate her frequent behavior of interrupting her work on the PC with a video on the smartphone. Two other participants indicated that *FeelHabits* was particularly useful to control behaviors involving the usage of the smartphone *while* using the PC.

Besides the positive aspects, some participants highlighted the need of having some statistics about their usage of their different devices, e.g., to understand whether their define intentions have a positive effect on their own behaviors. Providing users with statistics about their multi-device use would be also important to assist them in defining appropriate intentions. In line with previous work analyzing "single-device" DSCTs [13], indeed, some users defined limits that were either too strict or too weak, therefore not reflecting their actual interaction with their personal devices.

5 Conclusions and Future Directions

This paper presented a first attempt to design a novel multi-device DSCT able to make sense of data coming from different technological sources and adapting interventions to different devices and services. Our *FeelHabits* prototype, in particular, allows users to set up their own intentions, i.e., temporal and/or launch limit for the simultaneous and/or alternate usage of the PC and the smartphone. Intentions can be defined at device or app level, and they can be linked to specific temporal contexts. *FeelHabits* monitors the multi-device usage of the user, and it adopts different levels of severity, from simple notifications to access blockers, to warn the user about a reached limit on the device that is currently in use.

Our work opens the way for future research exploring multi-device and cross-device interactions in the field of digital wellbeing [16]. The preliminary in-the-wild study, in particular, suggests that *FeelHabits* could be effective for reducing some multi-device behaviors, but also highlights several opportunities that need to be explored and further studied. First of all, our evaluation involved a small sample of 7 participants of roughly the same age, and it lasted 2 weeks, only. Longer studies with larger and diverse populations might be needed. That being said, our work only scraped the surface of how interventions in DSCTs could adapt to multi-device scenarios. Our study, for instance, showed that blockers were respected more often than simple notifications, and that participants liked the possibility of adapting interventions to specific services, e.g., social networks, independently of the used device. We argue that such an adaptability of interventions is one of the most important and interesting challenges to be explored in the field of multi-device digital wellbeing. Future works could explore how to adapt the level of severity of an intervention to the target device, either automatically or through user-defined preferences. Finally, we only considered 2 devices in our prototype: the spread of new devices further increases the possibility of investigating multi-device DSCTs from different perspectives [22].

Acknowledgment

The authors wish to thank all the anonymous participants of our study, and the MSc student Elia Bravo for developing the FeelHabits prototype.

References

1. Latest mobile trends show how people use their devices (2016), https://www.thinkwithgoogle.com/advertising-channels/mobile-marketing/device-use-marketer-tips/, accessed: 2020-07-17
2. Connected consumer survey 2017 (2017), https://www.thinkwithgoogle.com/intl/en-145/perspectives/local-articles/connected-consumer-survey-2017/, accessed: 2020-07-17
3. Coronavirus disease (covid-19) pandemic (2020), https://www.who.int/emergencies/diseases/novel-coronavirus-2019, accessed: 2020-07-17
4. Our commitment to digital wellbeing (2020), https://wellbeing.google/, accessed: 2020-07-17
5. Use screen time on your iphone, ipad, or ipod touch (2020), https://support.apple.com/en-us/HT208982, accessed: 2020-07-17
6. Zoom meetings & chat (2020), https://zoom.us/, accessed: 2020-07-17
7. Ames, M.G.: Managing mobile multitasking: The culture of iphones on stanford campus. In: Proceedings of the 2013 Conference on Computer Supported Cooperative Work. p. 1487–1498. CSCW '13, Association for Computing Machinery, New York, NY, USA (2013). https://doi.org/10.1145/2441776.2441945
8. Cellan-Jones, R.: Confessions of a smartphone addict (2018), https://www.bbc.com/news/technology-44972913, accessed: 2020-07-17
9. Einstein, G., Mcdaniel, M.: Prospective memory: Multiple retrieval processes. Current Directions in Psychological Science **14** (12 2005). https://doi.org/10.1111/j.0963-7214.2005.00382.x
10. Hiniker, A., Hong, S.R., Kohno, T., Kientz, J.A.: Mytime: Designing and evaluating an intervention for smartphone non-use. In: Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems. pp. 4746–4757. CHI '16, ACM, New York, NY, USA (2016). https://doi.org/10.1145/2858036.2858403
11. Ko, M., Choi, S., Yatani, K., Lee, U.: Lock n' lol: Group-based limiting assistance app to mitigate smartphone distractions in group activities. In: Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems. pp. 998–1010. CHI '16, ACM, New York, NY, USA (2016). https://doi.org/10.1145/2858036.2858568
12. Ko, M., Yang, S., Lee, J., Heizmann, C., Jeong, J., Lee, U., Shin, D., Yatani, K., Song, J., Chung, K.M.: Nugu: A group-based intervention app for improving self-regulation of limiting smartphone use. In: Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing. pp. 1235–1245. CSCW '15, ACM, New York, NY, USA (2015). https://doi.org/10.1145/2675133.2675244
13. Kovacs, G., Wu, Z., Bernstein, M.S.: Rotating online behavior change interventions increases effectiveness but also increases attrition. Proceedings of ACM Human-Computer Interaction **2**(CSCW) (Nov 2018). https://doi.org/10.1145/3274364
14. Lanaj, K., Johnson, R.E., Barnes, C.M.: Beginning the workday yet already depleted? consequences of late-night smartphone use and sleep. Organizational Behavior and Human Decision Processes **124**(1), 11 – 23 (2014). https://doi.org/https://doi.org/10.1016/j.obhdp.2014.01.001
15. Lanette, S., Chua, P.K., Hayes, G., Mazmanian, M.: How much is 'too much'?: The role of a smartphone addiction narrative in individuals' experience of use. Proceedings of the ACM on Human-Computer Interaction **2**(CSCW), 101:1–101:22 (Nov 2018). https://doi.org/10.1145/3274370

16. Lascau, L., Wong, P.N.Y., Brumby, D.P., Cox, A.L.: Why are cross-device interactions important when it comes to digital wellbeing? (2019)
17. Lee, U., Lee, J., Ko, M., Lee, C., Kim, Y., Yang, S., Yatani, K., Gweon, G., Chung, K.M., Song, J.: Hooked on smartphones: An exploratory study on smartphone overuse among college students. In: Proceedings of the 32Nd Annual ACM Conference on Human Factors in Computing Systems. pp. 2327–2336. CHI '14, ACM, New York, NY, USA (2014). https://doi.org/10.1145/2556288.2557366
18. Lyngs, U., Lukoff, K., Slovak, P., Binns, R., Slack, A., Inzlicht, M., Van Kleek, M., Shadbolt, N.: Self-control in cyberspace: Applying dual systems theory to a review of digital self-control tools. In: Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems. pp. 131:1–131:18. CHI '19, ACM, New York, NY, USA (2019). https://doi.org/10.1145/3290605.3300361
19. Marino, C., Gini, G., Vieno, A., Spada, M.M.: A comprehensive meta-analysis on problematic facebook use. Computers in Human Behavior **83**, 262 – 277 (2018). https://doi.org/https://doi.org/10.1016/j.chb.2018.02.009, `http://www.sciencedirect.com/science/article/pii/S0747563218300670`
20. Mark, G., Wang, Y., Niiya, M.: Stress and multitasking in everyday college life: An empirical study of online activity. In: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems. pp. 41–50. CHI '14, ACM, New York, NY, USA (2014). https://doi.org/10.1145/2556288.2557361
21. Monge Roffarello, A., De Russis, L.: The race towards digital wellbeing: Issues and opportunities. In: Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems. pp. 386:1–386:14. CHI '19, ACM, New York, NY, USA (2019). https://doi.org/10.1145/3290605.3300616
22. Monge Roffarello, A., De Russis, L.: Coping with digital wellbeing in a multi-device world. In: Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems. Association for Computing Machinery, New York, NY, USA (2021). https://doi.org/10.1145/3411764.3445076
23. Pinder, C., Vermeulen, J., Cowan, B.R., Beale, R.: Digital behaviour change interventions to break and form habits. ACM Transaction on Computer-Human Interaction **25**(3) (Jun 2018). https://doi.org/10.1145/3196830, `https://doi.org/10.1145/3196830`
24. Satchell, C., Dourish, P.: Beyond the user: Use and non-use in hci. In: Proceedings of the 21st Annual Conference of the Australian Computer-Human Interaction Special Interest Group: Design: Open 24/7. pp. 9–16. OZCHI '09, ACM, New York, NY, USA (2009). https://doi.org/10.1145/1738826.1738829
25. Webb, T., Sheeran, P.: Does changing behavioral intentions engender behavior change? a meta-analysis of the experimental evidence. Psychological bulletin **132**, 249–68 (04 2006). https://doi.org/10.1037/0033-2909.132.2.249