A Longitudinal In-the-Wild Investigation of Design Frictions to Prevent Smartphone Overuse

Luke Haliburton
luke.haliburton@ifi.lmu.de
LMU Munich
Munich, Germany
Munich Center for Machine Learning (MCML)
Munich, Germany

David J. Grüning
david.gruening@psychologie.uni-heidelberg.de
Heidelberg University
GESIS - Leibniz Institute for the Social Sciences
Heidelberg, Germany

Frederik Riedel
frederik@riedel.wtf
riedel.wtf GmbH
Berlin, Germany

Albrecht Schmidt
albrecht.schmidt@ifi.lmu.de
LMU Munich
Munich, Germany

Nađa Terzimehić
nadja.terzimehic@ifi.lmu.de
LMU Munich
Munich, Germany

ABSTRACT

Smartphone overuse is hyper-prevalent in society, and developing tools to prevent this overuse has become a focus of HCI. However, there is a lack of work investigating smartphone overuse interventions over the long term. We collected usage data from $N = 1,039$ users of *one sec* over an average of 13.4 weeks and qualitative insights from 249 of the users through an online survey. We found that users overwhelmingly choose to target Social Media apps. We found that the short design frictions introduced by *one sec* effectively reduce how often users attempt to open target apps and lead to more intentional app-openings over time. Additionally, we found that users take periodic breaks from *one sec* interventions, and quickly rebound from a pattern of overuse when returning from breaks. Overall, we contribute findings from a longitudinal investigation of design frictions in the wild and identify usage patterns from real users in practice.

CCS CONCEPTS

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

KEYWORDS

smartphone overuse, design frictions, long-term, behavior change

ACM Reference Format:
Luke Haliburton, David J. Grüning, Frederik Riedel, Albrecht Schmidt, and Nađa Terzimehić. 2024. A Longitudinal In-the-Wild Investigation of Design Frictions to Prevent Smartphone Overuse. In *Proceedings of the CHI Conference on Human Factors in Computing Systems (CHI '24), May 11–16, 2024, Honolulu, HI, USA.* ACM, New York, NY, USA, 16 pages. https://doi.org/10.1145/3613904.3642370

CHI '24, May 11–16, 2024, Honolulu, HI, USA

ACM ISBN 979-8-4007-0330-0/24/05
https://doi.org/10.1145/3613904.3642370

1 INTRODUCTION

Smartphones have become ubiquitous in daily life, with over six billion users around the world [73]. While smartphones provide many benefits, enabling users to access information, connect with distant contacts [23], and manage chronic diseases [2], there are also myriad negative consequences. Excessive smartphone use has been connected to decreased sleep quality [35], reduced activity [58], increased anxiety [36], and increased loneliness [59]. Users are increasingly striving to regain control of their smartphone use [50], aiming to maintain the utility benefits of a smartphone without absentminded and meaningless interactions [41].

Past work in Human-Computer Interaction (HCI) has developed numerous potential solutions to tackle smartphone overuse based on several different approaches. Prior work has tracked usage time and used pop-up notifications [38] and goal-setting [20, 43] to encourage users to reflect on their smartphone behaviors. Researchers have also investigated blocking [6], restricting [27, 71], and discouraging [54] smartphone use. Additionally, several groups have shown successful results from incorporating reflection on the real world [8, 76] and using design frictions [17]. Several of the developed methods have shown promise in their investigations, but there is a general lack of long-term usage studies to understand how these interventions impact user behavior in practice [64]. Commercially available mobile apps have recently grown in popularity with rising public interest in regaining self-control over smartphone use. Such commercial apps present an opportunity to study user behavior related to smartphone overuse interventions in the real world.

In this paper, we investigate how users interact with design friction [11, 48] smartphone overuse interventions in everyday life by analyzing longitudinal organic usage data of existing users ($N = 1,039$) of a commercial mobile app, *one sec*[1], collected in-the-wild. These users contributed historical usage data related to their use of this design friction intervention. A subset of 249 users responded to qualitative questions in an additional online survey. By investigating usage patterns over a long time period in the wild, we aim to investigate the following research questions:

[1]https://one-sec.app/

RQ1 *What motivates smartphone users to employ design friction interventions in practice?*

RQ2 *How do users set up and use design friction interventions in practice?*

RQ3 *How do design frictions impact user behavior over time in everyday use?*

We found that users primarily use *one sec* to target social media apps. We also found that the design frictions effectively reduce the number of app open attempts and lead to more intentional smartphone usage over time, as participants open their target apps less often but continue through the design friction a larger fraction of the time. Additionally, we found that participants take periodic breaks, and their usage appears to go up during these breaks, but it quickly recovers when they resume using the friction. In all, we contribute a dataset of longitudinal in-the-wild historical usage logs from 1,039 organic users of the commercial design friction app, *one sec*, and results from both quantitative and qualitative analyses of the data. Our results provide valuable insights for researchers investigating smartphone overuse, ideally helping to steer us toward a future with less problematic and more mindful smartphone use.

2 RELATED WORK

Our work strongly aligns with the digital wellbeing research area [80], as our aim is to understand people's long-term intervention use patterns for the sake of improving their wellbeing. As such, we present related work in terms of the causes and effects of disrupted digital wellbeing, followed by current HCI solutions on how to mitigate the disruptive effects, with emphasis on employing design frictions [48]. We conclude with large-scale HCI works on understanding people to address the gap of insufficient long-term studies suggested by a recent systematic review [64].

2.1 Digital Wellbeing

Smartphones have become ubiquitous, ever-present companions as ownership continues to grow [53]. Excessive smartphone use has negative consequences for both physical and mental health. Overuse causes neck pain [84] and poor posture [1], has been linked to depression and anxiety disorders [13, 60], and degrades memory [7].

Modern mobile technologies are designed to be as engaging as possible [19] as part of the attention economy [12], which serves as a partial explanation for smartphone overuse. Overuse is linked to digital stress, i.e., stress resulting from interactions with digital technology, potentially leading to burnout, depression, and anxiety symptoms [62].

Smartphone overuse has gained attention in industry, reflected by both Google[2] and Apple[3] pre-installing Digital Wellbeing features in their operating systems, and social media apps such as TikTok including screen time limits and break suggestions[4]. From a research perspective, there have been manifold attempts to understand mechanisms to enable users to regain control of their phones (e.g., [18, 20, 76]).

[2]https://wellbeing.google/

[3]https://support.apple.com/en-us/HT208982

[4]https://newsroom.tiktok.com/en-us/investing-in-our-communitys-digital-well-being

One dichotomy that complicates smartphone overuse is the fact that smartphones are a convenient and powerful tool. Many aspects of modern life depend on smartphones, and it is therefore not feasible for many users to stop use altogether. However, when users open their phone for a utility reason, they are often dragged into *rabbit holes* of mindless use [74]. Past work has distinguished between general and absentminded use in questionnaires [47], where absentminded use involves aimless scrolling, compulsive phone checking, and other use without a purpose.

2.2 Smartphone Overuse Interventions

The numerous tools and interventions in HCI developed to tackle smartphone overuse can broadly be categorized into passive self-monitoring reflection tools and active interventions that intercept smartphone use [50]. Within the active category, Lyngs et al. [43] distinguishes between temporary limits, goals, rewards, and punishments.

Several researchers have investigated use limits on specific apps with mixed results [20, 45, 54]. MyTime [20] used aspirations to motivate users by reminding them of their own daily goals. Kim et al. [26] created GoalKeeper to adaptively block use and found that light restrictions have the best balance between user experience and effectiveness. Other researchers have used social pressure as a motivator [25, 30]. Park et al. [55] employed positive reinforcement through micro-financial rewards. More recent research efforts explore the potential responsibility shift from end users to system designers [39] and educators [51] by introducing a design that toggles between explorational and intentional use, and through a university course on wellbeing, respectively.

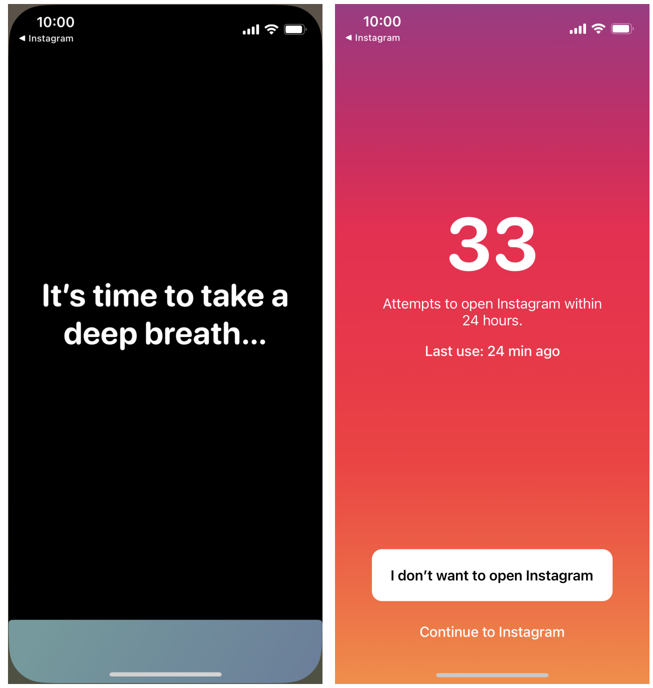
2.2.1 Design Frictions for Technology Overuse. One common pattern in several works is the use of frictions. Frictions are designed to impede the user long enough to spark reflection without fully blocking their actions, switching people's behavior from being driven by the automated system to the more deliberate, rational system [11, 52]. Cox et al. [11] argue for intentional and careful design frictions to spark reflection and mindfulness, as in *"deliberate and intentional [...] experience of the present moment"*. Kim et al. [27] investigated various effortful tasks [64] (such as typing random digits) as an implementation of design frictions and found that they reduced screen time. Park et al. [56] apply similar principles and name the strategy *"interaction restraint"*. Song et al. [68] required users to turn a physical hand crank in order to engage in social media content. A further group of studies introduced a time lag to access the device or service of interest [31–33, 66]. Lyngs et al. [44] explored inquiring about users' intention for using Facebook before opening the application, with subsequent reminders of the stated intention. Their results suggest that inquiring about intention decreases average daily time on Facebook and the number of daily visits, with a trend towards shorter visits. MindPhone [76] investigated a mindfulness-based intervention at unlock that prompts the users to reflect on either why they are opening their phone or what they plan to do afterward. They found that reflecting on what users plan to do after using their phones significantly decreased usage, indicating that a focus on the real world may be an effective intervention.

The app which makes up the focus of our evaluation, *one sec*, employs a combination of methods that appear in the literature. The app primarily introduces brief frictions for a specified amount of time when a user tries to open a target app. It can also provide customizable prompts, apply schedule-based breaks from the intervention, and other similar interventions. The use of frictions and the ability to prompt the user closely relate to the approach in MindPhone [76]. Due to the presence of multiple features from HCI research as well as the large user base, *one sec* is an appropriate medium to investigate user interactions with smartphone overuse interventions in everyday life settings.

Perhaps most relevant to our work is the recent investigation by Grüning et al. [17], in which the authors also use the app *one sec*. The paper describes psychological mechanisms that enable *one sec* to change user behavior. They found that offering the option to dismiss consumption has the strongest impact on lowering consumption behavior, and combining this with a friction and a message (i.e., the full *one sec* intervention) is also significantly effective compared to a control. In their investigation, Grüning et al. [17] recruited users who were new to *one sec* to participate for six weeks and identified a reduction in app open attempts for the targeted apps. We extend this work by analyzing a fundamentally different dataset, that is, historical usage data from existing *one sec* users over a longer period of time. Our data, therefore, represents truly in-the-wild and organic usage and is a crucial step toward understanding how smartphone overuse interventions are used in daily life.

2.2.2 Long-Term Evaluations. Past work suggests that long-term evaluations are both rare and necessary in HCI [78], while other works have directly called for more longitudinal and truly in-the-wild HCI investigations [29]. In the area of wellbeing, there is a scarce amount of long-term, in-the-wild evaluations, as a recent systematic review suggests [64]. The review's authors collect, within another work [63], over 130,000 smartphone usage sessions over three weeks to quantitatively extract smartphone use habits. This was followed by an in-the-wild study of evaluating the effectiveness of proposing alternatives upon an automated habit discovery with 20 participants for a minimum of 21 days to a maximum of 113 days. They found that participants not only decreased the time spent on pre-specified target apps but also reduced their overall smartphone usage. Where Roffarello and De Russis [63] aim to characterize smartphone use habits, we target the specific group of users who engage with smartphone overuse interventions. In another longitudinal study, Kovacs et al. [33] explored users' intervention preferences over time by investigating logs from over 8,000 users on HabitLab, a web platform whose goal is to help users decrease their time spent online. Their findings cast doubt on whether users will return to a more strict intervention setup once abandoned, yet users themselves remain optimistic that they will pick up a stronger intervention level in the future. We draw inspiration from their work by also using usage logs as our primary source and using prompts to gain additional insight from a portion of the participants during the study. While they investigate a browser-based solution for behavior change, our work specifically targets smartphone use.

Our work primarily extends the listed investigations by analyzing long-term data from organic users of a commercially available app that employs design frictions as an intervention for smartphone overuse. As such, we follow the call for more truly in-the-wild longitudinal studies in HCI [29] and long-term investigations [78] in general. On a more notional level, we align with large-scale studies on understanding people in HCI (e.g., [34, 37, 49]).



(a) The Breathing Exercise intervention displays a message along with an animation coming from the bottom.

(b) When the animation is complete, *one sec* displays stats and buttons to either dismiss opening the target app or to continue.

Figure 1: How *one sec* interrupts a user opening a target app.

3 METHODOLOGY

We conducted a longitudinal in-the-wild study with existing users of the commercial mobile app *one sec*. Participants contributed historical app usage data, with a portion additionally participating in a qualitative online survey.

3.1 Apparatus

We use a commercially available smartphone overuse intervention, *one sec*, as a platform for our research. The app is triggered (see Figure 1) when a user attempts to open a user-defined target app and serves as a self-nudge [17, 61]. The primary intervention in the app is based on a combination of a design friction and providing the user an explicit option to dismiss opening the target app:

Design Friction. When users try to open a target app, *one sec* imposes a short delay of 3 to 60 seconds (6 seconds by default), customizable by the user. The delay is accompanied by a short animation and acts as a design friction, providing users with additional time to consider their choice, which has been shown to increase deliberate decision-making [15, 70].

Table 1: Design friction interventions available in *one sec*.

Intervention	Description
Breathing Exercise	An animation moves up and down the screen to guide the user's breath (Figure 1a).
Minimal Breathing Exercise	A minimal version of the Breathing Exercise
Follow the dot	The user follows a dot moving over the screen with their finger.
Rotate phone	The user physically rotates their phone three times.
Mirror	Displays the user's face, captured via the selfie camera.
Black Screen	Displays a black screen.

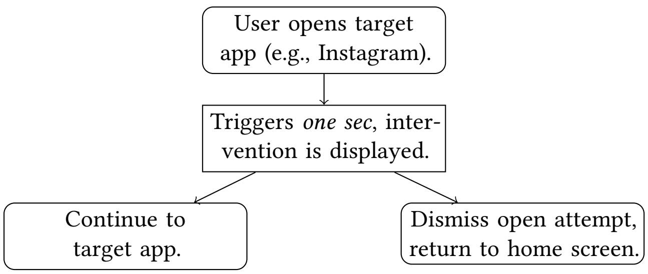


Figure 2: Technical flow chart of how the *one sec* intervenes between the target app and the user. The intervention is triggered when a user attempts to open a target app and the user is given a choice to continue or dismiss opening.

Option to Dismiss. After displaying the friction animation, *one sec* presents users with an explicit option to dismiss opening the target app or to continue. This nudge changes the users' choice architecture, making it easier for users to avoid consumption. Changes to choice architecture have been successfully employed in the digital world, for example, by pop-ups that give users a chance to reconsider sharing decisions or aggressive comments [24].

By combining a design friction with an option to dismiss, users have the opportunity to reflect and make deliberate decisions about their smartphone consumption. This aligns with dual systems theory by enabling analytical and rational control [44, 52]. The interaction flow is outlined in Figure 2. Users can customize different interventions[5] to occur during the design friction, with different lengths of time and levels of interactivity, elaborated in Table 1.

3.2 Participants & Data Collection

We recruited existing users of *one sec* on a rolling basis between December 15^{th}, 2022 and April 4^{th}, 2023 via a banner shown within the app. Users completed a consent form and a short introductory survey. As part of a larger research project, the participants were given the opportunity to optionally contribute their historical data and consent to six weeks of future data collection for research purposes. We only consider the historical data (i.e., organic use of the app) for this study. In total, 1,039 participants contributed their historical usage data, which we pulled on September 5^{th} 2023. All quantitative data is logged directly via the *one sec* app.

To complement our quantitative findings with qualitative statements, we ran an additional online survey among the 1,039 participants between May 7^{th} and September 5^{th}, 2023. The survey link was only displayed to participants after they contributed their historical quantitative data. 24.0% of the participants responded in full to our survey ($N = 249$). This approach of recruiting a portion of the participants to contribute additional qualitative information has been used by prior work in HCI (c.f. [14, 21, 33, 77]). However, all questions were marked as optional. Almost 60% of participants identify as male ($n = 151$) and 32% as female ($n = 77$). 11 participants are of diverse gender, and 7 identify as non-binary. Two participants chose not to disclose their gender. The average age is $M = 25.8$ ($SD = 6.92$, $min = 13$, $max = 49$).

We aimed to collect user data in a privacy-conserving manner. We did not collect any information that could link data to individuals. Instead, on study participation, the app generates a universally unique identifier (UUID) that is used to link app usage data with survey responses. The study and data collection has been approved by the ethics board at Heidelberg University. The ethics board specifically approved the inclusion of children and minors in the study on the basis that the app is publicly available on the App Store, and therefore, anyone could download and participate in the study.

3.3 Quantitative Data Scheme and Analysis

We obtained the quantitative data as a list of users' interactions with *one sec*. Each entry in the list represents an intervention interaction; the fields are displayed in Table 2[6].

As seen in Figure 3, which provides an overview of when all users participated in the study, there are a small number of participants who have been using the app for a long time (over one year in several instances). To improve the robustness of our analysis, we defined an upper cutoff point of time, beyond which we do not include the data because it is contributed by a small number of users. We defined the cutoff point using an outlier method. The cutoff is calculated as two standard deviations above the mean, equal to 43.8 weeks (309 days). The cutoff time is visualized in Figure 4, along with the distribution of how many users contributed different lengths of usage data. It is important to note that the cluster of short usage times does not represent users dropping out but rather is a representation of the fact that there are more users with a short period of historical data (e.g., they installed *one sec* fairly recently) compared to the number of users who have been using the app for a long time.

[5]https://tutorials.one-sec.app/interventions

[6]Fields not relevant to our analysis are omitted from the description

Table 2: The format in which we obtained data for quantitative analysis.

Field	Description
Participant UUID	A unique identifier for each participant.
Target app	The app the user is attempting to open (e.g., , Instagram, WhatsApp, etc.)
Resolution	User response to intervention: *openedApp* if user continued to target app; *dismissedAppOpening* if user did not continue to target app. An optional *closedApp* action records the target app closing but is not recorded for each UUID.
Timestamp	Unix time stamp of interaction.
Intervention type	Type of design friction presented from the set described in Table 1.
Intervention duration	Duration of the design friction in seconds/number of repetitions required to complete intervention.

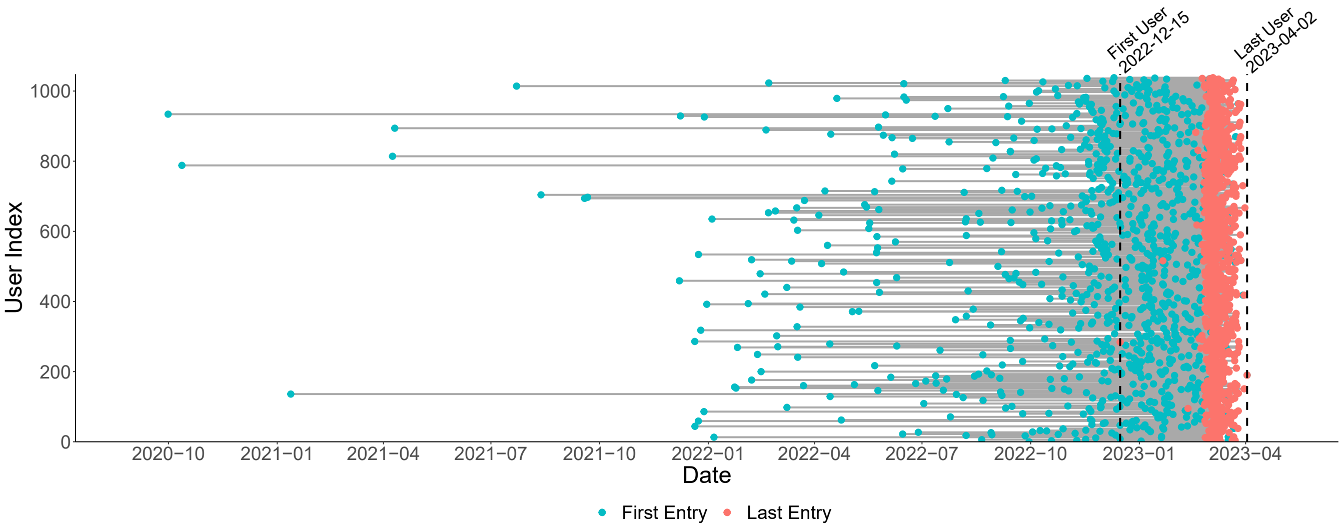


Figure 3: A timeline of when the participants used *one sec* and contributed their data to the study. All of the data collected represents organic, historical usage of the app, resulting in different start times for the participants.

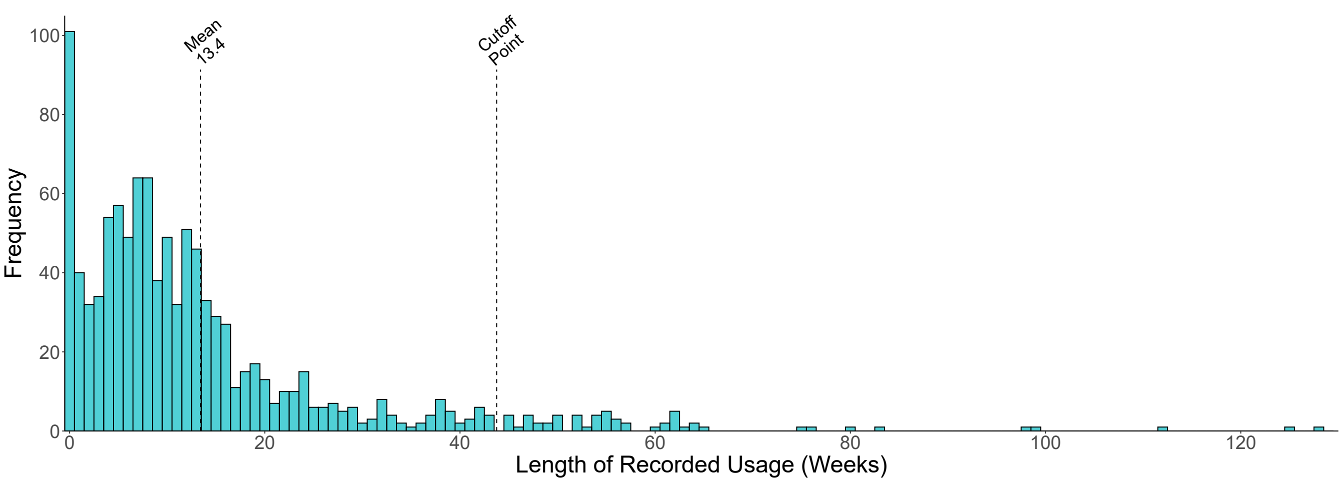
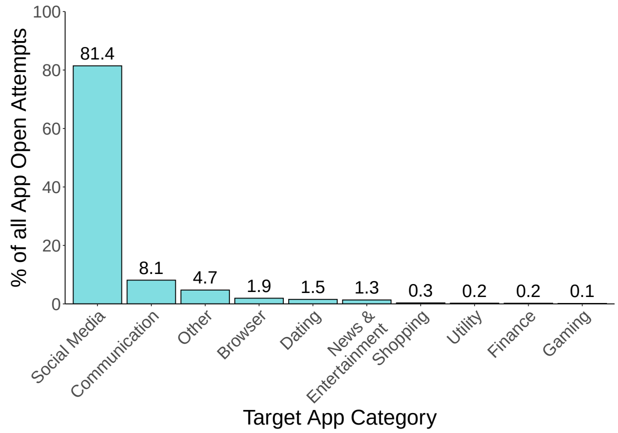
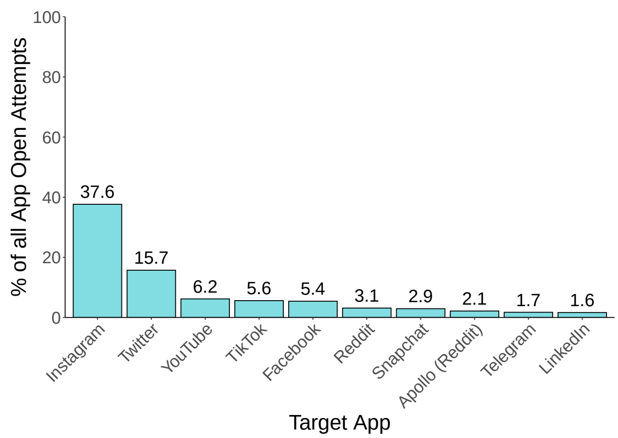


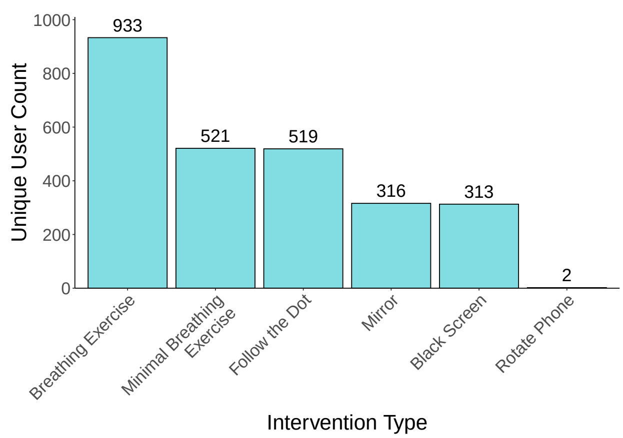
Figure 4: The distribution of the length of recorded usage data each participant contributed to the study. As all of the data is historical usage, a shorter length indicates that the user downloaded *one sec* more recently.



(a) Distribution of app open attempts across app categories. Over 80% of all open attempts target a social media app.



(b) Percentage of total app opens associated with the 10 most opened apps. Instagram is the most common target app.



(c) The distribution of interventions. Breathing Exercise (the default setting) was the most common setting, employed by 90% of users.

Figure 5: The most common target apps and interventions.

3.4 Qualitative Online Survey

The qualitative online survey prompted six open-ended text questions and demographic questions on gender and age. The text questions were centered around individuals' motivation to start using *one sec*, the benefits and drawbacks of using *one sec*, the individuals' perceived use and setup patterns, their feature wishes, and finally, any other open feedback. The survey questions are included in the supplementary material.

One author analyzed the qualitative quotes from the online survey using a top-down, non-exhaustive coding method. Two authors then discussed the codes. We let the qualitative analysis be guided by our quantitative findings, similar to Lukoff et al. [39]. As such, we do not introduce any new results solely based on the qualitative data, but rather the insights should be observed as supplemental to our quantitative insights.

4 RESULTS

We collected 1,318,331 interactions across 1,039 participants for an average of 1,268 interactions per person. In this, an interaction refers to an attempt to open an app that was interrupted by *one sec*. The participants, on average, used *one sec* for 13.4 weeks (SD = 15.2 $weeks$, max = 128 $weeks$). The collected quantitative data serve as objective measures of use that we triangulate with responses from the online survey to reveal subjective experiences with *one sec* and its perceived effectiveness.

In the following, we present the results of our mixed-method analysis divided by our research questions. First, we address motivations for using design frictions. Next, we present results related to how users set up and use the app in practice. Finally, we present findings relating to usage over time and periodic breaks.

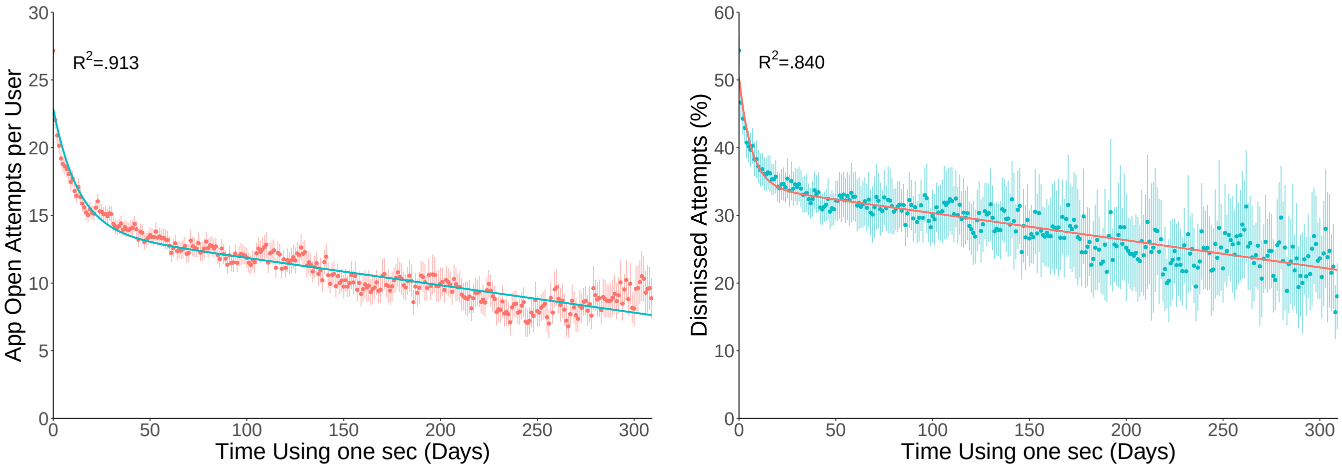
4.1 Motivations for Use (RQ1)

Over 80% of the interventions target social media apps (see Figure 5a), predominantly Instagram (see Figure 5b). All 1,039 users (100%) had at least one app open attempt associated with a social media app.

A qualitative analysis of participants' answers to the question of why they began using *one sec* corroborates this information. 62% of participants (n = 154) use the phrase *social media* or the specific names of popular social media platforms such as Instagram and Facebook when explaining their reasons for adopting *one sec*. Additionally, 103 participants expressed their intent to manage the *time* they spent on their smartphones, while 36 participants used phrases related to *mindfulness, mindlessness, awareness*, or *intentional use* in their statements, indicating a desire to decrease passive or habitual checking behavior and consequently increase intentional use:

> *"I am tired of mindlessly using my phone and have a difficult time stopping myself. [...] It is so easy to waste time and to actually lose track of time altogether. [...] I hoped one sec would help me reduce my usage and become more thoughtful about spending time on my phone."* (P87)

We also counted motivations that included phrases on *addiction*, *productivity* or *control*. In all, 23 participants mentioned being addicted to smartphone use. Desires for increased *productivity* and



(a) The number of *one sec* interventions (app open attempts) per user per day.

(b) The percentage of interventions resulting in the user *not* continuing to the intended app.

Figure 6: Average user behavior over time. App open attempts and dismissal rates both demonstrate negative trends and are described by exponential models.

decreased *procrastination*, or an increased sense of *control* were present in similar ratios ($n = 24$ and $n = 19$ participants, respectively).

Several participants mentioned seeking the friction mechanism after failing to fulfill their use goals with other solutions, such as iOS' default Screen Time app limits and popups[7], or completely deleting the apps of (dis)interest. These participants found existing mechanisms either not restrictive enough or too restrictive, respectively:

> *"I'd tried things like setting screen time limits and deleting the apps but I always just passed by that or used my browser to access social media or shopping."* (P46)

> *"Rather than just deleting everything, I just wanted to make sure every time I was using these apps was a conscious choice."* (P43)

A subset of participants felt their activities in the physical world were suffering due to their smartphone use, with particular emphasis on their free time:

> *"Breaks at work were wasted, after-work hours not really turned off, etc."* (P2)

4.2 Setup and Use in Practice (RQ2)

4.2.1 Interventions Setup. We analyze how participants set up and use the different types of design frictions, which we refer to as intervention types, introduced in Table 1. On average, participants set up 2.51 different intervention types ($SD = 1.52$, $\tilde{x} = 2$). Figure 5c shows the distribution of how many unique participants used each of the six intervention types. The default Breathing Exercise intervention type was used by 90% of the participants at some point ($n = 933$).

[7]https://support.apple.com/guide/iphone/set-up-screen-time-for-yourself-iphbfa595995/ios

The average duration of the interventions, i.e., the design frictions, is 7.82 seconds long ($SD = 7.77\ s$, $\tilde{x} = 6\ s$, $max = 560\ s$). Again, 90% of participants ($n = 937$) used the default intervention duration of 6 seconds in at least one intervention setup. Participants set up an intervention for 3.73 different target apps on average ($SD = 2.9$, $\tilde{x} = 3$, $max = 26$).

We analyzed the variety in intervention setups based on the appearance of different chains of *target app – intervention type – intervention duration* within the data set for each participant. We found that participants are confronted with 28.4 different intervention setups on average ($SD = 52.7$, $\tilde{x} = 8$, $max = 426$). The most popular intervention setup among our participants is a 6-second Breathing Exercise for the Instagram app ($n = 641$ participants). The top five chains all have a duration of 6 seconds. Three of the top five include Instagram (641, 279, and 265 participants, respectively), with Twitter (279 participants) and YouTube (252 participants) being the other two.

Qualitative insights gathered from participants showcase a wide range of setups and *one sec* usage patterns. Whereas some participants invest significant time and effort in customizing their settings to enhance self-efficacy, others opt for simpler and default configurations, with numerous variations in between. These diverse setup patterns highlight the personalized nature of individuals' requirements when it comes to determining the level of restrictiveness and effectiveness of *one sec*:

> *"I use more or less a majority of all the settings, on occasion I will tweak them to see what works best for me so say currently I'm trying shorter times to see if the impact is any different. I'm using it for YouTube (mainly because of the Shorts, which lead to doom scrolling till 4am. . .), Amazon (to see if I save money, need more time on that one to see!), and previously Twitter which I had on much stricter settings."* (P35)

> *"I used the deep breathing setting. Tried them all out including the journaling and I think the simplest is working for me the best and least irritating."* (P130)

Several participants reported the time restrictions imposed by *one sec*'s interventions to sometimes interfere with their typical ways of using target apps, resulting in usability issues:

> *"I only set Instagram because I often want to take snapshots with Snapchat, which requires a quick opening."* (P19)

However, a few participants expressed feelings of being overwhelmed when setting up the interventions in *one sec*. As the app offers various intervention options and customization features, users likely find it challenging to determine the most suitable settings to align with their specific usage patterns and preferences:

> *"I would use the blocking sessions but I can't figure out how to configure that properly."* (P122)

4.2.2 Use in Practice. Figure 6 shows the number of *one sec* interventions per user over time. For each intervention, the user either continues to their intended app or closes *one sec* and does not continue (labeled as a dismissed attempt). Overall, users continued to the target app on 67.0% of open attempts and dismissed opening the target app 33.0% of the time.

Participants mentioned their app openings to be of increased instrumental value thanks to *one sec*, yet at times report struggling due to the dual nature of apps, e.g., Instagram can serve as both a content consumption platform and a means of social interaction through messages.

> *"Sometimes if I'm looking for something specific (for example, looking at my favourite paper crafting profile on Instagram for journaling ideas) or if I'm creating a post for an organisation, I'll have to open up the apps despite the intervention, but if I'm just bored, I'm more easily encouraged to do something else."* (P88)

> *"Yesterday I also set it up for Instagram and it [is] definitely harder since I use Instagram more as a social platform. It's difficult when the messages come into the same app that you're overusing."* (P93)

4.3 Usage Over Time (RQ3)

We investigated whether there is a significant change in total and dismissed attempts over time, shown in Figure 6.

First, regarding total open attempts, Mann-Kendall trend testing revealed a significant negative trend for app open attempts per user per day ($\tau = -0.772$, $p < .001$). However, as seen in Figure 6a, the slope is steeper at the beginning and levels out over time. Consequently, we fit an exponential function to the data using a non-linear least squares regression and tested it against a linear model. We found a significant difference between the models and a large effect size ($F(2, 306) = 288$, $p < .001$, $\eta = .485$), indicating that the exponential fit describes more of the variance in the data. The exponential component captures the steep decline in initial use and demonstrates that users reduce their app open attempts over time while using the design friction intervention.

For the percentage of dismissed attempts per day, visualized in Figure 6b, Mann-Kendall trend testing revealed a significant negative trend ($\tau = -0.721$, $p < .001$). We again fit an exponential function to the data using a non-linear least squares regression method and tested it against a linear model. We found a significant difference between the models ($F(2, 306) = 104$, $p < .001$, $\eta = .253$) and a large effect size. Once again, this indicates that the exponential model is a better fit for the data and explains the initial steep decline. This indicates that users tend to dismiss opening target apps at a lower ratio and, therefore, continue to target apps in a larger fraction of attempts over time.

Correspondingly, qualitative statements report that more recent opening attempts are more intentional rather than being rooted in automated actions, as the following quotes demonstrate:

> *"In the beginning, after the intervention, I was not continuing to the apps often because I had been clicking on to them mindlessly and the intervention grounded me. Now, I usually continue to the app but it's because when I click on it I tend to have an objective."* (P43)

> *"I have noticed that I opened apps more 'on purpose,' which resulted in me actually using the app almost every time the intervention was shown."* (P6)

Many participants reported having undergone some sort of self-control *"training"* (P57) to *"brain rewir[ing]"* (P1), with some participants explicitly describing the long-term effects of decreased use, pursuing alternative activities, or embracing boredom.

> *"[M]y screen time has gone down from 3 hours to less than 1hr daily - most of which is texting or calling my girlfriend or taking notes on apple notes. [I] consider that exactly how [I] want to use my phone so [I] wouldn't want to reduce my screen time further. [I]'ve kicked my [R]eddit, [I]nstagram, and [Y]outube habits largely thanks to one sec. With that additional time, [I] read, meditate, write, walk, and spend more time with friends. The effects have now lasted for over 2 months so they feel fairly securely lifestyle changes not just a digital diet as it were."* (P100)

> *"The app has definitely made me appreciate how productive boredom can be, instead of just going on my phone I can use it to do creative, or important things."* (P79)

Yet, there are still participants who report getting used to the friction in the long run, with the initial annoyance fading.

> *"After using the app for a couple months I think my brain has gotten used to the waiting before an app opens. It is no longer an inconvenience or annoying thing to enter the app it's just something that I have to do to get into Instagram and that has kind of make the waiting redundant as it doesn't stop me as much as it did at the start of my use with the app."* (P162)

Regarding days of the week, we found no significant differences between the normalized app open attempts per user on different days of the week ($p > .05$).

4.4 Periodic Breaks (RQ3)

Motivated by RQ3, we sought to identify usage patterns beyond the overall trends presented in Section 4.3. We found that a notable

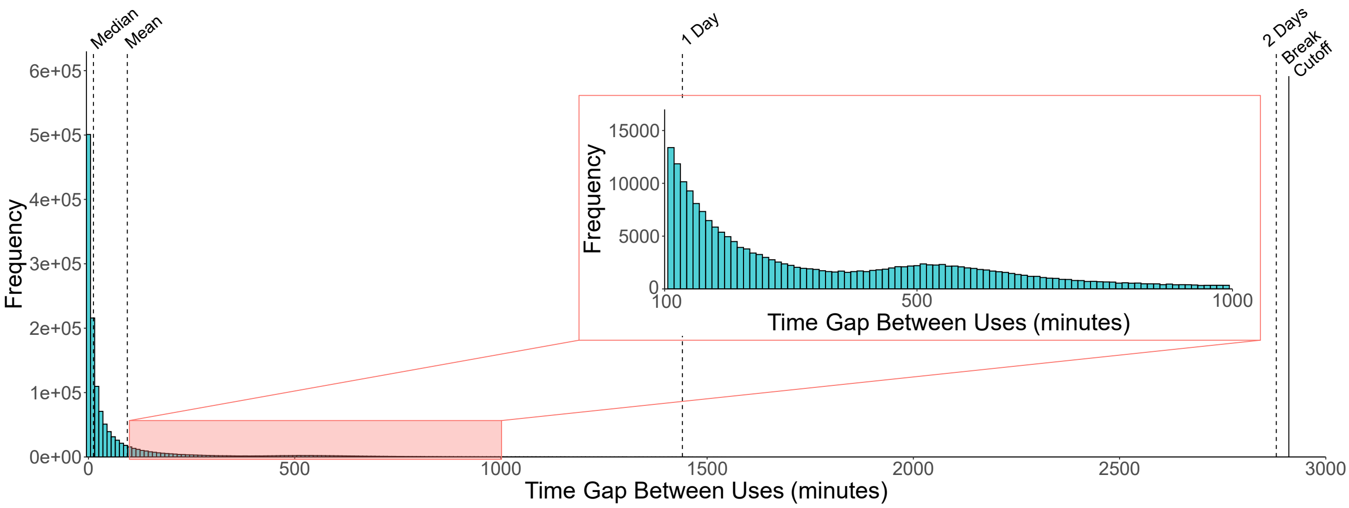


Figure 7: The distribution of the lengths of breaks taken by users. There is a notable bump in frequency around 500 minutes, which is equal to 8.3 hours and likely corresponds to time spent sleeping.

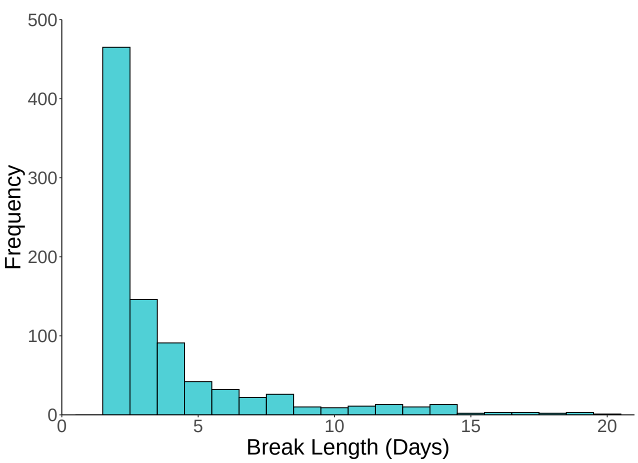


Figure 8: The distribution of the lengths of breaks taken by users – most breaks are approximately two days in length.

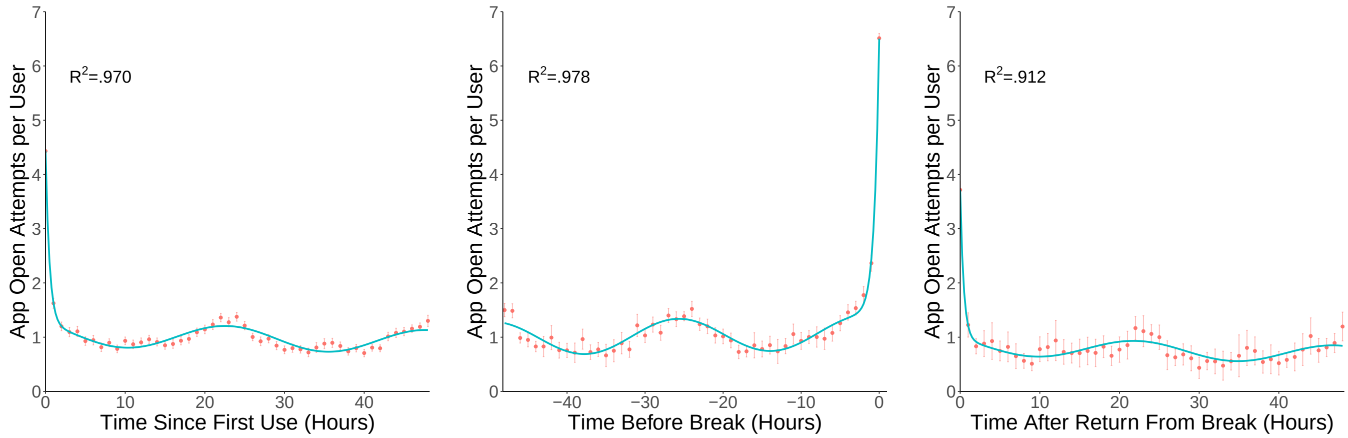
portion of users had large gaps between usage sessions. Based on this observation, we sought to analyze usage patterns before and after periods of non-use. In particular, in the following section we identify a cutoff point to differentiate a "break" (i.e., temporarily ceasing to use *one sec*) from a normal gap between uses. We then characterize usage before and after breaks, and investigate if breaks are more likely to occur on certain days of the week.

4.4.1 Defining a Break. To identify the cutoff point defining a break, we used an outlier method. We define an upper outlier as any gap between successive uses that is greater than two standard deviations above the mean. As shown in Figure 7, the distribution is heavily skewed towards short gaps and has a very long tail. The mean gap time is 78.4 minutes ($SD = 1280\ min$, $\tilde{x} = 12.0\ min$), resulting in a cutoff point of 2,890 minutes (48.2 hours or 2.01 days).

Based on this cutoff, we see that there are 280 users (26.9%) with at least one break and 970 total breaks, an average of 3.46 breaks per user with at least one break. Breaks ranged from 48 to 17,323 hours (2 to 721 days), with a mean length of 220 hours (9.15 days). The distribution of break lengths is shown in Figure 8, revealing that approximately two days was the most common break length.

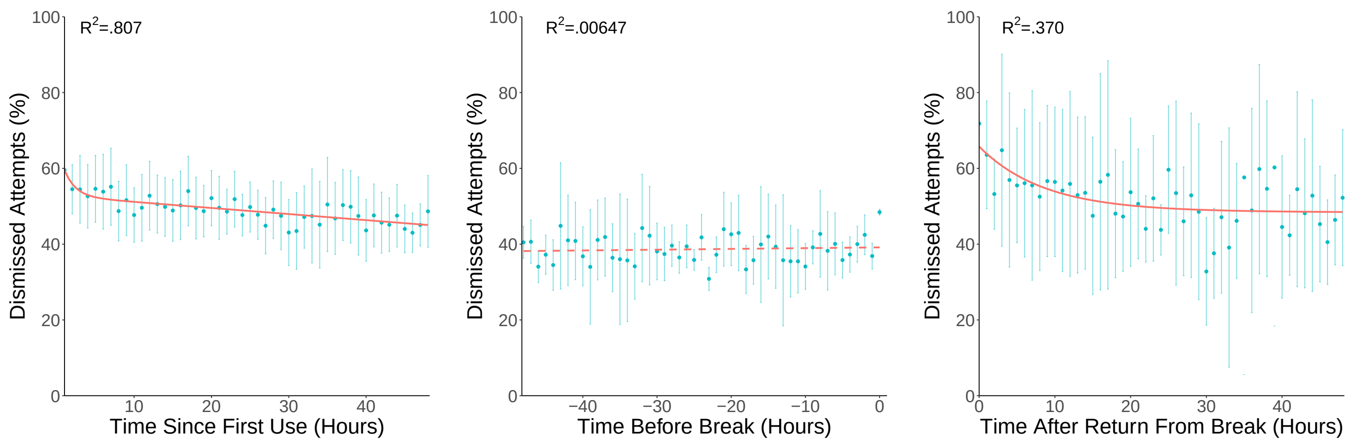
4.4.2 Usage Patterns Before and after Breaks. We examined the hours immediately before and after a break. For this analysis, we used the break length (48.2 hours) as a cutoff and captured snapshots from each user aligned to the beginning and end of each break instance. The total app open attempts per hour are visualized in Figure 9 for the first hours of use, the hours preceding a break, and the hours immediately following a return from a break. Mann-Kendall trend testing revealed a significant positive trend leading up to a break ($\tau = 0.238$, $p = .0165$), while the first hours and hours after returning from a break showed no significant monotonic trend. To further characterize the usage patterns, we fit linear, sinusoidal, exponential, and sinusoidal-exponential models to the data using a non-linear least squares regression. We considered sinusoidal functions because daily fluctuations are visible in the hour-scale data. Guided by BIC criteria [4, 57] for all converging models, we found that sinusoidal-exponential models fit the data best for all three scenarios, first use ($F(4, 42) = 260$, $p < .001$, $\eta = .432$), pre-break ($F(4, 42) = 359$, $p < .001$, $\eta = .449$), and post-break ($F(4, 42) = 87.7$, $p < .001$, $\eta = .402$). The models for first use and post-break both characterize a steep decline from initially high usage followed by periodic fluctuations on a 24-hour cycle. The pre-break model identifies a similar 24-hour fluctuation period followed by a steep increase immediately before the break occurs.

We also examined the ratio of open attempts where users chose to dismiss opening the target app, shown in Figure 10. Mann-Kendall trend tests revealed significant negative trends after the first use ($\tau = -0.590$, $p < .001$) and after returning from a break ($\tau = -0.364$, $p < .001$), and no significant trend leading up to a break. We again conducted non-linear least squares regression guided by



(a) Hourly usage after first use. **(b) Hourly usage before a break.** **(c) Hourly usage following a break.**

Figure 9: App open attempts per user per hour for 48 hours after first use, preceding a break, and after returning from a break. All three patterns are described by sinusoidal-exponential models with 24-hour periods.



(a) Hourly dismissal rates after first use. **(b) Hourly dismissal rates before a break.** **(c) Hourly dismissal rates following a break.**

Figure 10: Dismissal rates for 48 hours after first use and after returning from a break show negative trends and are fit by exponential models, while dismissal rates preceding a break have no significant fit.

BIC criteria [4, 57]. The hours after first use and following a break are both best described by exponential models ($F(1,45) = 137$, $p < .001$, $\eta = .391$) and ($F(1,45) = 26.4$, $p < .001$, $\eta = .126$) respectively, while we found no significant results for the hours leading up to a break. The negative trends identified by Mann Kendall testing for first use and post-break are reflected in the exponential models, highlighting that users dismiss opening the target app less often over time. The dismissal rate leading toward a break does not appear to exhibit any meaningful characteristics.

4.4.3 Days of the Week. We investigated whether Day of Week has a significant impact on when users begin and return from breaks (Figure 11).

To characterize when users begin breaks, we conducted a linear mixed-effects analysis to investigate whether Day of Week is a significant predictor. We fit a linear mixed model ($R^2 = 0.16$) with a REML and nloptwrap optimizer random intercept for individual participants according to the formula: `count ~ day_of_week + (1|participant)`. The model's intercept corresponds to Wednesday at 1.37 ($CI_{95\%} = [0.97, 1.77]$, $t_{616} = 6.70$, $p < .001$) Within the model, Friday shows a significantly positive effect, with a beta value of 0.793 ($t = 2.96$, $p = .00318$), while all other days have non-significant negative effects, excepting Saturday, which has a non-significant positive effect. This finding indicates that users are significantly more likely to begin a break on a Friday.

Similarly, for returning from breaks, we fit a linear mixed-effects model ($R^2 = 0.12$) to investigate the impact of Day of Week. We used the same formula (`count ~ day_of_week + (1|participant)`) with a random intercept for individual participants. The intercept corresponds to Wednesday at 1.32 ($CI_{95\%} = [0.95, 1.68]$, $t_{628} = 7.09$,

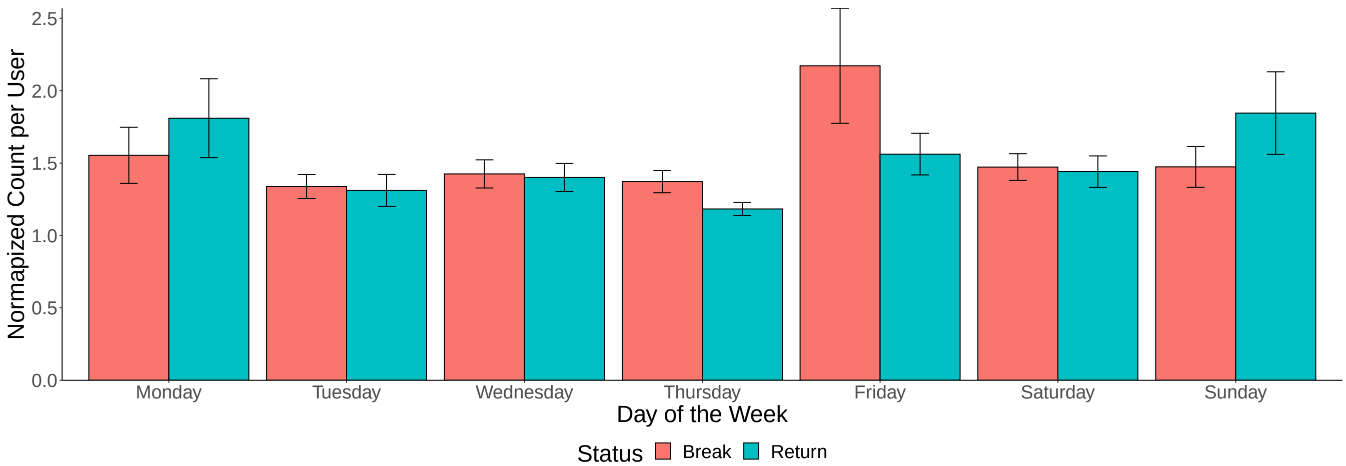


Figure 11: The distribution of app open attempts per user on each day of the week for the last entry before or after a break.

$p < .001$). We found a significant positive effect for Sunday, demonstrated by a beta value of 0.497 ($t = 1.97$, $p = .0499$). All other days have non-significant effects, with Monday, Friday, and Saturday being positive and the rest negative. These findings indicate that users are most likely to return from a break on a Sunday.

4.4.4 Qualitative Insights on Breaks. Several participants reported that they intentionally tweaked their settings to take a break from *one sec* interventions when they found themselves with excess free time, such as during holidays or leisure time. This might explain the increased likelihood of taking breaks on Fridays in Figure 11, as the users would have free time on the coming weekend.

> *"I switch [one sec] off sometimes (if I'm on holiday and I know I want to post on social media a lot) but as soon as I notice I'm spending a few hours watching Reels I NOTICE now and I actively go back to one sec to switch it back on. It's definitely made me more mindful of the apps I'm using, even if I am still sinking time into them."* (P209)

> *"Not sure if this is the app or it's me (probably me) but I find myself changing my 'blocking schedule' if I'm free and bored."* (P168)

5 DISCUSSION

Our work contributes to research in digital wellbeing and HCI with findings from a large data set of design friction interventions, collected organically and in-the-wild with a commercially available mobile app, to tackle absentminded and excessive smartphone use. We guided our explorations with the three research questions. (**RQ1**) *What motivates smartphone users to employ design friction interventions in practice?* (**RQ2**) *How do users set up and use design friction interventions in practice?* (**RQ3**) *How do design frictions impact user behavior over time in everyday use?* We discuss how our findings relate to these research questions and highlight insights into how users organically engage with smartphone overuse interventions in long-term practice.

5.1 Users Employ Design Frictions to Target Social Media (RQ1)

Our results show that users overwhelmingly target social media apps with the design friction intervention. Within our data set, every user had at least one open attempt targeting a social media app, over 80% of the total open attempts for all users were social media apps, and 62% of survey participants specifically mentioned social media as motivation for using *one sec*. This finding echoes results in related work with users recruited to use the same app as a research tool, which reports similar levels of social media use [17]. Such findings from within a study setting appear to translate directly to usage patterns in organic users in the wild. Indeed, currently, three out of five most downloaded mobile apps worldwide belong to the social media category, with TikTok and Instagram leading the way[8]. Interestingly, these results are in striking contrast with the seminal work from just over a decade ago by Böhmer et al. [5], which found communication to be the dominant category of smartphone use (49.5%), with social media in third place (4.77%). Although they measured total app open attempts, while we only record open attempts for apps that users have chosen to target, they report communication app launches to be approximately ten times more than social media launches, while our results show that users launched social media apps ten times more often than communication apps. Besides suggesting that smartphone usage patterns have changed over time, resulting in a larger share of total usage for social media apps, this difference possibly represents a vast gap in importance that users place on limiting social media compared to communication.

The prevalence of social media in our blocked apps results suggests that, rather than targeting smartphone use [10, 13, 38, 42], smartphone non-use [20], or absentminded smartphone use [76], researchers should be specifically investigating interventions for *social media* overuse. There is a growing body of related work

[8]https://www.statista.com/statistics/1285960/top-downloaded-mobile-apps-worldwide/, last accessed: February 8, 2024

investigating potential negative impacts of social media use in particular, including degraded memory performance [7, 69] and links to anxiety and depression [60]. Other research has suggested that passive social media use contributes to feelings of meaninglessness in smartphone use [42] and that specific design features of social media platforms decrease users' sense of agency [40]. There is a growing number of studies in HCI that already target social media overuse, e.g., Youtube [39], Facebook [44], Twitter [85] or Instagram [8], among others. Our results now provide a strong justification to persist in this targeted focus on social media overuse rather than overall smartphone use.

5.2 Use in Practice (RQ2)

Our analysis reveals that participants most commonly employ the Breathing Exercise friction for the duration of 6 seconds. On average, participants opt for two intervention types, indicating that users do try out the available options to a minimal extent but rarely employ a wide range in practice. The least employed friction was the Rotate Phone option. We interpret this result as a consequence of the Rotate Phone friction being the most noticeable option, discouraging its use in public. When considering unique intervention combinations (i.e., target app – intervention type – intervention duration), we see a wider variance of setups with an average of 28.4 different setups per participant. However, this can be traced to a feature in the app where users can optionally incrementally increase or double the design friction duration with each app opening attempt. Overall, these results reflect the trend towards using the default setting demonstrated in Figure 5c and the most common target apps, shown in Figure 5b.

As such, these findings align with previous work on notification management [81] and contextually-adaptive smartphone overuse tools [75], suggesting that few users actively seek to customize a technological solution. Correlating these findings with participant's technological affinity might offer insights into which participants actively engage in customization. Consequently, some users may not have the motivation or awareness to invest time in customizing their system [3, 46], even though customization has demonstrated its ability to enhance system usability and overall user experience [82]. These results suggest two research directions for future work. First, more efforts are needed to explore relevant default settings based on, e.g., participant's context or intervention goal. Second, as has been explored in other works [22, 65, 67], we need more investigations into how to automatically adjust settings to users' specific contexts. However, replacing manual customization with automated settings can lead to users mistrusting a system or feeling that they have relinquished control [16].

5.3 Less, But More Intentional, Use Over Time (RQ3)

Our results demonstrate that users significantly reduce the frequency at which users attempt to open target apps over time when using a design friction intervention. This can be seen in Figure 6a, which shows that the total app open attempts over time decreases exponentially. However, we also see that the rate at which users dismiss continuing to the target app decreases over time. These results together mean that although users are reducing the number of open *attempts* over time, they are actually opening the target apps on a greater fraction of those attempts. This might suggest that users are being more intentional with their app open attempts over time, and are attempting to open their target apps when they truly intend to use those apps, as qualitative statements confirm. As highlighted in 4.1, users were motivated to try design frictions in an effort to make their usage "*more thoughtful*" instead of only decreasing time spent engaged with their devices. This finding corroborates the benefits of micro design frictions discussed by Cox et al. [11].

Mindful use has become a focus of recent related work in HCI. For example, Lukoff et al. [42] investigated factors leading to meaningfulness in smartphone use and identified habitual use, entertainment, and passive social media as motivators for meaninglessness and loss of autonomy. Other recent work has attempted to shift the prior focus in the field from restricting use through abstinence [45, 83] towards more intentional and mindful use [76, 79]. The goal of such works is for users to regain autonomy and control over their own behavior and to use their phones in a way that aligns with their own values [20]. Based on these goals, the design frictions implemented in *one sec* appear to be successful. Users are attempting to open self-identified problem apps less often but more intentionally.

Design frictions in other research works have also reported success in reducing usage [27, 76], suggesting that this mechanism is a useful mechanism in tackling absentminded smartphone use. These findings stand in somewhat contrast to previous results on the failure of (insufficiently) restrictive solutions to tame smartphone addiction, as described in [50]. Whereas we do not report any effects on screen time as a proxy for smartphone addiction, the qualitative statements suggest an increase in satisfaction with participant's patterns of smartphone use. As one potential research direction, future work could explore the personal differences in preferences for interventions.

Although we see that the overall app open attempts decrease over time, the steep exponential decrease at the beginning of use has important consequences for research in digital wellbeing. In Figure 6a, the decrease in app open attempts begins to flatten after approximately 20 days of use (roughly 3 weeks). This suggests that the largest behavior changes for smartphone overuse interventions should be present within the first three weeks of use. Although not conclusive, this finding suggests that smartphone intervention experiments could be conducted over a three-week period to understand the magnitude of their behavioral impact. Given that many related works conduct two- to four-week field experiments (e.g., [20, 26, 27, 76]), this finding reflects positively on the methods currently employed in the research field.

Our results build on the investigation by Grüning et al. [17]. Where their study involves new *one sec* users, we contribute a new perspective by recruiting existing users of the app to contribute their historical usage data (i.e., usage that occurred when they were not yet aware of being in a study). Grüning et al. [17] report app open attempts with a similar level to our results and a similar decrease over the six weeks. We also extend these results by providing data over a longer period of time (13.4 weeks on average) and additionally by identifying and characterizing breaks as a behavior pattern. Grüning et al. [17] also investigated the impact of different mechanisms – a message, a friction, an option to dismiss, and a combination – relative to a control. They found that offering the option to dismiss consumption had the strongest effect. Accordingly, we expect that the same mechanism explains the behavioral changes seen in our study.

5.4 Spontaneous Break Taking with a Quick Rebound (RQ3)

Guided by RQ3, we investigated our dataset for usage patterns over time beyond the decrease in overall use. We identified that over one-quarter of the participants took at least one break from the design frictions. We see (Figure 9 and Figure 10) a sharp increase in use immediately preceding a break, which is echoed by high usage the first hour after ending the break. However, similar to when users first start using the intervention, the number of open attempts quickly drops. The fact that usage only rises shortly before a break may indicate that the decision to pause the intervention is an in-the-moment choice rather than a slow build-up towards frustration or a steady decline towards self-sufficiency. This in-the-moment decision-making is consistent with prior work showing that smartphone overuse is associated with short-term decision-making at the expense of long-term benefits [72].

Concurrently, our findings show that users are significantly more likely to begin a break on a Friday and return on a Sunday. This usage pattern suggests a weekend cycle where users either schedule the app not to intervene on weekends or otherwise periodically disable the functionality on weekends. As results in the qualitative findings suggest, some users wish they were able to separately block different parts of apps (e.g., separate messaging from Instagram). This coupling could explain the weekend break pattern, as users may wish to use the communication functions of the target social media apps. This also aligns with previous work [9] on more nuanced interventions – one where users can specify not only target apps but target functions or tabs in apps.

Past work has discussed activating smartphone overuse interventions periodically [76]. This periodic intervention scheme echoes the way we take medicine to treat acute conditions, with specified doses at a predetermined frequency (e.g., once per day), rather than acting as a continuous crutch. This approach encourages self-efficacy and relies on the effects of a smartphone overuse intervention lasting beyond its active implementation. If this were true, it would theoretically be possible to calculate the rate at which user behavior returns to unwanted levels, and a dosage schedule could be developed. However, our results suggest that this may not be the case. Users periodically took breaks from *one sec*, and we see that usage sharply increases preceding a break, and when users return from a break, they also have high usage. Similar to when users initially installed the intervention, their usage quickly drops back down within a matter of hours after re-activating the intervention. These results suggest that the impact of the design friction does not last beyond its application. However, as users recover quickly from breaks and overall usage continues to trend down over time, our results also suggest that periodic breaks from the intervention are not detrimental to the overall goal of reduced, more intentional usage.

Our results, which highlight that periodic spontaneous breaks are a relatively pervasive phenomenon, motivate the need for future studies to investigate break-taking in more detail. In particular, a future study could be designed to characterize usage patterns while on a break, which we did not measure inherently due to that activity occurring outside of the influence of *one sec*.

5.5 Reflection on Methodology for Long-Term Evaluations

We conducted this investigation by recruiting existing, organic users of a commercially available mobile app to donate their historical usage data. This study design has several advantages as well as several notable disadvantages to acknowledge. There is, overall, a lack of truly in-the-wild field studies in HCI, as highlighted by the emphasis on field *experiments* in these reflections on mobile HCI research methods [28, 29]. Furthermore, wellbeing self-control tools have so far been evaluated within a rather short time frame of an average duration of 3.22 weeks (SD = 1.49), as a recent systematic review suggests [64]. Since users donated their data retrospectively, the information represents their behavior when they are not being observed. As such, these insights provide an invaluable opportunity to investigate whether findings observed in lab studies and field experiments translate to real users in practice. This data collection methodology also enabled us to collect usage data over a relatively longer period of time (13.4 weeks on average for a maximum of 128 weeks, $SD = 15.2$ *weeks*). Actively conducting a field experiment for this amount of time would require considerable effort. One of the primary disadvantages of this methodology is that we have much less control over the study. All of the data is collected retrospectively, and therefore, we could not apply constraints or controls in advance. As we rely on a commercially available mobile app as a data collection tool rather than a custom-built research platform, we also had less control over the user experience and interventions. This absence of control is, of course, balanced by the ecological validity of our data and the fact that *one sec* consistently, i.e., with fewer programming bugs as a commercial tool, incorporates many features highlighted in past work on smartphone overuse (see Section 3.1).

We made data privacy a priority in our data collection methodology. Participants were recruited through a passive banner that appeared for all users, and they were able to join the study directly without any direct contact with the research team. Each user was assigned a UUID through the app, ensuring that the participants maintain complete anonymity. When we rolled out the qualitative online survey, we recruited users through the app. This banner was displayed to users who had already donated their data to the original study, and their responses are correlated through UUID only. As such, we were able to maintain full anonymity throughout the study and were still able to reach out to users for additional data collection.

5.6 Limitations & Future Work

One limitation to our work is due to our study design. Although collecting historical data from existing users has clear benefits and is one of the main contributions of our work, there are also disadvantages to this method. For one, as the datasets were contributed by existing users, it is inherently not possible to capture dropout patterns and attrition rates. Additionally, since the data is collected by *one sec*, we do not have usage information from before installation, nor do we have usage information for apps not associated with *one sec*. Our data collection method is aligned with a privacy-first approach. It would be highly interesting for future work to use an alternative study design to answer additional research questions. In particular, recruiting users to install *one sec* and then collecting data for several weeks before implementing any interventions would enable a within-subjects control to robustly quantify the effectiveness of the interventions. Such a study setup could enable dropouts to be identified, although the motivation of participating in a study would likely bias this measure. Collecting additional usage data for apps not associated with *one sec* could provide even further insights as to whether the interventions reduce overall smartphone use, but this would be considerably more privacy-invasive and would thus require additional ethical considerations. In these alternative study designs, as well as in ours, there is a self-selection bias. The participants represent users who think that they are overusing their phones and are attempting to solve the problem. Yet, such users are exactly the target demographic for such interventions, which mitigates any negative impacts from the self-selection bias.

A second limitation to our work is that we did not collect sociodemographic information for all of the participants in the study. We intentionally designed the initial sign-up process for users to have low overhead and to preserve anonymity. However, a subset of participants voluntarily provided demographic information when participating in the online survey. As such, we have demographic information from a representative sample of 24% of the study population. As sociodemographic variables were not the primary focus of our research, we determined that collecting a representative sample is satisfactory for the purposes of this work.

Another limitation to our work is the fact that we do not have location information for the participants. As such, we were unable to reliably conduct any analysis on time-of-day usage, as the participants were likely spread across multiple time zones. Although we acknowledge this limitation, our work now motivates future research to delve deeper into patterns of use associated with in-the-wild design friction users.

Furthermore, our top-down, non-exhaustive qualitative analysis might be limiting in the fact that, by complementing quantitative results only, we potentially confirm existing biases and miss the discovery of unexpected and more nuanced insights. However, this method of analysis provides additional insightful context to the quantitative data and serves as a useful initial step before moving into subsequent in-depth qualitative explorations.

Finally, due to the nature of mobile operating systems and our data collection methodology, we do not have information about overall screen time or usage of any apps that the users did not associate with *one sec*. This limits the insights we can glean from the data regarding smartphone use *in general*, but our research focuses on the subset of smartphone use that users identify as problematic for themselves. With this focus in mind, the information we collected is appropriate to investigate our research questions.

6 CONCLUSION

In this paper, we investigated how users interact with design frictions to prevent smartphone overuse. We recruited 1,039 existing users of a commercially available mobile app for smartphone overuse, *one sec*, to contribute their historical usage data. The participants contributed an average of 13.4 weeks of usage data and 249 users additionally provided qualitative responses through an online survey. Our results show that users primarily target social media apps and that the design frictions are effective in reducing the number of app open attempts. Users are more intentional in opening target apps over time. Additionally, users take periodic breaks from the intervention and quickly regain control of their smartphone use after the breaks. Overall, we contribute results from a longitudinal in-the-wild investigation into smartphone overuse intervention behaviors. Our results contribute to a future in which users are mindfully in control of their own smartphone behaviors, leading to a more symbiotic relationship between users and their phones.

7 OPEN SCIENCE

In order to facilitate reproducing and extending our results and analysis, our dataset and analysis scripts are available online for research purposes: https://github.com/mimuc/one-sec

REFERENCES

[1] Fadi Al-Hadidi, Isam Bsisu, Saif Aldeen AlRyalat, Belal Al-Zu'bi, Rasha Bsisu, Mohammad Hamdan, Tareq Kanaan, Mohamad Yasin, and Omar Samarah. 2019. Association between mobile phone use and neck pain in university students: A cross-sectional study using numeric rating scale for evaluation of neck pain. *PLOS ONE* 14, 5 (May 2019), e0217231. https://doi.org/10.1371/journal.pone.0217231

[2] Meshari F Alwashmi, Beverly Fitzpatrick, Jamie Farrell, John-Michael Gamble, Erin Davis, Hai Van Nguyen, Gerard Farrell, and John Hawboldt. 2020. Perceptions of patients regarding mobile health interventions for the management of chronic obstructive pulmonary disease: mixed methods study. *JMIR mHealth and uHealth* 8, 7 (2020), e17409.

[3] Paritosh Bahirat, Martijn Willemsen, Yangyang He, Qizhang Sun, and Bart Knijnenburg. 2021. Overlooking Context: How do Defaults and Framing Reduce Deliberation in Smart Home Privacy Decision-Making?. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*. ACM, Yokohama Japan, 1–18. https://doi.org/10.1145/3411764.3445672

[4] Dale J. Barr, Roger Levy, Christoph Scheepers, and Harry J. Tily. 2013. Random effects structure for confirmatory hypothesis testing: Keep it maximal. *Journal of Memory and Language* 68, 3 (2013), 255–278. https://doi.org/10.1016/j.jml.2012.11.001

[5] Matthias Böhmer, Brent Hecht, and Johannes Schöning. 2011. Falling asleep with Angry Birds, Facebook and Kindle: a large scale study on mobile application usage. In *MobileHCI*. ACM, Stockholm, Sweden, 10.

[6] Nancy A. Cheever, Larry D. Rosen, L. Mark Carrier, and Amber Chavez. 2014. Out of sight is not out of mind: The impact of restricting wireless mobile device use on anxiety levels among low, moderate and high users. *Computers in Human Behavior* 37 (Aug. 2014), 290–297. https://doi.org/10.1016/j.chb.2014.05.002

[7] Francesco Chiossi, Luke Haliburton, Changkun Ou, Andreas Butz, and Albrecht Schmidt. 2023. Short-Form Videos Degrade Our Capacity to Retain Intentions: Effect of Context Switching On Prospective Memory. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems (CHI '23)*. ACM, Hamburg, Germany, 14. https://doi.org/10.1145/3544548.3580778

[8] Hyunsung Cho, DaEun Choi, Donghwi Kim, Wan Ju Kang, Eun Kyoung Choe, and Sung-Ju Lee. 2021. Reflect, Not Regret: Understanding Regretful Smartphone Use with App Feature-Level Analysis. *Proc. ACM Hum.-Comput. Interact.* 5, CSCW2, Article 456 (oct 2021), 36 pages. https://doi.org/10.1145/3479600

[9] Hyunsung Cho, DaEun Choi, Donghwi Kim, Wan Ju Kang, Eun Kyoung Choe, and Sung-Ju Lee. 2021. Reflect, Not Regret: Understanding Regretful Smartphone Use with App Feature-Level Analysis. *Proc. ACM Hum.-Comput. Interact.* 5, CSCW2, Article 456 (oct 2021), 36 pages. https://doi.org/10.1145/3479600

[10] Emily I. M. Collins, Anna L. Cox, and Ruby Wootton. 2015. Out of Work, Out of Mind?: Smartphone Use and Work-Life Boundaries. *International Journal of Mobile Human Computer Interaction (IJMHCI)* 7, 3 (July 2015), 67–77. https://doi.org/10.4018/ijmhci.2015070105

[11] Anna L. Cox, Sandy J.J. Gould, Marta E. Cecchinato, Ioanna Iacovides, and Ian Renfree. 2016. Design Frictions for Mindful Interactions: The Case for Microboundaries. In *Proceedings of the 2016 CHI Conference Extended Abstracts on Human Factors in Computing Systems* (San Jose, California, USA) *(CHI EA '16)*. Association for Computing Machinery, New York, NY, USA, 1389–1397. https://doi.org/10.1145/2851581.2892410

[12] Thomas H. Davenport and John C. Beck. 2001. *The attention economy: Understanding the new currency of business*. Harvard Business Press.

[13] Kadir Demirci, Mehmet Akgönül, and Abdullah Akpinar. 2015. Relationship of smartphone use severity with sleep quality, depression, and anxiety in university students. *Journal of Behavioral Addictions* 4, 2 (June 2015), 85–92. https://doi.org/10.1556/2006.4.2015.010

[14] Daniel A. Epstein, Nicole B. Lee, Jennifer H. Kang, Elena Agapie, Jessica Schroeder, Laura R. Pina, James Fogarty, Julie A. Kientz, and Sean Munson. 2017. Examining Menstrual Tracking to Inform the Design of Personal Informatics Tools. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems (CHI '17)*. Association for Computing Machinery, New York, NY, USA, 6876–6888. https://doi.org/10.1145/3025453.3025635

[15] Lisa Fazio. 2020. Pausing to consider why a headline is true or false can help reduce the sharing of false news. *Harvard Kennedy School Misinformation Review* 1, 2 (2020).

[16] Kurt Geihs and Christoph Evers. 2016. User intervention in self-adaptive context-aware applications. In *Proceedings of the Australasian Computer Science Week Multiconference*. ACM. https://doi.org/10.1145/2843043.2843373

[17] David J. Grüning, Frederik Riedel, and Philipp Lorenz-Spreen. 2023. Directing smartphone use through the self-nudge app one sec. *Proceedings of the National Academy of Sciences* 120, 8 (Feb. 2023), e2213114120. https://doi.org/10.1073/pnas.2213114120

[18] Luke Haliburton, Maximilian Lammel, Jakob Karolus, and Albrecht Schmidt. 2022. Think Inside the Box: Investigating the Consequences of Everyday Physical Opt-Out Strategies for Mindful Smartphone Use. In *Proceedings of the 21st International Conference on Mobile and Ubiquitous Multimedia (MUM '22)*. Association for Computing Machinery, New York, NY, USA, 37–46. https://doi.org/10.1145/3568444.3568452

[19] Luke Haliburton and Albrecht Schmidt. 2020. Technologies for healthy work. *Interactions* 27, 3 (April 2020), 64–66. https://doi.org/10.1145/3386391

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

[21] Linda Hirsch, Beat Rossmy, and Andreas Butz. 2021. Shaping Concrete for Interaction. In *Proceedings of the Fifteenth International Conference on Tangible, Embedded, and Embodied Interaction*. ACM, Salzburg Austria, 1–11. https://doi.org/10.1145/3430524.3440625

[22] Rahul Jain, Joy Bose, and Tasleem Arif. 2013. Context based adaptation of application icons in mobile computing devices. In *2013 Third World Congress on Information and Communication Technologies (WICT 2013)*. IEEE. https://doi.org/10.1109/wict.2013.7113104

[23] Michelle Janning, Wenjun Gao, and Emma Snyder. 2018. Constructing Shared "Space": Meaningfulness in Long-Distance Romantic Relationship Communication Formats. *Journal of Family Issues* 39, 5 (April 2018), 1281–1303. https://doi.org/10.1177/0192513X17698726

[24] Matthew Katsaros, Kathy Yang, and Lauren Fratamico. 2022. Reconsidering tweets: Intervening during tweet creation decreases offensive content. In *Proceedings of the International AAAI Conference on Web and Social Media*, Vol. 16. 477–487.

[25] Inyeop Kim, Gyuwon Jung, Hayoung Jung, Minsam Ko, and Uichin Lee. 2017. Let's FOCUS: Mitigating Mobile Phone Use in College Classrooms. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 1, 3, Article 63 (Sept. 2017), 29 pages. https://doi.org/10.1145/3130928

[26] Jaejeung Kim, Hayoung Jung, Minsam Ko, and Uichin Lee. 2019. GoalKeeper: Exploring Interaction Lockout Mechanisms for Regulating Smartphone Use. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 3, 1, Article 16 (March 2019), 29 pages. https://doi.org/10.1145/3314403

[27] Jaejeung Kim, Joonyoung Park, Hyunsoo Lee, Minsam Ko, and Uichin Lee. 2019. LocknType: Lockout Task Intervention for Discouraging Smartphone App Use. *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (2019).

[28] Jesper Kjeldskov and Connor Graham. 2003. A Review of Mobile HCI Research Methods. In *Human-Computer Interaction with Mobile Devices and Services (Lecture Notes in Computer Science)*, Luca Chittaro (Ed.). Springer, Berlin, Heidelberg, 317–335. https://doi.org/10.1007/978-3-540-45233-1_23

[29] Jesper Kjeldskov and Mikael B. Skov. 2014. Was it worth the hassle? ten years of mobile HCI research discussions on lab and field evaluations. In *Proceedings of the 16th international conference on Human-computer interaction with mobile devices & services (MobileHCI '14)*. Association for Computing Machinery, New York, NY, USA, 43–52. https://doi.org/10.1145/2628363.2628398

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

[31] Geza Kovacs, Drew Mylander Gregory, Zilin Ma, Zhengxuan Wu, Golrokh Emami, Jacob Ray, and Michael S. Bernstein. 2019. Conservation of Procrastination: Do Productivity Interventions Save Time Or Just Redistribute It?. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (Glasgow, Scotland Uk) *(CHI '19)*. Association for Computing Machinery, New York, NY, USA, 1–12. https://doi.org/10.1145/3290605.3300560

[32] Geza Kovacs, Zhengxuan Wu, and Michael S. Bernstein. 2018. Rotating Online Behavior Change Interventions Increases Effectiveness But Also Increases Attrition. 2, CSCW, Article 95 (nov 2018), 25 pages. https://doi.org/10.1145/3274364

[33] Geza Kovacs, Zhengxuan Wu, and Michael S. Bernstein. 2021. Not Now, Ask Later: Users Weaken Their Behavior Change Regimen Over Time, But Expect To Re-Strengthen It Imminently. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems (CHI '21)*. Association for Computing Machinery, New York, NY, USA, 1–14. https://doi.org/10.1145/3411764.3445695

[34] Elina Kuosmanen, Aku Visuri, Saba Kheirinejad, Niels van Berkel, Heli Koskimäki, Denzil Ferreira, and Simo Hosio. 2022. How Does Sleep Tracking Influence Your Life? Experiences from a Longitudinal Field Study with a Wearable Ring. *Proceedings of the ACM on Human-Computer Interaction* 6, MHCI (Sept. 2022), 185:1–185:19. https://doi.org/10.1145/3546720

[35] Sakari Lemola, Nadine Perkinson-Gloor, Serge Brand, Julia F Dewald-Kaufmann, and Alexander Grob. 2015. Adolescents' electronic media use at night, sleep disturbance, and depressive symptoms in the smartphone age. *Journal of youth and adolescence* 44, 2 (2015), 405–418.

[36] Andrew Lepp, Jacob E Barkley, and Aryn C Karpinski. 2014. The relationship between cell phone use, academic performance, anxiety, and satisfaction with life in college students. *Computers in human behavior* 31 (2014), 343–350.

[37] Brian Y. Lim, Judy Kay, and Weilong Liu. 2019. How Does a Nation Walk?: Interpreting Large-Scale Step Count Activity with Weekly Streak Patterns. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 3, 2 (June 2019), 1–46. https://doi.org/10.1145/3328928

[38] Karina Loid, Karin Täht, and Dmitri Rozgonjuk. 2020. Do pop-up notifications regarding smartphone use decrease screen time, phone checking behavior, and self-reported problematic smartphone use? Evidence from a two-month experimental study. *Computers in Human Behavior* 102 (Jan. 2020), 22–30. https://doi.org/10.1016/j.chb.2019.08.007

[39] Kai Lukoff, Ulrik Lyngs, Karina Shirokova, Raveena Rao, Larry Tian, Himanshu Zade, Sean A. Munson, and Alexis Hiniker. 2023. SwitchTube: A Proof-of-Concept System Introducing "Adaptable Commitment Interfaces" as a Tool for Digital Wellbeing. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems* (Hamburg, Germany) *(CHI '23)*. Association for Computing Machinery, New York, NY, USA, Article 197, 22 pages. https://doi.org/10.1145/3544548.3580703

[40] Kai Lukoff, Ulrik Lyngs, Himanshu Zade, J Vera Liao, James Choi, Kaiyue Fan, Sean A Munson, and Alexis Hiniker. 2021. How the design of youtube influences user sense of agency. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*. 1–17. https://doi.org/10.1145/3411764.3445467

[41] Kai Lukoff, Cissy Yu, Julie Kientz, and Alexis Hiniker. 2018. What makes smartphone use meaningful or meaningless? *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 2, 1 (2018), 1–26.

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

[43] Ulrik Lyngs, Kai Lukoff, Petr Slovak, Reuben Binns, Adam Slack, Michael Inzlicht, Max Van Kleek, and Nigel Shadbolt. 2019. Self-Control in Cyberspace: Applying Dual Systems Theory to a Review of Digital Self-Control Tools. *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (May 2019), 1–18. https://doi.org/10.1145/3290605.3300361

[44] Ulrik Lyngs, Kai Lukoff, Petr Slovak, William Seymour, Helena Webb, Marina Jirotka, Jun Zhao, Max Van Kleek, and Nigel Shadbolt. 2020. *'I Just Want to Hack Myself to Not Get Distracted': Evaluating Design Interventions for Self-Control on Facebook*. Association for Computing Machinery, New York, NY, USA, 1–15. https://doi.org/10.1145/3313831.3376672

[45] Markus Löchtefeld, Matthias Böhmer, and Lyubomir Ganev. 2013. AppDetox: helping users with mobile app addiction. In *Proceedings of the 12th International Conference on Mobile and Ubiquitous Multimedia* (Luleå, Sweden) *(MUM '13)*. Association for Computing Machinery, New York, NY, USA, Article 43, 2 pages. https://doi.org/10.1145/2541831.2541870

[46] Wendy E Mackay. 1991. Triggers and barriers to customizing software. In *Proceedings of the SIGCHI conference on Human factors in computing systems*. 153–160.

[47] Jeremy Marty-Dugas, Brandon Ralph, Jonathan Oakman, and Daniel Smilek. 2018. The Relation Between Smartphone Use and Everyday Inattention. *Psychology of Consciousness: Theory, Research, and Practice* 5, 1 (March 2018), 46–62. https:

//doi.org/10.1037/cns0000131

[48] Thomas Mejtoft, Sarah Hale, and Ulrik Söderström. 2019. Design Friction. 41–44. https://doi.org/10.1145/3335082.3335106

[49] Jochen Meyer, Merlin Wasmann, Wilko Heuten, Abdallah El Ali, and Susanne C.J. Boll. 2017. Identification and Classification of Usage Patterns in Long-Term Activity Tracking. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems (CHI '17)*. Association for Computing Machinery, New York, NY, USA, 667–678. https://doi.org/10.1145/3025453.3025690

[50] Alberto Monge Roffarello and Luigi De Russis. 2019. The Race Towards Digital Wellbeing: Issues and Opportunities. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems (CHI '19)*. Association for Computing Machinery, New York, NY, USA, 1–14. https://doi.org/10.1145/3290605.3300616

[51] Alberto Monge Roffarello and Luigi De Russis. 2023. Teaching and learning "Digital Wellbeing". *Future Generation Computer Systems* 149 (2023), 494–508. https://doi.org/10.1016/j.future.2023.08.003

[52] Donald A. Norman and Tim Shallice. 1986. Attention to action: Willed and automatic control of behavior. In *Consciousness and self-regulation: Advances in research and theory volume 4*. Springer, 1–18.

[53] S O'Dea. 2020. Smartphone users worldwide 2016-2021. https://www.statista.com/statistics/330695/number-of-smartphone-users-worldwide/

[54] Fabian Okeke, Michael Sobolev, Nicola Dell, and Deborah Estrin. 2018. Good vibrations: can a digital nudge reduce digital overload?. In *Proceedings of the 20th International Conference on Human-Computer Interaction with Mobile Devices and Services*. ACM, Barcelona Spain, 1–12. https://doi.org/10.1145/3229434.3229463

[55] Joonyoung Park, Hyunsoo Lee, Sangkeun Park, Kyong-Mee Chung, and Uichin Lee. 2021. *GoldenTime: Exploring System-Driven Timeboxing and Micro-Financial Incentives for Self-Regulated Phone Use*. Association for Computing Machinery, New York, NY, USA. https://doi.org/10.1145/3411764.3445489

[56] Joonyoung Park, Jin Yong Sim, Jaejeung Kim, Mun Yong Yi, and Uichin Lee. 2018. Interaction Restraint: Enforcing Adaptive Cognitive Tasks to Restrain Problematic User Interaction. In *Extended Abstracts of the 2018 CHI Conference on Human Factors in Computing Systems* (Montreal QC, Canada) *(CHI EA '18)*. Association for Computing Machinery, New York, NY, USA, 1–6. https://doi.org/10.1145/3170427.3188613

[57] Heng Peng and Ying Lu. 2012. Model selection in linear mixed effect models. *Journal of Multivariate Analysis* 109 (2012), 109–129. https://doi.org/10.1016/j.jmva.2012.02.005

[58] Fabiano Souza Pereira, Guilherme Guimarães Bevilacqua, Danilo Reis Coimbra, and Alexandro Andrade. 2020. Impact of problematic smartphone use on mental health of adolescent students: Association with mood, symptoms of depression, and physical activity. *Cyberpsychology, Behavior, and Social Networking* 23, 9 (2020), 619–626.

[59] Becky Phu and Alan J Gow. 2019. Facebook use and its association with subjective happiness and loneliness. *Computers in Human Behavior* 92 (2019), 151–159.

[60] Brian A. Primack, Ariel Shensa, César G. Escobar-Viera, Erica L. Barrett, Jaime E. Sidani, Jason B. Colditz, and A. Everette James. 2017. Use of multiple social media platforms and symptoms of depression and anxiety: A nationally-representative study among U.S. young adults. *Computers in Human Behavior* 69 (April 2017), 1–9. https://doi.org/10.1016/j.chb.2016.11.013

[61] Samuli Reijula and Ralph Hertwig. 2022. Self-nudging and the citizen choice architect. *Behavioural Public Policy* 6, 1 (Jan. 2022), 119–149. https://doi.org/10.1017/bpp.2020.5

[62] Leonard Reinecke, Stefan Aufenanger, Manfred E. Beutel, Michael Dreier, Oliver Quiring, Birgit Stark, Klaus Wölfling, and Kai W. Müller. 2017. Digital Stress over the Life Span: The Effects of Communication Load and Internet Multitasking on Perceived Stress and Psychological Health Impairments in a German Probability Sample. *Media Psychology* 20, 1 (Jan. 2017), 90–115. https://doi.org/10.1080/15213269.2015.1121832

[63] Alberto Monge Roffarello and Luigi De Russis. 2021. Understanding, Discovering, and Mitigating Habitual Smartphone Use in Young Adults. *ACM Trans. Interact. Intell. Syst.* 11, 2, Article 13 (July 2021), 34 pages. https://doi.org/10.1145/3447991

[64] Alberto Monge Roffarello and Luigi De Russis. 2022. Achieving Digital Wellbeing Through Digital Self-Control Tools: A Systematic Review and Meta-Analysis. *ACM Trans. Comput.-Hum. Interact.* https://doi.org/10.1145/3571810

[65] Iqbal H. Sarker, A. S. M. Kayes, and Paul Watters. 2019. Effectiveness analysis of machine learning classification models for predicting personalized context-aware smartphone usage. *Journal of Big Data* 6, 1 (July 2019). https://doi.org/10.1186/s40537-019-0219-y

[66] R.X. Schwartz, Alberto Monge Roffarello, Luigi De Russis, and Panagiotis Apostolellis. 2021. Reducing Risk in Digital Self-Control Tools: Design Patterns and Prototype. In *Extended Abstracts of the 2021 CHI Conference on Human Factors in Computing Systems* (Yokohama, Japan) *(CHI EA '21)*. Association for Computing Machinery, New York, NY, USA, Article 334, 7 pages. https://doi.org/10.1145/3411763.3451843

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

[68] Katherine W Song, Janaki Vivrekar, Lynn Yeom, Eric Paulos, and Niloufar Salehi. 2021. Crank That Feed: A Physical Intervention for Active Twitter Users. In *Extended Abstracts of the 2021 CHI Conference on Human Factors in Computing Systems* (Yokohama, Japan) *(CHI EA '21)*. Association for Computing Machinery, New York, NY, USA, Article 433, 6 pages. https://doi.org/10.1145/3411763.3451817

[69] Allyson Spence, Kierian Beasley, Holly Gravenkemper, Alexandra Hoefler, Anthony Ngo, Danielle Ortiz, and Jay Campisi. 2020. Social media use while listening to new material negatively affects short-term memory in college students. *Physiology & Behavior* 227 (Dec. 2020), 113172. https://doi.org/10.1016/j.physbeh.2020.113172

[70] Cass R. Sunstein. 2021. *Sludge: What stops us from getting things done and what to do about it.* MIT Press.

[71] Trine Syvertsen. 2020. *Digital Detox: The Politics of Disconnecting*. Vol. 26. Emerald Group Publishing. 1269–1283 pages. https://doi.org/10.1177/1354856519847325

[72] Zixuan Tang, Huijun Zhang, An Yan, and Chen Qu. 2017. Time Is Money: The Decision Making of Smartphone High Users in Gain and Loss Intertemporal Choice. *Frontiers in Psychology* 8 (2017). https://www.frontiersin.org/articles/10.3389/fpsyg.2017.00363

[73] H Tankovska. 2021. Most used social media platform. Statista.

[74] Nađa Terzimehić, Florian Bemmann, Miriam Halsner, and Sven Mayer. 2023. A Mixed-Method Exploration into the Mobile Phone Rabbit Hole. *Proceedings of the ACM on Human-Computer Interaction* 7, MHCI (2023), 194. https://doi.org/10.1145/3604241

[75] Nađa Terzimehić, Fiona Draxler, Mariam Ahsanpour, and Albrecht Schmidt. 2023. Implicit Smartphone Use Interventions to Promote Life-Technology Balance: An App-Market Survey, Design Space and the Case of Life-Relaunched. In *Proceedings of Mensch Und Computer 2023* (Rapperswil, Switzerland) *(MuC '23)*. Association for Computing Machinery, New York, NY, USA, 237–249. https://doi.org/10.1145/3603555.3603578

[76] Nađa Terzimehić, Luke Haliburton, Philipp Greiner, Albrecht Schmidt, Heinrich Hussmann, and Ville Mäkelä. 2022. MindPhone: Mindful Reflection at Unlock Can Reduce Absentminded Smartphone Use. In *Designing Interactive Systems Conference (DIS '22)*. ACM, New York, NY, USA, 1818–1830. https://doi.org/10.1145/3532106.3533575

[77] Nađa Terzimehić, Svenja Yvonne Schött, Florian Bemmann, and Daniel Buschek. 2021. MEMEories: Internet Memes as Means for Daily Journaling. In *Designing Interactive Systems Conference 2021*. ACM, Virtual Event USA, 538–548. https://doi.org/10.1145/3461778.3462080

[78] Richard C. Thomas. 2012. *Long Term Human-Computer Interaction: An Exploratory Perspective*. Springer Science & Business Media.

[79] Jonathan Tran, Katie Yang, Katie Davis, and Alexis Hiniker. 2019. Modeling the Engagement-Disengagement Cycle of Compulsive Phone Use. 14. https://doi.org/10.1145/3290605.3300542

[80] Mariek M P Vanden Abeele. 2020. Digital Wellbeing as a Dynamic Construct. *Communication Theory* 31, 4 (10 2020), 932–955. https://doi.org/10.1093/ct/qtaa024

[81] Alexandra Voit, Dominik Weber, and Niels Henze. 2018. Qualitative Investigation of Multi-Device Notifications. In *Proceedings of the 2018 ACM International Joint Conference and 2018 International Symposium on Pervasive and Ubiquitous Computing and Wearable Computers* (Singapore, Singapore) *(UbiComp '18)*. Association for Computing Machinery, New York, NY, USA, 1263–1270. https://doi.org/10.1145/3267305.3274117

[82] Ying Wang, Chee-Wee Tan, et al. 2016. Do You Get Better User Experiences when You Customize your Smartphone?: an Experiment with Object and Behavior-based Beliefs and Attitudes.. In *Proceedings of the European Conference on Information Systems*. AIS Electronic Library (AISeL).

[83] Thomas Wilcockson, Ashley Osborne, and David Ellis. 2019. *Digital detox: The effect of smartphone abstinence on mood, anxiety, and craving.* Technical Report. PsyArXiv. https://doi.org/10.31234/osf.io/c85kx

[84] Woojin Yoon, Seobin Choi, Hyeseon Han, and Gwanseob Shin. 2020. Neck Muscular Load When Using a Smartphone While Sitting, Standing, and Walking. *Human Factors: The Journal of the Human Factors and Ergonomics Society* 00, 0 (Feb. 2020), 001872082090423. https://doi.org/10.1177/0018720820904237

[85] Mingrui Ray Zhang, Kai Lukoff, Raveena Rao, Amanda Baughan, and Alexis Hiniker. 2022. Monitoring Screen Time or Redesigning It? Two Approaches to Supporting Intentional Social Media Use *(CHI '22)*. Association for Computing Machinery, New York, NY, USA, Article 60, 19 pages. https://doi.org/10.1145/3491102.3517722