LocknType: Lockout Task Intervention for Discouraging Smartphone App Use

Jaejeung Kim, Joonyoung Park, Hyunsoo Lee, Minsam Ko[†], Uichin Lee
KAIST [†]Hanyang University
{jjk,zelatore85,hslee90,uclee}@kaist.ac.kr,minsam@hanyang.ac.kr

ABSTRACT

Instant access and gratification make it difficult for us to self-limit the use of smartphone apps. We hypothesize that a slight increase in the interaction cost of accessing an app could successfully discourage app use. We propose a proactive intervention that requests users to perform a simple lockout task (e.g., typing a fixed length number) whenever a target app is launched. We investigate how a lockout task with varying workloads (i.e., pause only without number input, 10-digit input, and 30-digit input) influence a user's decision making, by a 3-week, in-situ experiment with 40 participants. Our findings show that even the pause-only task that requires a user to press a button to proceed discouraged an average of 13.1% of app use, and the 30-digit-input task discouraged 47.5%. We derived determinants of app use and non-use decision making for a given lockout task. We further provide implications for persuasive technology design for discouraging undesired behaviors.

CCS CONCEPTS

• **Human-centered computing → Empirical studies in HCI**;

KEYWORDS

smartphone overuse, intervention design, lockout task, interaction restraint

ACM Reference Format:
Jaejeung Kim, Joonyoung Park, Hyunsoo Lee, Minsam Ko[†], Uichin Lee. 2019. LocknType: Lockout Task Intervention for Discouraging Smartphone App Use. In *CHI Conference on Human Factors in Computing Systems Proceedings (CHI 2019), May 4–9, 2019, Glasgow, Scotland UK*. ACM, New York, NY, USA, 12 pages. https://doi.org/10.1145/3290605.3300927

ACM ISBN 978-1-4503-5970-2/19/05…$15.00
https://doi.org/10.1145/3290605.3300927

1 INTRODUCTION

Smartphones have introduced much convenience to our daily lives. However, recent studies also highlight the negative impacts of smartphones on productivity [24], safety [26], and physical/mental health [19, 39]. Individuals are well-aware of these negative aspects and often employ various strategies (e.g., muting or turning off the phones) in an attempt to regulate usage. However, empirical studies have emphasized the difficulties associated with self-regulation and the needs for supporting tools [18, 24, 25, 29].

A large body of prior studies on supporting tools approached this problem by utilizing smartphone usage tracking and visualization to encourage mindfulness [33]. In addition, the use of social learning and competition were determined to have positive results in mitigating smartphone use [27, 28]. Alternatively, there are more *direct interventions* such as enabling a blocking mode for self-restricting use [8, 24, 29, 35]. Furthermore, various forms of direct interventions can be delivered in a proactive way; e.g., creating inconvenience by delaying user interaction [7], generating irritative vibration for overuse limitation [40], inserting a mandatory cognitive task before app use [44], and proactively blocking in a predefined context [22, 23].

In this work, we view these direct interventions from a more fundamental *human decision making perspective* between use and non-use. Individuals are motivated to make decisions that produce the greatest outcome value [16] among the alternatives. All the aforementioned intervention approaches mentioned can be grouped into one of increasing the value of non-use (e.g., mindfulness, social competition/learning), decreasing the value of use (e.g., creating inconvenience), or eliminating the option of use (e.g., restriction/limiting/blocking) that leaves non-use the only behavioral choice to make. Furthermore, expectancy-value theory (EVT) [46] defines the subjective value of a choice as one of the key determinants of decision making, which consists of four sub-categorical values: people evaluate their interest and attainment by considering utility and cost. In particular, the cost could be the amount of time/effort and the negative psychological consequences, which negatively contributes to the net value of a choice.

In this work, we examine *proactive intervention* methods with this theoretical lens. In particular, we consider a range of intervention methods that create inconveniences by placing an extra and mandatory interaction process that requires the user to spend extra time and effort prior to utilizing the target app or device [7, 44]. We call this mandatory interaction process a "lockout task." We hypothesize that introducing a lockout task before an app or device use could decrease the total value of the target use behavior which consequently reduces the likelihood of the corresponding behavior. Our goal is to examine whether or not the approach of increasing the interaction cost using lockout tasks affects the use/non-use decisions. Furthermore, we aim to identify the key determinants of a decision making process in various contexts in the wild. Towards these goals, we set the following research questions:

- RQ1) To what extent can lockout tasks with varying workloads discourage app use? Are there any variations across task workloads and app types?
- RQ2) What are the key determinants of decision making considering various lockout tasks under diverse usage contexts?
- RQ3) What are the follow-up behaviors after making app use/non-use decisions?

We conducted an in-the-wild controlled experiment with 40 participants for 3 weeks. We considered three task workloads: 30-digit-input (LT30), 10-digit-input (LT10), and a simple "press OK to continue" (LT0), which are applied to three app categories (i.e., web-browser, social media, and entertainment). Our results show that task workloads of LT30, LT10, and LT0 discouraged an average of 46.2%, 26.5%, and 12.9% of total encounters respectively across users. The app category was not one of the determinants of non-use behavior. By conducting an exit interview with the participants we derived three themes (user states, LT workload context, and task context) that affected the use/non-use decisions. In addition, our analysis of follow-up behaviors highlighted both positive and negative effects of the proposed intervention.

2 THEORETICAL BACKGROUNDS AND RELATED WORK

We review existing theories related to smartphone use, human-decision making, and behavioral interventions. In addition, we review recent HCI studies on smartphone intervention.

Theoretical Backgrounds

Uses and Gratification Theory (UGT) aims to understand why and how people actively use specific media to meet their needs. UGT was originally used to study mass media such as television and radio, but later it was also used to understand various digital media such as mobile phones, Internet, social media, mobile social games [51] and instant messaging. For example, the UGT approach was used to find the motives of Facebook: social connection, shared identities, content, social investigation, social network surfing, and status updating [20].

Owing to the diversity of media, EVT is often used as a general theory of action to explain a user's specific media choice [46]. This view shows that a user's media choice and usage is dependent on the strength of expectancy that media use will produce an outcome, and the value of that outcome to the user. A user who positively values maintaining social connection and believes (expects) that Facebook facilitates this outcome will be motivated to use this medium. If the user achieves the expected need for social connection, this outcome is likely to reinforce the user's belief about this medium. A user's value for media use is often multifaceted, as it includes interest, utility, identity attainment, and cost [4]. Recent literature highlights the importance of cost because it acts as a barrier to inhibiting a user from engaging in a media use [4]. This barrier could be the amount of time/effort and negative psychological consequences. Likewise, the theory of planned behavior (TPB) that relates one's beliefs to behavior indicates that an individual's perceived ease or difficulty of performing a behavior (or perceived behavioral control) influences behavioral intention [2]. As shown later, lockout tasks are associated with additional costs for self-gratifying behaviors that involve the interaction with certain digital devices or apps, by requesting that users perform additional tasks (e.g., number input tasks) prior to any initial interaction sequence. When a lockout task is encountered, a user is likely to perform a cost-benefit analysis involving a comparison of the cost (i.e., time and effort) of an input task and expected gratification of app usage. We hypothesize that lockout tasks can discourage low benefit gratification seeking behaviors.

Social cognitive theory of self-regulation further explains the self-regulation process of human behavior, including media usage. According to Bandura [3], self-regulation has three sub-processes: self-observation (i.e., monitoring one's behaviors and outcomes), judgment process (i.e., evaluation of observed behaviors as opposed to norms), and self-reaction (i.e., adjusting behaviors based on evaluation results). For example, an individual who spent too much time on smartphone use observes usage amount, judges usage behavior based on her perceived norm, and utilizes self-control methods (e.g., usage tracking, blocking software) to regulate usage behaviors. Previous addiction studies have shown that problematic behaviors originate from a deficiency in the self-regulation owing to a lack of awareness and attention to the behavior (or attentional bias) and a lack of self-control [31, 32].

Self-regulation theories indicate that individuals who lack this trait are more likely to have desire thoughts and fail to self-control media usage. Smartphones facilitate easy and convenient access to a large amount of online digital content (e.g., music, news, and games) and the maintenance of social relationships. Such diverse and easy access provides instant gratifications to users (e.g., interpersonal utility, pastimes, information seeking, and entertainment), and reinforces continuous usage [31]. Repeated usage of specific media strengthened habit formation, and various triggers may lead to the automatic execution of certain behaviors [15]. According to the dual-process accounts of reasoning, habit formation shifts an individual's reasoning for action from system 2 (i.e., slow, conscious, controlled judgments) to system 1 (i.e., fast, automatic, emotional reasoning) [11]. Despite the presence of two mental processes, system 1 and system 2 can be active concurrently. Automatic and controlled cognitive operations compete with one another in determining behavioral choices [11, 13].

In our work, we embed a lockout task into a user's gratification seeking process. When a user launches an app for gratification purposes, we impose a short pause to the instant access and make the interaction burdensome using a lockout task of inputting numbers. This can undermine the desire and intention of using the app. It results in a notable *gulf of execution* on gratification seeking and can encourage the switch from system 1 to system 2 thinking for self-reflection/judgment, which is also known as "microboundaries" for facilitating mindful interactions [7]. We extend this concept by imposing workloads in the form of lockout tasks within the user interaction processes of interactive systems, which help to facilitate cost-benefit analyses under diverse contexts.

HCI Studies on Smartphone Intervention

Existing intervention techniques can be classified into two categories: usage tracking/reflection and direct interventions. Usage tracking and visualization are often used to foster mindfulness in digital technology use [36, 42, 48]. Regarding reflection strategies, prior studies have emphasized the importance of framing usage information (e.g., positive vs. negative usage) [25, 36] and of leveraging social support (e.g., learning from the behavior of others) [29]. Beyond self-tracking and reflection, direct intervention can be used to encompass a broad range of reactive and proactive intervention methods of smartphone usage, including goal-setting, reinforcing, and restricting. Users can set daily usage goals for specific mobile apps and intervenes in cases of over-usage by consistently sending timeout messages if usage goals are violated [18]. Instead of disruptive warnings, it is also possible to nudge users using a subtle, repeating phone vibrations, which has also been shown to be effective [40]. Awarding badges or (cheat) points helps to reinforce the intended behavior [1, 12]. In addition, users can self-restrict their usage by temporarily locking their phones [29] based on predefined rules; e.g., time/activity-based blocking [35], social activity based blocking [28], location-based blocking [22], and study contexts. Alternatively, researchers have explored a range of intervention methods that introduce minor inconveniences or discomfort to facilitate behavioral changes (e.g., encouraging physical activities or smiling) [5, 7, 47]. Self-regulated usage can be promoted by introducing microboundaries for mindful interactions [7], possibly in the form of lockout tasks [44]. These studies provided the foundations for user behavior intervention by introducing inconvenience (i.e., interaction costs). However, none of the prior studies considered these interventions from the perspective of human decision making. Moreover, they did not conduct in-situ experimental studies with the objective of comparatively understanding their effectiveness and underlying decision-making factors.

3 LOCKOUT TASK INTERVENTION DESIGN

We briefly summarize our intervention principles and elaborate on the four important design dimensions of lockout tasks: timing, mutability, task type and workload, and target scope. As mentioned earlier, we hypothesize that a lockout task that creates a slight pause and request that a user performs a number input task at the time of app launch could discourage usage. Figure 1 shows the lockout task intervention process integrated with the general app use process. We elaborate on the design space of the intervention app.

Intervention Principles

Lockout is a widely used approach for preventing undesired behaviors. Our initial objective of a general lockout is to make an action mandatory to proceed. The most well-known example of lockout screen is the password input screen on smartphones for security and privacy. The lockout was found to have many indirect positive effects such as inducing rechecking behavior to avoid errors [14], thereby increasing the safety of various control systems.

According to the *uses and gratification theory*, a user's media choice and use for gratification seeking is dependent on the strength of expectancy that media use will produce an outcome (or gratification), and the value of that outcome to the user [46]. We embed a lockout task into a user's gratification seeking process by redirecting a user's task to a lockout task. This redirection provides a notable *gulf of execution* on gratification seeking and can possibly switch a user's mind from system 1 to system 2 for self-reflection/judgment, which is also known as micro-boundaries for facilitating mindful interactions [7]. In addition, a lockout task is related to the concept of inconvenient interactions [47] based on temptation bundling (or association) [38] where gratifying use is granted only if a user engages in a goal-consistent behavior (e.g., exercise to use a microwave). Our work instead aims to *dissociate* gratification seeking thoughts via lockout tasks. Our work attempts to utilize these findings in the process of *user interactions in the interactive systems*. Furthermore we extend the concept of micro-boundaries by incorporating *task workload* in that lockout tasks bring additional "costs" to an existing *gratification seeking process with interactive systems*, which helps users to facilitate a *cost-benefit analysis* as the expectancy-value theory states.

Intervention Timing

Intervention timing is one of the critical design criteria for behavior change. Behavioral interventions, in general, have four timing opportunities: before, starting, during, and ending of a target behavior that needs to be mitigated. They are dependent on the intervention objectives. Mindfulness research usually aims for before and after the undesired behavior to help to maintain one's self-regulation and behavioral orientation toward their goal. Intervention delivered at the onset of a target behavior is also called just-in-time intervention (JITI) [49]. It emphasizes the importance of breaking the urge or impulse at the moment of a problematic behavior. This is because once the problematic behavior takes place, the behavior can be reinforced; for example, the first lapse of smoking leads to full relapse [50]. Similarly, empirical studies report that once engaged in a smartphone app, it is difficult to stop, thereby resulting in unexpected overuse [24, 29]. Furthermore, from the experiment design perspective, we are interested in understanding how our intervention can successfully discourage the impulsive and habitual use at the decision making moment in the face of lockout tasks. Lockout tasks can be naturally integrated at the time of app launch.

Task Mutability

An important design aspect to consider is the *mutability* (whether the initially designed rule can be changed or not). The mutability of the lockout relates to the scope of target lockout apps, and the lockout intervention as a whole. For example, if we allow the users to change the intervention target app anytime, the user under the impulsive state can eliminate the intervention on the target app, or even the whole lockout itself. Such workaround behavior has been observed in prior studies that degrade the intervention effect as well as the experiment validity [24]. Therefore, we did not allow such modification once the target app has been selected in the intervention experiment.

Task Type and Workload

We defined a lockout task as *a mandatory task that needs to be completed to access to the gratifying app*. The main objective of embedding a "task" to the lockout is to create a certain level of cost or workload to the target task, which is the app use behavior. There could be various task design alternatives for increasing this cost to interaction, such as number or textual input, touch or movement gesture, mathematical problem to solve, and many more. Also the amount of workload can be defined as an intervention design. In this study, we have employed a simple number input task as the lockout task. Number input tasks are widely used in our daily contexts (e.g., password entry) and thus, we can minimize the confounding effects that come from individual differences in competence and familiarity. In addition, number inputs are easy to randomize, and the results are easy to quantify.

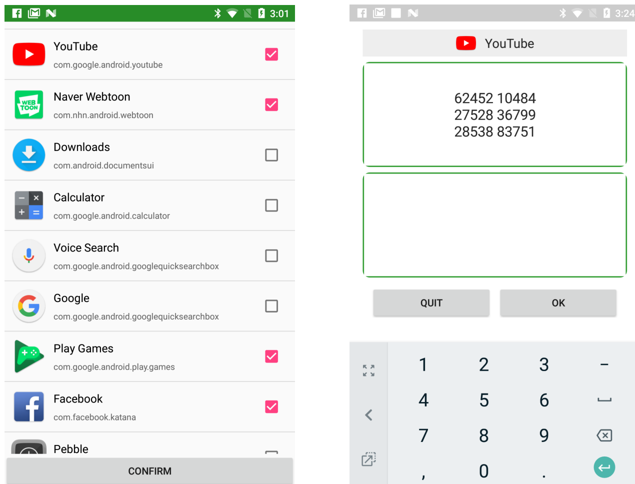
Target Scope

The scope of lockout targets needs to be properly defined. We can think of device- or app-level lockout, but we can narrow down to a specific user interaction feature that needs to be intervened. Adding contextual conditions further narrows the scope even more. In our current design, we target an app-level intervention, to discourage particular apps that could be of negative influence on the user. We will detail the app selection procedure for individual users in the main experiment section. It is also important to note who is in charge of defining/enforcing the intervention scope.

4 PRELIMINARY STUDY

Before proceeding to the main study, we conducted a pilot study to determine 1) appropriate lockout task workloads to be assigned to the experimental conditions, 2) scope of lockout target apps, and 3) potential workarounds that may compromise the internal validity of our experimental design. This pilot study process was particularly important because the study was conducted in-the-wild.

After several in-lab testing, we chose 10/20/30 digit input tasks. An Android app was developed that presents a lockout task with randomized workload selection (10/20/30) at each app launch. For target app selection, we considered apps that are generally perceived as counter-productive (i.e., social media, entertainment etc.). In addition, we included web-browsers, email apps, and instant messengers that were considered to be neutral. However, they also often reported counter-productive apps owing to their frequent interruptions [10]. We recruited 10 participants (2 Female, 8 Male, Mean Age=28.75, SD=4.67) from a large university community portal. Each participant used our intervention app for 3 days. We did not log their usage data, but instead conducted a



(a) LT app selection (b) 30-digit-entry (LT30)

Figure 1: Screenshots of lockout task intervention app. LT0 and L10 had the same UI except the digit entry section (LT0: empty and LT10: 10 digits)

semi-structured interview either face-to-face or via text-chat communication.

Lockout task workload: The majority of the participants reported that there was not much workload difference between the 10 and 20 digit inputs. However, they experienced a clear difference between 10 and 30. Based on this feedback, we eliminated 20 digit input. Instead, we included a 0 digit input, meaning that it is not necessary for the participants to input any number, only requiring them to press 'OK' to proceed. We were interested in observing how such minimal workload differs from that of task requiring digit input.

Scope of lockout target: Most participants strongly suggested that instant messengers and emails should be excluded from the intervention mainly because of two reasons. First, they were primarily used for work and communication purposes, and there was no perceived need for an intervention. Second, when the lockout tasks were given on instant messengers, users experienced a need for immediate access owing to peer pressure, which often resulted in frustration. Some users also reported similar frustrations when waiting for important emails that required a prompt response. Based on these reasons, we decided to exclude instant messengers and emails in our main experiment.

Potential workarounds: We asked if they discovered any workarounds that could override the lockout. There were two strategic workarounds found. One method was deselecting the target app from the intervention app list. This behavior was mainly associated with the repeated "30 digit input on an instant messenger." Repeatedly relaunching the target app in search of a lower number of digits was another workaround. From these observations, we disabled deselection options after the initial setting, and the same workload was maintained for a fixed time duration (60 minutes) to address repeated relaunching workarounds.

5 MAIN STUDY

In our main study, we aimed to understand 1) if the insertion of a lockout task at the time of app launch can discourage app usage, 2) to explore the determinants that influence such non-use decisions in detail, and 3) to analyze the follow-up behaviors after the use/non-use choices were made. The lockout task was applied to the three categories of web browsers, social media, and entertainment. The reason for targeting social media and entertainment were they are the main types of apps that can potentially undermine productivity [21] and reinforce habitual usage of smartphones [34, 41]. Web browsers were included for the same reasons as users can access both social media and entertainment contents. These categories roughly account for about a half of smartphone use according to the prior study [18].

Participants

Forty participants were recruited (18 Female, Mean Age=23, SD=3.09) using an online university community. The inclusion criteria were Android users and who have the intention to reduce their smartphone use. We controlled this using a recruitment survey on Transtheoretical Model (TTM) of behavior change stage [45], which we limited to those who were either in stage two (considering reduction) or three (ready to reduce smartphone use). The survey also asked individuals to list at least one app from each category of browsers, social media, and entertainment that were currently installed on their smartphones to ensure that all target apps were available for intervention. We compensated all participants with approximately $40 for the 3 weeks of participation.

Procedure

Our experiment consisted of 1 week of baseline data collection and following 2 weeks of intervention. The 3-week-experiment was designed as within-subject. In the first week, participants attended an offline orientation and were briefed on the overall process of the experiment and each function of the app prior to commencing the experiment. Subsequently, we helped each participant to install the logging app. The logging app was used as a baseline to track and collect data on normal smartphone usage. Thus, we asked participants to use their smartphone as usual. At the end of the first week, we analyzed each participant's app use behaviors based on three categories, i.e., web browsers, social media, and entertainment. For each participant, we then selected a set of target apps from each category to serve as personalized intervention target apps as of the second week. During the classification of apps into these categories, two researchers performed classification of the apps for interrater reliability, borrowing the category classification standard used in the Google Play Store. As a result, 99% of the classifications were in agreement (Cohen's Kappa = 0.97).

At the beginning of the second week, we deployed the lockout task intervention app via email and asked each participant to install and register the personalized target apps based on their baseline use logs. Each user typically received an average of 8.9 (SD=2.4) intervention target apps to register. After the third week, we notified participants upon completion of the experiment and conducted a half hour semi-structured, in-depth interview with 31 randomly selected participants.

The main themes of the questions were 1) the reason behind their decisions for use or non-use on the encountering of the lockout task and 2) the follow-up behaviors after the being locked out of the intervention target apps including attempts of workarounds.

6 RESULTS

Over the 3-week study, we logged a total of 86,290 app executions, 83,915 minutes of app usage time, and 26,272 lockout task encounters from the 40 participants. These quantitative usage log data were analyzed along with the qualitative data from the exit interview.

Effectiveness of LT Intervention

Our first research question was to determine the efficacy of the LT intervention in discouraging app usage. In particular, we wanted to establish whether discourage rates vary across different LT workloads and app categories. We first measured the task workloads of each LT and analyzed the results to determine these if LTs successfully discouraged the app usage.

LT workload. Participants experienced three different types of LT workloads in a random manner. We assessed the LT workload using three measures of NASA-TLX, completion time, and the initial success rate to understand the cost of each LT. In this case, the initial success rate measures the success rate of initial submissions (i.e., the first submission of an LT without any error).

As Figure 2 indicates, the NASA-TLX results showed that participants perceived LT30 (M=31.1, SD=6.81) as the most burdening task followed by LT10 (M=20.22, SD=6.72) and LT0 (M=12.4, SD=5.66). A repeated measures ANOVA result confirmed a statistically significant difference among these three LTs: (F(2, 117)=75.42, p<.001). A Tukey's HSD post-hoc test confirmed pairwise differences as well (p<.001).

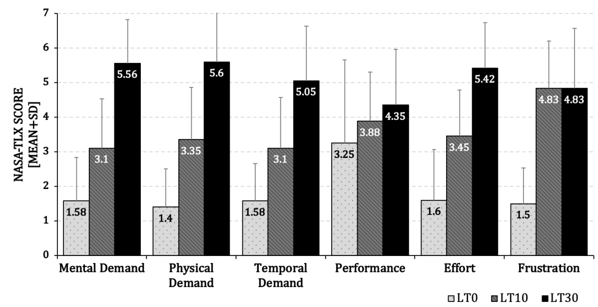


Figure 2: Perceived lockout task workload

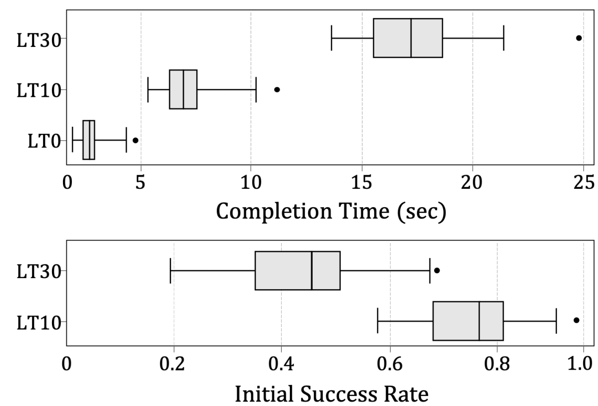


Figure 3: Measurements of lockout task workloads

We examined the subscales of NASA-TLX to find clearly observable differences among the three LTs. Another repeated measures ANOVA test revealed that all subscales of NASA-TLX LTs were different with significance levels of p<.001, except for the performance scale that represents the rate of success in completing the digit input task. We conducted a Tukey's HSD and found statistical significance between LT0 and LT30, but not the other pairs.

We considered the completion time of the LT input as another measure of the workload, because heavier workloads require more time. The completion time also includes the time for correcting errors (i.e., involving deleting and retyping). We derived an average completion time for each participant (Figure 3). We found that on average, LT0 required 1.85 seconds to complete (SD = 0.66), whereas LT10 needed 7.2 seconds (SD = 1.40) and LT30 demanded over 17 seconds (SD = 2.59).

We also measured the "initial success rate", which represents how accurately a user completed each LT on the first trial without making any errors (Figure 3). This is an important measure because input errors aggravate the perceived workload in both input-wise and time-wise. The success rate of LT0 was always 100%, and LT0 was excluded. The average

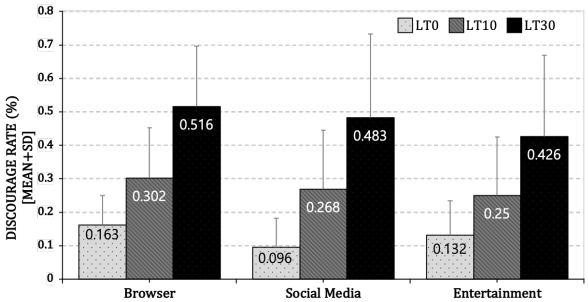


Figure 4: Discouraged rate

initial success rates of LT10 and LT30 were 77.1% and 45.1%, respectively. This result clearly shows that LT30 incurred more errors than LT10.

Discourage Rate of App Use. Each user encountered an average of 657 LTs (SD=428.94) during the two week intervention period. We define that an app use attempt is discouraged if a user fails to complete a given LT task, which is referred to as "an LT non-completion instance". The discourage rate is defined as the fraction of failed (or LT non-completion) instances. We calculated each LT type's discourage rate. Figure 4 shows the discourage rates of LT0, LT 10, and LT30, which are 0.131 (SD=0.096), 0.274 (SD=0.17), and 0.475 (SD=0.23), respectively.

Next we ran a two-way ANOVA test to observe the effect of LT workload and app category type on the discourage rate of app use. The results show that there was a statistically significant main effect of the LT workload (F=119.34, p<.001) with a very large effect size of $\eta 2$=.413. In addition, there was a significant main effect of app category (F=3.72, p=.025) with a small effect size $\eta 2$=.021. No interaction effects were found between the two variables (F=.767, p=.548, $\eta 2$=.009). We further conducted pairwise post-hoc tests using Fisher's LSD and found that all LT workload pairs were significantly different (p<.001). In case of app categories, we found significant differences in the browser-social media pair (p=.041) and the browser-entertainment pair (p=.010), but not in the social media and entertainment pair (p=.626).

Post-task Usage Behavior. We analyzed LT non-completion instances (i.e., users deciding not to complete a lockout task). Our analysis revealed that users chose the following options: 1) turning off the device (M=25.5%, SD=11.5%), 2) using a non-lockout app (M=50.4%, SD=16.9%), and 3) using another lockout app (M=24.1%, SD=12.4%).

First of all, the participants turned off the device on average 25.5% (SD=11.5%). Our interview analysis showed that participants typically went back to what they have been doing, or found a non-device activity (e.g., face-to-face chatting with friends/family members and going to bed). These were considered positive and meaningful tasks.

However, our participants continued using the non-lockout apps in 50.5% (SD=16.9%) of the LT non-completion cases. To further understand app types, we extracted top 3 non-lockout apps from each individual (taking up more than 90% of uses), and three of the authors performed manual category coding. The results showed the following distribution: i.e., communication apps (e.g., KakaoTalk, an instant messaging app): 55%, productivity (e.g., emails, calendar, schedulers): 13%, photos and camera: 7.5%, music (5%), maps (5%). We also found approximately 10% of app use cases that were supposed to be blocked according to our LT app categories. Our manual investigation showed that these apps were either not captured during the baseline monitoring or newly downloaded by our participants.

The reason why instant messaging was most frequently used was likely due to the popularity and checking habits. P3 said, "*I did not intend to send any messages, but I just checked new messages.*" Also, P22 stated, "*I checked the [notification disabled] group chats to keep up with friends.*" Failure of an initially intended (more valued) app leads this user to select the next valued task of socializing. Several participants mentioned that the lockout reminded them of an important task such as "scheduling a meeting" or "checking for new announcements," leading them to productivity apps.

Finally, we found that 24.1% (SD=12.4%) was followed by an attempt to use another lockout target or LT app. We initially hypothesized that the participants would maintain their initial intention and use the app of the same category. From the interview, we found that a large portion of participants indeed continued to the similar apps. However, our quantitative results revealed that regardless of the LT app category, approximately half cases transitioned to the browsers, 25% to the entertainment, and 25% to the social media. It is likely due to the fact that web browsers are multi-faceted and can be used for accessing entertainment and social networking services.

Usage Time and Frequency. We examined the overall effect of the LT interventions, by comparing the average daily app usage time and frequency between the baseline and intervention periods. For both measures, we calculated the ratio of the value from the intervention period to the value from the baseline period. We separately calculate the ratios for the LT intervention apps (LT apps) and non-LT-intervention apps (non-LT apps). This division allowed us to examine whether the usage time and frequency of LT apps have changed, and whether such changes have influenced the usage time and frequency of non-LT apps. We ran one-sample t-tests with the null hypothesis of no change (i.e., mean value of 1.0). The results of the t-test showed that the frequency ratio for

Table 1: Comparison results: baseline vs. treatment

Change Ratio	Mean(SD)	95% CI	p-value
LT Freq.	0.505(0.163)	[0.162, 0.476]	0.000
LT Time	0.922(0.322)	[-0.185, 0.028]	0.143
Non-LT Freq.	1.245(0.347)	[0.134, 0.356]	0.000
Non-LT Time	1.319(0.490)	[-0.162, 0.476]	0.000
Total Freq.	0.970(0.242)	[-0.030, -0.107]	0.442
Total Time	1.062(0.243)	[0.062, -0.015]	0.113

the LT intervened apps was significantly reduced; i.e., close to 50% compared to the baseline (M=.505, SD=.163, p<.001) (Table 1). This result confirms LT's usefulness in mitigating frequent use. There was no significant difference in the time ratio of LT intervened apps (with only marginal decrement). The usage frequency of the non-LT apps increased (i.e., 20%), and there was no significant difference in the overall usage ratios (non-LT + LT apps). This implies that LT intervention only helped users to better manage interruptions or the frequent urge to use LT apps, by bundling frequent short sessions into less frequent long sessions. Indeed, the average session duration of the LT apps has increased from 84.4s during the baseline period to 158.2s during the treatment period. In contrast, there were no significant changes in the average session duration of non-LT apps (30.8s compared to 33.1s).

Determinants of Use/Non-use

We extracted the key determinants of making decisions related to use and non-use (i.e., user states, LT workload context, and task context) based on a thematic analysis of the interview data [6].

User States. The user state at the point of encountering the LT influenced use and non-use decision making: i.e., time availability, self-regulation (willingness and mindfulness), physical/mental states, and subjective social norm. First, our participants considered how much time was available at the moment. P2 commented, *"With only 3 minutes left prior to class, I decided not to use a smartphone, because 3 minutes is not sufficient enough for desired tasks."*

Second, the participants who were mindful about usage behaviors (and willing to reduce usage) actively self-regulated phone use. P4 mindfully controlled app usage, by saying *"I think I just tried not to use my phone and pulled myself together when I grabbed the phone unconsciously. At the moment when the 10 and 30 digit input task was shown, I was like, 'Woah, what was I thinking? I don't need this right now.' "*

Third, users' physical/mental conditions influenced their decision making. Smartphone use sometimes helped our participants to regain their spirit, which led them to use phones. For example, P1 noted, *"I used my smartphone when I was feeling down. You know, just getting a little comfort from surfing social media and feeling like you're connected to this world. So, yes, when I felt depressed, I would unlock my phone anyway even if the 30 digit input was given."*

Finally, we discovered that the subjective social norms related to smartphone use also contributed to decision making. For example, P14 stated his concern about his relationship, by noting *"My girlfriend hates it when I look at my phone when we're talking to each other. I used to do that quite often, but since the input task was given and I know it is rude to type it in her presence, I simply focused more on our conversation instead of staring at my phone."*

LT Workload Context. Our participants evaluated LT workload contexts such as temporal, mental, and physical demands associated LT tasks at the time of use. If the time required to perform an LT task (i.e., expected temporal demand) was relatively longer than the time a user wishes to use an app (i.e., expected use time), they tended to choose not to use the app. As the number of digits increases, the mental demand also increases. In the case of LT30, our participants often experience a considerable cognitive burden, which discouraged their use attempts. P12 said, *"0 was good, 10 was okay. ... I didn't really have any thought on it. But 30 was a bit frustrating. ... After all the effort I've put into this task and I still got it wrong! I'm not doing this."* This negative experience induces decision biases in time comparison (i.e., app use time vs. LT task time). LT30 typically takes less than 20 seconds (M = 17, SD = 2.59), whereas our participants perceived that the overall effort spent for LT30 was comparable with that of app use that took a much longer time than LT30. P16 said, *"Once I got a 10-minute break and 30 digit input task appeared on my game screen. I just gave up. I can't spend time and energy on a 30 digit input for a 10-minute break. I thought it was inefficient."* The number input requires fairly low physical demand, but a user's current context of task execution may increase the physical demand. Usage was discouraged particularly when a user was tired or physically unavailable or less capable of interaction (e.g., only one hand available, usage while walking). P16 reflected on usage while walking, by saying *"when longer digits popped up, it was hard for me to recognize numbers on the screen, type them and walk at the same time."*

Task Context. The degree of urgency and importance at a given circumstance affected users' decision. Obviously, our participants tended to use their phones when the task at hand was urgent and important. P10 said, *"I really needed to search for the definition of a word to keep up with the lecture.*

Table 2: Determinants that influence use/non-use decisions

Category	Sub-category	Description
User States	Time Availability	How much free time a user has at the moment
	Willingness/Mindfulness	How willing or mindful a user is about self-regulating phone usage
	Physical/Mental Condition	Whether a user is in a good physical/mental condition to perform a goal task
	Subjective Social Norm	The degree to which one is aware of (and follows) the social norm
LT Workload Context	Temporal Demand	How much time will cost to perform a given LT task
	Physical Demand	How much physical effort should be exerted to perform a given LT task
	Mental Demand	How much mental effort should be exerted to perform a given LT task
Task Context	Task Urgency	How quickly does the task needs to be completed
	Task Importance	How important is the task to be completed
	Alternative App Availability	Whether there are alternative apps of achieving the goal task

I had to unlock low to high number input screens every time." Also, our participants considered whether alternative means of achieving use goals (e.g., similar apps, alternative devices, or other people nearby) are available. For example, P22 tried multiple browsers, by saying *"When my Naver (browser) was blocked with 30 digit input, I tried to access Samsung Internet and Chrome on rotation to avoid longest digit input."* In contrast, urgent but less important use was often discouraged. P19 said, *"I was watching television with mom and we were guessing a celebrity's age. I decided to look it up using a browser but the 30 digit input popped up. Although I've tried, I typed the wrong digits so I gave up and just told mom that I'll let her know later."* However, in non-urgent situations, participants tended to use the phone even under high LT workload. P15 said, *"All I got is time, and I don't have anything else to do. Why not do this 30 digital input?"* In some cases, our participants explored alternative activities after encountering with an LT. P25 said, *"I was on the bus with nothing much to do, so I turned on my smartphone and the number input appeared. I thought, Well, let's just not do this. ... Then I just watched outside the window, enjoying sceneries that I've never even considered looking at before."*

7 DISCUSSION

We discuss the use of lockout tasks as behavioral inhibitors, the cost-benefit balancing issues in lockout design, and the follow-up behavior guidance.

Lockout Task as a Behavioral Inhibitor

Our results demonstrated that lockout task intervention is an effective tool for discouraging the app use. The lockout tasks create a momentary pause from fluid app execution within interactive systems. Unlike traditional concept of fluid interaction design, we artificially created "gulf of execution," which engendered what is referred to as a "microboundary" within interactive systems [7]. Lockout tasks (as microboundaries between app use and non-use) gave the participants room to reconsider their app use intentions. Our qualitative findings from the interview regarding the re-evaluation process at the moment of lockout suggest that the lockout directed System 1 thinking toward System 2 thinking [11]. Similar findings were observed in Gould et al.'s work [14] that reported the increase in lockout delay during a number-entry task assisted users to reduce errors, but too lengthy delays drove them to move away from the task. In our work, we systematically induced task workload in lockout tasks and hypothesized that introducing additional "costs" to an existing gratification seeking process with interactive systems would facilitate a *cost-benefit analysis* as the *expectancy-value theory* affirms [46]. Our results showed that the effectiveness of light and gentle interventions on the discouragement of app use was low (13.1%), whereas introducing a slightly higher interaction cost with LT10 doubled the effectiveness (27.4%), and even higher cost with LT30 nearly quadrupled the effectiveness (47.5%). These results confirm our hypothesis that lockout tasks as behavioral inhibitors helped people to engage in cost-benefit analysis for self-regulating frequent app use.

Balancing the Cost-Benefit

There were a few participants who adhered well to the slight pause of LT0, stating that this was good enough for them to self-control app use. From the interview, we observed that their willingness for usage reduction was very high. Their only problem was not being mindful and being interrupted by the habitual, mindless use. This result was in line with Hiniker et al. [18] that the reduction focused users (i.e., participants who had a strong will to reduce) were more likely to adhere to the warning message than the non-reduction focused users. Therefore, we expect a small workload with little inconvenience is good enough to discourage these users from usage. Meanwhile, the users who already placed a high value on app require intervention with high workload lockout tasks that could discourage their use intention.

Overall, our thematic analysis on the determinants for decision making indicates that not only the users' willingness to reduce their use, but also the users' intention and contextual factors greatly influence the cost-benefit analysis to decide between use and non-use. However, our participants' usage intentions were often nuanced, and it is not easy to clearly delineate which uses are "bad" or "meaningless" [30, 37]. For example, some participants used web-browsers for productive activities such as information search during work, while other passively browsed the social media to pass time, which is deemed to be less meaningful use [37]. Instead of completely blocking use, we introduced "proactive lockout tasks" to help users to reevaluate the potentially meaningless use as in decisional balancing exercise that resolves a user's ambivalence in the pros and cons of such a behavioral change [9, 43]. Nonetheless, there could be false-positive lockouts for "good" or "meaningful" use, which incurs considerable inconvenience to users. Thus, the trade-off between mindful intervention and usage inconvenience needs to be carefully considered in the future lockout design.

One of the design choices is the leveraging of context-awareness for adaptive lockout task administration, which can reduce false-positive lockout instances that negatively affect user experience and productivity. Furthermore, the contextual norm (e.g., smartphone use during class, during a family meal, before sleeping) can be considered in adaptively controlling the lockout task workload for a more effective outcome. Such flexibility can be realized with a "temporary exception" mode which allows users to bypass the intervention for a limited number of times. Such an approach was reported to be very useful in providing flexibility against the rigid rules [23, 28, 29].

Follow-up Behavior Guidance

Our results show that the lockout task discouraged nearly half of the app use intentions at LT30. The thematic analysis of follow-up behaviors revealed that most of the discouraged cases were followed by positive behaviors. There were also other use cases, which were not for positive or productive intentions, but just for pastime. A pastime use itself is not always bad, but many participants mentioned that initial intention to use the app for a short period often became out of their control, resulting in a regretfully-long use [37]. Such negative behaviors were often observed in prior studies [24, 29, 37].

We focused on understanding specific aspects of how a lockout task as a decision balancer inhibited the initial app use intention. There is an open design space for combining our intervention approach with a positive follow-up behavior guidance. Coco's Video [17] supports the follow-up behavior by presenting the user with a predefined goal at the end of a video viewing session. In addition, MyTime [18] notifies the user with the self-defined aspiration message when their smartphone use time is over. Both works have shown a positive outcome relative to non-guidance cases. As we have demonstrated the powerful effect of a lockout task as a behavioral inhibitor provides an intervention for follow-up behavioral guidance could introduce more positive behavioral outcome as a whole.

8 LIMITATION AND FUTURE WORK

There are several limitations of this work. First, our work did not consider the user's positive/negative intention of app use, which potentially increased false-positive lockouts. Also, we designated the intervention target apps rather than leaving it for the participants to voluntarily choose, which may have contributed to increasing the rate of false-positive lockouts. In current work, we rather focused on understanding both positive and negative lockout experiences despite the app use intention was a positive or a negative one. Future work may consider using either experience sampling method similar to Lukoff et al.'s work [37] or use of context-aware methods to understand user's intention. This may deepen the analysis on understanding how the LT is adhered according to the meaningfulness of the app usage instance.

Second, the intervention scope (or LT app categories) is limited. Future work can consider other diverse apps with different characteristics (e.g., emails or instant messengers). There should be further studies on what problematic usage behaviors exist, and how LT can be designed to address such problems.

Third, we controlled the participants to those who at least have considered or tried to reduce their smartphone use. There still seems to be individual differences in the degree of willingness to reduce usage, as well as their self-regulatory capabilities. Examining the details of user traits will further provide insightful contributions to LT intervention studies.

9 CONCLUSION

Our work attempted to gain an understanding of lockout task intervention, which aims to discourage the user from accessing smartphone apps. We demonstrated the effectiveness of the intervention as well as the behavior and experience associated with the intervention moments. These quantitative and qualitative results provide a new perspective toward the design space for smartphone non-use. We expect our intervention approach to be extended to various behavior change domains.

ACKNOWLEDGEMENTS

This research was supported by Next-Generation Information Computing Development Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Science and ICT (NRF-2017M3C4A7083534).

REFERENCES

[1] Elena Agapie, Daniel Avrahami, and Jennifer Marlow. 2016. Staying the Course: System-Driven Lapse Management for Supporting Behavior Change. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*. ACM, 1072–1083.

[2] Icek Ajzen. 1991. The theory of planned behavior. *Organizational behavior and human decision processes* 50, 2 (1991), 179–211.

[3] Albert Bandura. 1991. Social cognitive theory of self-regulation. *Organizational behavior and human decision processes* 50, 2 (1991), 248–287.

[4] Kenneth E Barron and Chris S Hulleman. 2015. Expectancy-value-cost model of motivation. *Psychology* 84 (2015), 261–271.

[5] Steve Benford, Chris Greenhalgh, Gabriella Giannachi, Brendan Walker, Joe Marshall, and Tom Rodden. 2012. Uncomfortable interactions. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM, 2005–2014.

[6] Virginia Braun and Victoria Clarke. 2006. Using thematic analysis in psychology. *Qualitative research in psychology* 3, 2 (2006), 77–101.

[7] Anna L Cox, Sandy JJ 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*. ACM, 1389–1397.

[8] Janet I Creaser, Christopher J Edwards, Nichole L Morris, and Max Donath. 2015. Are cellular phone blocking applications effective for novice teen drivers? *Journal of safety research* 54 (2015), 75–e29.

[9] John A Cunningham, Linda C Sobell, Mark B Sobell, and Geeta Kapur. 1995. Resolution from alcohol problems with and without treatment: reasons for change. *Journal of substance abuse* 7, 3 (1995), 365–372.

[10] Laura Dabbish, Gloria Mark, and Víctor M González. 2011. Why do i keep interrupting myself?: environment, habit and self-interruption. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM, 3127–3130.

[11] Jonathan St BT Evans. 2003. In two minds: dual-process accounts of reasoning. *Trends in cognitive sciences* 7, 10 (2003), 454–459.

[12] David Gibson, Nathaniel Ostashewski, Kim Flintoff, Sheryl Grant, and Erin Knight. 2015. Digital badges in education. *Education and Information Technologies* 20, 2 (2015), 403–410.

[13] Thomas Gilovich, Dale Griffin, and Daniel Kahneman. 2002. *Heuristics and biases: The psychology of intuitive judgment.* Cambridge university press.

[14] Sandy JJ Gould, Anna L Cox, Duncan P Brumby, and Alice Wickersham. 2016. Now check your input: brief task lockouts encourage checking, longer lockouts encourage task switching. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*. ACM, 3311–3323.

[15] Mark Griffiths. 1995. Technological addictions. In *Clinical psychology forum*. Division of Clinical Psychology of the British Psychol Soc, 14–14.

[16] E Tory Higgins. 2000. Making a good decision: value from fit. *American psychologist* 55, 11 (2000), 1217.

[17] Alexis Hiniker, Sharon S Heung, Sungsoo Ray Hong, and Julie A Kientz. 2018. Coco's Videos: An Empirical Investigation of Video-Player Design Features and Children's Media Use. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*. ACM, 254.

[18] 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*. ACM, 4746–4757.

[19] Esra Erkol İNal, kadİr DemİrcĪ, Azİze ÇetİntürK, Mehmet Akgönül, and Serpİl Savaş. 2015. Effects of smartphone overuse on hand function, pinch strength, and the median nerve. *Muscle & nerve* 52, 2 (2015), 183–188.

[20] Adam N Joinson. 2008. Looking at, looking up or keeping up with people?: motives and use of facebook. In *Proceedings of the SIGCHI conference on Human Factors in Computing Systems*. ACM, 1027–1036.

[21] Reynol Junco and Shelia R Cotten. 2012. No A 4 U: The relationship between multitasking and academic performance. *Computers & Education* 59, 2 (2012), 505–514.

[22] Inyeop Kim, Gyuwon Jung, Hayoung Jung, Minsam Ko, and Uichin Lee. 2017. Let's focus: location-based intervention tool to mitigate phone use in college classrooms. In *Proceedings of the 2017 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2017 ACM International Symposium on Wearable Computers*. ACM, 101–104.

[23] Inyeop Kim, Gyuwon Jung, Hayoung Jung, Minsam Ko, and Uichin Lee. 2017. Let's FOCUS: Mitigating Mobile Phone Use in College Classrooms. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 1, 3 (2017), 63.

[24] Jaejeung Kim, Chiwoo Cho, and Uichin Lee. 2017. Technology Supported Behavior Restriction for Mitigating Self-Interruptions in Multidevice Environments. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 1, 3 (2017), 64.

[25] Young-Ho Kim, Jae Ho Jeon, Eun Kyoung Choe, Bongshin Lee, KwonHyun Kim, and Jinwook Seo. 2016. TimeAware: Leveraging framing effects to enhance personal productivity. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*. ACM, 272–283.

[26] Sheila G Klauer, Feng Guo, Bruce G Simons-Morton, Marie Claude Ouimet, Suzanne E Lee, and Thomas A Dingus. 2014. Distracted driving and risk of road crashes among novice and experienced drivers. *New England journal of medicine* 370, 1 (2014), 54–59.

[27] Minsam Ko, Seungwoo Choi, Subin Yang, Joonwon Lee, and Uichin Lee. 2015. FamiLync: facilitating participatory parental mediation of adolescents' smartphone use. In *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing*. ACM, 867–878.

[28] 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, 998–1010.

[29] Minsam Ko, Subin Yang, Joonwon Lee, Christian Heizmann, Jinyoung Jeong, Uichin Lee, Daehee Shin, Koji Yatani, Junehwa Song, and Kyong-Mee Chung. 2015. NUGU: a group-based intervention app for improving self-regulation of limiting smartphone use. In *Proceedings of the 18th ACM conference on computer supported cooperative work & social computing*. ACM, 1235–1245.

[30] Simone Lanette, Phoebe K Chua, Gillian Hayes, and Melissa Mazmanian. 2018. How Much is' Too Much'?: The Role of a Smartphone Addiction Narrative in Individuals' Experience of Use. *Proceedings of the ACM on Human-Computer Interaction* 2, CSCW (2018), 101.

[31] Robert LaRose. 2007. Uses and gratifications of Internet addiction. *Internet addiction: A handbook and guide to evaluation and treatment* (2007), 55–72.

[32] Robert LaRose, Carolyn A Lin, and Matthew S Eastin. 2003. Unregulated Internet usage: Addiction, habit, or deficient self-regulation? *Media Psychology* 5, 3 (2003), 225–253.

[33] Heyoung Lee, Heejune Ahn, Samwook Choi, and Wanbok Choi. 2014. The SAMS: Smartphone addiction management system and verification. *Journal of medical systems* 38, 1 (2014), 1.

[34] Uichin Lee, Joonwon Lee, Minsam Ko, Changhun Lee, Yuhwan Kim, Subin Yang, Koji Yatani, Gahgene Gweon, Kyong-Mee Chung, and Junehwa Song. 2014. Hooked on smartphones: an exploratory study on smartphone overuse among college students. In *Proceedings of the 32nd annual ACM conference on Human factors in computing systems*. ACM, 2327–2336.

[35] 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*. ACM, 43.

[36] Danielle Lottridge, Eli Marschner, Ellen Wang, Maria Romanovsky, and Clifford Nass. 2012. Browser design impacts multitasking. In *Proceedings of the human factors and Ergonomics Society Annual Meeting*, Vol. 56. SAGE Publications Sage CA: Los Angeles, CA, 1957–1961.

[37] 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), 22.

[38] Katherine L Milkman, Julia A Minson, and Kevin GM Volpp. 2013. Holding the Hunger Games hostage at the gym: An evaluation of temptation bundling. *Management science* 60, 2 (2013), 283–299.

[39] Karla Klein Murdock. 2013. Texting while stressed: Implications for students' burnout, sleep, and well-being. *Psychology of Popular Media Culture* 2, 4 (2013), 207.

[40] Fabian Okeke, Michael Sobolev, Nicola Dell, and Deborah Estrin. 2018. Good Vibrations: Can a Digital Nudge Reduce Digital Overload? (2018).

[41] Antti Oulasvirta, Tye Rattenbury, Lingyi Ma, and Eeva Raita. 2012. Habits make smartphone use more pervasive. *Personal and Ubiquitous Computing* 16, 1 (2012), 105–114.

[42] Viktoria Pammer and Marina Bratic. 2013. Surprise, surprise: activity log based time analytics for time management. In *CHI'13 Extended Abstracts on Human Factors in Computing Systems*. ACM, 211–216.

[43] Hancheol Park and Gahgene Gweon. 2015. Initiating moderation in problematic smartphone usage patterns. In *Proceedings of the 33rd Annual ACM Conference Extended Abstracts on Human Factors in Computing Systems*. ACM, 1585–1590.

[44] 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*. ACM, LBW559.

[45] James O Prochaska. 2013. Transtheoretical model of behavior change. In *Encyclopedia of behavioral medicine*. Springer, 1997–2000.

[46] John D Rayburn and Philip Palmgreen. 1984. Merging uses and gratifications and expectancy-value theory. *Communication Research* 11, 4 (1984), 537–562.

[47] Jun Rekimoto and Hitomi Tsujita. 2014. Inconvenient interactions: an alternative interaction design approach to enrich our daily activities. In *Proceedings of the 2014 International Working Conference on Advanced Visual Interfaces*. ACM, 225–228.

[48] John Rooksby, Parvin Asadzadeh, Mattias Rost, Alistair Morrison, and Matthew Chalmers. 2016. Personal tracking of screen time on digital devices. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*. ACM, 284–296.

[49] Hillol Sarker, Moushumi Sharmin, Amin Ahsan Ali, Md. Mahbubur Rahman, Rummana Bari, Syed Monowar Hossain, and Santosh Kumar. 2014. Assessing the Availability of Users to Engage in Just-in-time Intervention in the Natural Environment. In *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing (UbiComp '14)*. ACM, New York, NY, USA, 909–920. https://doi.org/10.1145/2632048.2636082

[50] Saul Shiffman, Jean A Paty, Maryann Gnys, Jon A Kassel, and Mary Hickcox. 1996. First lapses to smoking: within-subjects analysis of real-time reports. *Journal of consulting and clinical psychology* 64, 2 (1996), 366.

[51] Pei-Shan Wei and Hsi-Peng Lu. 2014. Why do people play mobile social games? An examination of network externalities and of uses and gratifications. *Internet Research* 24, 3 (2014), 313–331.