TypeOut: Leveraging Just-in-Time Self-Affirmation for Smartphone Overuse Reduction

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ABSTRACT

Smartphone overuse is related to a variety of issues such as lack of sleep and anxiety. We explore the application of Self-Affirmation Theory on smartphone overuse intervention in a just-in-time manner. We present TypeOut, a just-in-time intervention technique that integrates two components: an in-situ typing-based unlock process to improve user engagement, and self-affirmation-based typing content to enhance effectiveness. We hypothesize that the integration of typing and self-affirmation content can better reduce smartphone overuse. We conducted a 10-week within-subject field experiment (N=54) and compared TypeOut against two baselines: one only showing the self-affirmation content (a common notification-based intervention), and one only requiring typing non-semantic content (a state-of-the-art method). TypeOut reduces app usage by over 50%, and both app opening frequency and usage duration by over 25%, all significantly outperforming baselines. TypeOut can potentially be used in other domains where an intervention may benefit from integrating self-affirmation exercises with an engaging just-in-time mechanism.

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CCS CONCEPTS

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

KEYWORDS

Smartphone overuse, intervention design, self-affirmation

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1 INTRODUCTION

Advances in mobile technology over the past few decades have enabled users to access an enormous range of information and perform tasks almost anytime anywhere. However, there is a growing body of research revealing an increasing population with smartphone overuse caused by constant connectivity (*e.g.*, [28, 29, 42, 47, 75]). It may lead to a range of negative consequences such as distraction [18, 47], lack of sleep [42], family conflicts [75], anxiety [28], and depression [29]. Users are generally aware of this issue and often want to try to reduce phone overuse. A recent study of 114 smartphone users found that 64% felt they were overusing their devices and 60% wanted to change their usage habits [40]. This finding was validated by another survey of 232 users that found 58% wished to reduce their smartphone use [31].

There have been many prior studies of persuasive technology and mobile apps on the market to reduce smartphone overuse

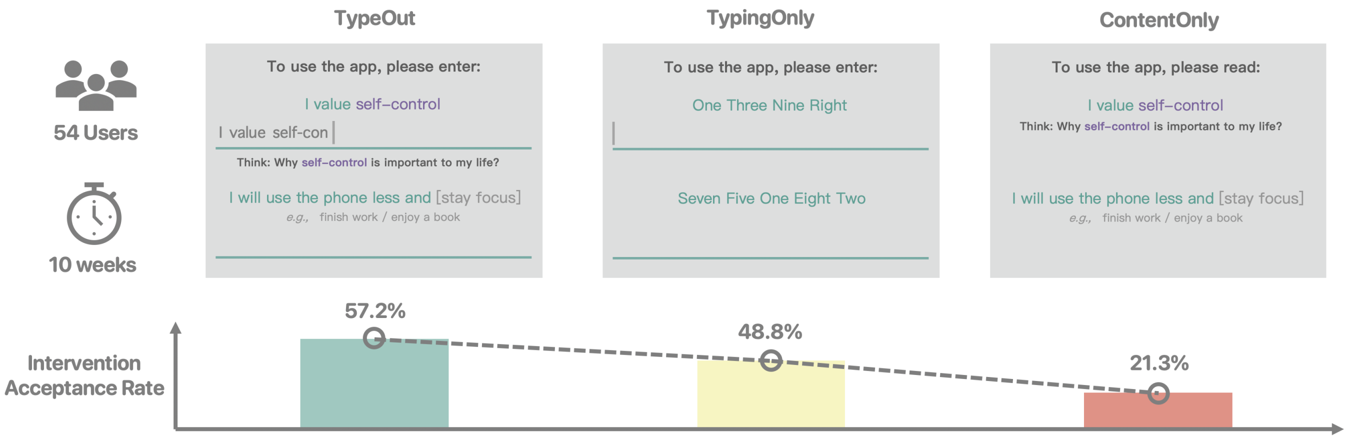


Figure 1: Overview of Our Intervention Design and Field Experiment Results. TypeOut: Our intervention technique that integrates two components: (1) a just-in-time typing-based intervention mechanism and (2) self-affirmation-based content design. ContentOnly: A baseline technique that only uses the self-affirmation content with a common notification-based mechanism. TypingOnly: A baseline technique that only has the typing mechanism with random words, a variant of a state-of-the-art method [37]. Intervention acceptance rate: the proportion of times when users encounter an intervention (the denominator), and decide not to enter the app (the numerator). TypeOut significantly reduces more smartphone overuse than the two baselines.

(*e.g.*, [8, 9, 47, 77]). Many of them use a "Just-in-Time" (JIT) approach to intervene at the moment when overuse is occurring [52]. Most of these intervention mechanisms can be categorized into two groups, either blocking users' apps/phones [36, 48], or sending notifications and reminders [31, 34, 39, 55, 63]. These mechanisms are usually accompanied by some persuasive content such as information about a user's app usage duration or reminders of a user's goals. However, restrictive blocking can sometimes cause a poor user experience and users could relapse after unblocking [14, 37], and notification-based interventions can be easily ignored or dismissed, leading to shallow engagement [36]. Recently, researchers proposed a technique where users have to type random digits to access an app, to balance restrictiveness and engagement [37]. However, the design of typing content is under-explored. The first two rows in Table 1 summarize these JIT techniques. In general, they use one of the following three strategies: (i) increasing the value of non-use, (ii) decreasing the value of use, or (iii) eliminating the option of use so that non-use is the only choice [37].

For behavior change intervention, the use of self-affirmation exercises is a popular method that has been proven to be effective [50, 65]. Self-Affirmation Theory [69] states that reminding users of their internal goals/identity can improve motivation to maintain "self-integrity" with those goals [19, 65]. It has been leveraged in a number of behavior change interventions [10, 19], such as health behavior change [19, 20], academic performance improvement [66], and well-being promotion [17, 53]. A typical self-affirmation intervention usually asks users to perform self-affirmation tasks (often via counseling, ranking personal values, filling out questionnaires, or writing), either at the beginning of a study (*e.g.*, [19, 72]) or at a certain frequency (*e.g.*, [49, 68]). However, to the best of our knowledge, there is no prior work leveraging self-affirmation in a JIT mechanism.

We speculate that content design for JIT typing interventions, and using self-affirmation in a JIT manner, can complement each other. We hypothesize that the integration of a JIT typing mechanism and self-affirmation content can effectively reduce app usage frequency and duration. We create TypeOut, a novel, simple, JIT intervention technique that embeds a brief self-affirmation task into the typing content to reduce smartphone overuse.

Our design consists of two components: (1) a typing-based app unlock process that introduces an additional interaction cost to decrease the value of app use (strategy i) [37, 51], and (2) value-based self-affirmation content that connects users' personal values and the overuse behavior to increase the value of non-use (strategy ii) [50]. Users first go through a list of phone-use-related value items and select those they think are important to themselves. Then, when users tend to overuse their phone (*e.g.*, staying up late to browse video streams), they need to first type two short sentences with persuasive content designed based on Self-Affirmation Theory: one about a value picked from their own item list (*e.g.*, "I value [health]"), and one about actions that requires in-situ improvisation (*e.g.*, "I could put down my phone and [sleep early]", where the bracket allows users to type freely). They can choose to quit the app, or access the app after they finish typing. We open-source our mobile application that implements TypeOut on GitHub [1].

We present a within-subjects field experiment (N=54) that compares our technique against two baselines: (1) A simple dialog pop-up window showing self-affirmation content (ContentOnly, *i.e.*, no typing mechanism), which adopts the common notification-based mechanism in many existing intervention techniques. Users can press a button to either quit or continue to use the app; and (2) A dialog pop-up window asking the user to input random, non-semantic

[1] https://github.com/OrsonXu/TypeOut

Intervention Content	**Just-in-Time Intervention Mechanism**		
	Blocking	Notification	Typing
Non-semantic	–	–	▲ Random text [37] (**TypingOnly**)
Semantic, non-self-affirmation	Rule [48], Goal setting [36]	Passive information [55, 63], Social/context awareness [34, 39], Goal setting [31]	Passive information, Goal setting
Semantic, self-affirmation	–	▲ Self-affirmation notification (**ContentOnly**)	★ **Self-affirmation typing (TypeOut)**

Table 1: Summary of Prior or Potential Work on Just-in-Time Intervention for Smartphone Overuse. ★ indicates our intervention technique TypeOut. Two ▲s indicate the baselines we compare against, one in the same row as TypeOut and the other in the same column. – means not applicable.

contents (TypingOnly, *i.e.*, no self-affirmation content), a lockout intervention mechanism proposed recently [37]. Each method has one design component of TypeOut, and thus can serve as baselines to evaluate the effectiveness of each component. Table 1 presents the design space for our technique and baselines Participants used each intervention method for two weeks, with a week of break inserted after every method. Our experiment results indicate that TypeOut can more effectively reduce smartphone usage, significantly outperforming baseline methods. Moreover, participants' subjective feedback further suggests that TypeOut is more acceptable and causes more reflection on phone usage. These outcomes validate our hypothesis that combining a JIT typing intervention and self-affirmation content can reduce smartphone overuse successfully.

The main contributions of our paper are summarized as follows:

- We developed (and will open-source) TypeOut, a theory-driven intervention technique for smartphone overuse. It integrates a JIT typing-based unlock process with self-affirmation content to persuade users to reduce smartphone overuse.
- We conducted a longitudinal field experiment (N=54) for 10 weeks and compared TypeOut against two common baseline techniques. Our results indicate that TypeOut discourages 57.2% of app usage, and reduces overall app opening frequency by 26.8% and usage duration by 25.4%, all significantly outperforming baselines.

Our method has the potential to be generalized to other behavior change intervention techniques. When focusing on another target behavior, an appropriate engaging JIT mechanism needs to be designed carefully (*e.g.*, a typing process when users are trying to access an app, in our case) and integrated with self-affirmation content adapted to the target behavior.

2 BACKGROUND

Smartphone use has taken on an essential role in people's daily life, however extreme use may have negative impacts on users. There is a growing body of research revealing smartphone overuse and smartphone addiction, especially among a young population [33, 44]. It may lead to negative consequences on physical health issues such as lack of sleep and reduced activity [11, 42], mental health issues such as increased anxiety and depression [28, 29], disrupted social relationships [2, 75], and reduced academic/work productivity [4, 16], *etc.* Below, we introduce the theoretical foundation beneath the design of our intervention technique TypeOut. We then summarize prior work on intervention techniques for smartphone overuse.

2.1 Theoretical Foundation: Dual Process and Self-Affirmation

To design an effective intervention, we need to first understand how users make the decision to engage in smartphone use or non-use. The Dual Process Theory [32] contends that human behavior is controlled by two processes or "systems": System 1, an impulsive process that represents spontaneous, automatic, and non-conscious influences on behavior, and System 2, a deliberative or reflective process which represents rational, deliberative, and conscious decision-making influences [26, 70]. Researchers can explain the failure of well-intended behavior control with this theory: the self-regulation from good intentions (System 2) is usually overridden by momentary impulses (System 1) [45, 47, 58]. In the smartphone overuse scenario, the easy access of rich information and immediate gratification from using smartphones drives users' impulses [43, 78]. Therefore, persuasive technologies usually aim to awaken System 2 and increase its strength, which is mediated by the expected value of control [64], so that System 2 can lead users' behavior [47]. There are 3 factors influencing the expected value of control, including the reward/punishment people perceive they could obtain, the expectancy or likelihood that people would be able to achieve a desired outcome, and the delay before the outcome [47]. These factors illuminate the direction of our smartphone overuse intervention design to effectively strengthen the control of System 2, thus achieving behavior regulation and reducing phone usage.

Self-affirmation is the act of bolstering or restoring a perception of oneself as being adequate [69]. The central assumption of Self-Affirmation Theory [69] is that people are strongly motivated to protect their sense of adaptive and moral adequacy, or "self-integrity" [19, 65]. Self-affirmation methods such as thinking about core personal values, important personal strengths, or valued social relations, can offset the threats to self-integrity [50]. Moreover, researchers find that the cognitive processes instigated by self-affirmation can help to better trigger System 2 in the Dual Process Theory [57, 76]. Prior studies have shown that self-affirmation is effective in a wide range of behavior change intervention domains, such as improving academic performance [12, 66], reducing stereotyping towards minority group members [5, 23], and promoting health behavior change [20, 22]. Some cognitive behavior therapy techniques employed self-affirmation exercises to reduce smartphone overuse [85, 86]. A typical self-affirmation task usually focuses on a specific value or positive personal characteristics. The specific task can vary, such as responding to specific scales, writing a list or an essay, or using imagery techniques on their positive qualities [50]. Recently, researchers have adapted traditional time-consuming self-affirmation exercises to be short, regularly delivered questionnaires for health eating behaviors that are more compatible with the smartphone platform [68]. There is a growing call for JIT intervention techniques that can better engage users at the right moment and that are integrated with self-affirmation content [49]. However, no prior work leverages self-affirmation exercises in a JIT manner yet.

2.2 Intervention for Smartphone Overuse

Researchers have built a large number of interventions from various perspectives to reduce smartphone overuse [9, 47]. To solve the problem of users spending too much time on smartphones, AppDetox allowed users to create rules to prevent them from using certain apps and social networking and messaging apps for which users wanted to suppress their usage [48]. MyTime let users select the apps they find distracting and establish usage time restrictions accordingly. The app used timer and timeout notifications as the intervention [31]. Shen *et al.* developed an app to provide alerts and reminders based on device usage statistical data [63]. In addition, vibrations have been explored as another reminder modality [55]. Regarding the problem of distraction or interruption, Lockn'LoL was developed as an intervention app to provide synchronous social awareness of a group of users' behaviors. The app was used to study connectedness among group members can reduce smartphone distraction [39, 40]. Let's FOCUS was implemented to solve the distraction problem during a class by offering context-aware reminders and a virtual limiting space where students could limit their smartphone use [34]. PromodoLock allowed users to set a timer for a period during which it would block certain kinds of interruptions, thereby reducing user's mental effort from self-interruptions [35]. Kim *et al.* developed GoalKeeper to study how different levels of lockout intensity could affect a user's usage behaviors. They found that stronger or more restrictive interventions are more effective while also being more stressful and frustrating [36]. In app marketplaces, apps such as Forest [3] allow users to set their own rules and lock their devices according to users' own commitments.

The intervention mechanisms of most of these existing techniques can be categorized into two types: blocking users' apps/-phones [3, 36, 48], or sending notifications and reminders [31, 34, 39, 55, 63] (see Table 1). Blocking access to smartphones can be effective [35, 36, 48], but may be overly restrictive, creating a bad user experience and even triggering greater usage [14, 37]. Notifications and reminders are the choice of intervention for many previous studies [39, 55, 63]. Some also engaged users in pre-establishing rules or goals [31]. However, these methods did not have a mechanism to encourage users to engage with the intervention content. Researchers found that users could easily ignore these notifications since they can be readily dismissed [36]. Perhaps the most related work to ours is LocknType [37]. It proposed a typing-based intervention mechanism that asked users to enter a list of random digits when a target app is launched. This method balanced restrictiveness and engagement, and was able to trigger users' System 2 and help to reduce the frequency of user's app usage. However, an unexpected disadvantage of LocknType was that the consequent usage time was longer, especially for non-target apps. This may be explained by the fact that the expected value from the app use could increase to balance the increasing cost of launching an app, causing reversed intervention outcomes [21]. Moreover, the design of the content that users have to type to launch an app is underexplored.

To summarize, on the one hand, most existing intervention techniques are either overly strict (blocking mechanism) or not engaging enough (notification mechanism), while the recently proposed typing mechanism, which improves on both of these flaws, does not explore content design as a way to address increased usage time. On the other hand, Self-Affirmation Theory has been proven to be effective for many behavior change interventions, but has not been applied in a JIT manner. To bridge the gap, our design integrates self-affirmation-based content with the JIT typing intervention for smartphone overuse. We introduce our design in the next section.

3 TYPEOUT DESIGN

We focus on addressing three questions to design an effective intervention. First, *when* should an intervention be triggered? Second, *how* should the intervention be presented? Third, and most importantly, *what* content should the intervention include?

Our design follows the Dual Process [32] and Expected Value of Control theories [64] as introduced in Section 2.1 when answering the three questions. For the questions about *when* and *how* (Section 3.1), our intervention introduces a cognitive task that increases the interaction cost of using apps (the first factor influencing the expected value of control). For the question of *what* (Section 3.2), the embedded self-affirmation content can amplify the expected reward people perceive (*i.e.*, maintaining self-integrity, related to the first factor) by reducing overuse without delay (second and the third factors), thus boosting the expected value of control and better awakening and strengthening the control of System 2. We present our design details in the rest of the section.

3.1 When & How to intervene?

We follow prior work on intervention techniques to answer the first two design questions.

3.1.1 When to intervene? A large body of prior work has adopted the JIT approach for smartphone overuse intervention. As overuse naturally occurs when users are using their phones, an intervention is usually introduced during these periods. There are a few options to determine the triggering moment, such as the moment when users are opening an app [37, 48], or when the usage duration for an app reaches an upper limit defined by users [31, 36]. As a starting point, we choose to trigger a JIT intervention when a target app is being launched. We envision our method is compatible with other JIT designs and plan to explore more JIT options in the future.

3.1.2 How to intervene? Most of the previous intervention techniques either present passive notifications/reminders that can be ignored by users [36], or introduce coercive prohibition that can cause reversed effect [35]. Recently, researchers proposed a typing-based unlock process (*i.e.*, users need to follow an instruction to type specific content before accessing the app) to balance the effectiveness and the restrictiveness [37]. Our method adopts this mechanism.

On the one hand, typing words following an instruction could enhance users' engagement, as they have to read the text and then type it out. Compared to notifications that can be dismissed easily, typing requires more attention, engagement and involvement from users [51]. On the other hand, typing does not strictly prevent users from using an app. It introduces additional interaction cost when accessing the app, but leaves users with the option to continue using the phone if they want to. Compared to more coercive prohibition methods, type-to-unlock is more flexible. Meanwhile, the additional interaction cost when entering the app introduces a notable gulf of execution on gratification seeking [15]. Such a micro-boundary can possibly switch a user's mind from System 1 to System 2 (as defined in the Dual Process Theory) for self-reflection/judgment [37].

More importantly, we suggest that such a typing process provides an opportunity to carefully design the typing content delivered to users. This offers an avenue to take user engagement one step further, leading to the next design question: what intervention content should be presented to users?

3.2 What to be delivered as intervention content?

As the typing process will better engage users with the intervention content, the content can go beyond presenting non-semantic content [37] or objective information (*e.g.*, the duration of app usage [31]), and be more thought-provoking (System 2) to improve its effectiveness. Leveraging Self-Affirmation Theory [69], we propose a content design that integrates value-based self-affirmation (Section 3.2.1) and JIT improvisation (Section 3.2.2). It can stimulate users to reflect on their own core personal values and connect these with the smartphone overuse behavior, thus motivating users to change their current behavior to protect their self-integrity [52]. Figure 2 presents our intervention design.

3.2.1 Value-based Self-Affirmation. Self-affirmation exercises have been employed by a wide range of behavior change interventions, mostly in a traditional way, such as answering surveys or writing an essay [20, 72, 74]. The main idea of self-affirmation-based intervention is to leverage users' intrinsic motivation for protecting their self-integrity to regulate their behavior (so that their adequacy is not violated). Our design adopts value-based self-affirmation, one of the most common self-affirmation exercises [19, 50]. Since a given value exists as a long-term belief for users, our design can be customized to each user based on their on set of values.

We employ a value list that is commonly used in acceptance and commitment therapy (ACT) [30], which contains a list of 58

Templates of Sentence 1 - Value
I { value, cherish } **X**
X is { important, crucial, meaningful } to me
I { think, believe } **X** is { important, crucial, meaningful }
I { think, believe } I am a **X** person
Templates of Sentence 2 - Action
I can put down the phone { to, and } [**improvisation**]
I can use the { phone, app } less { to, and } [**improvisation**]
I can { leave, quit } the app { to, and } [**improvisation**]
I can lock the screen { to, and } [**improvisation**]

Table 2: Templates for the two sentences delivered to users for the JIT self-affirmation typing exercise. Words in the brackets are picked randomly. "X" indicates a specific value (or its adjective form when appropriate), and "improvisation" indicates the just-in-time affirmation content created by users.

common value items [27]. To narrow down the list and filter out the ones unrelated to smartphone usage, we invited three experts to independently select no more than 20 related items. Moreover, we also delivered an online survey to ask end-users to select items from the long list that they perceive are related to smartphone overuse (N=98). We triangulated the results and found a consistent set of top seven values from both experts and end-users: *Self-control, Fitness, Order, Persistence, Self-awareness, Self-care,* and *Responsibility.* Based on the list of values, we adopt the common practices in affirmation [1, 60, 79] and propose a few short sentence templates that instantiate a value-based self-affirmation exercise, such as "I value X", "X is important to me" (X indicates a specific value tailored to each individual). Table 2 summarizes our templates. Each new user initializes their own list by performing a self-affirmation writing exercise and picking the value items from the list they think are important to themselves (see the left of Figure 2). After this initial setup, when an intervention is triggered, one value item will be randomly sampled from a user's personal list and inserted into the template. Moreover, we also present a hint to encourage users to reflect on the value.

3.2.2 Just-in-Time Improvisation. In addition to the sentence that emphasizes value, we also follow affirmation practices and design a second brief sentence template that states the specific actions to reduce overuse. Examples include "I can put down the phone", "I can let go of the app". Moreover, we also append a JIT improvisation at the end of the sentence to encourage users' engagement and stimulate more reflection. Self improvisation is also encouraged during regular self-affirmation exercises [65, 69]. At the moment when the intervention is introduced, users are asked to come up with a short phrase (no less than two words) about what they can do *if* they reduce overuse, such as "sleep early", "get focused", "finish my work". Concatenating the first half of the specific overuse-reducing actions and the second half of the improvised activities, an example sentence is: "I can put down the phone and finish my work". The templates of the second short sentence are summarized

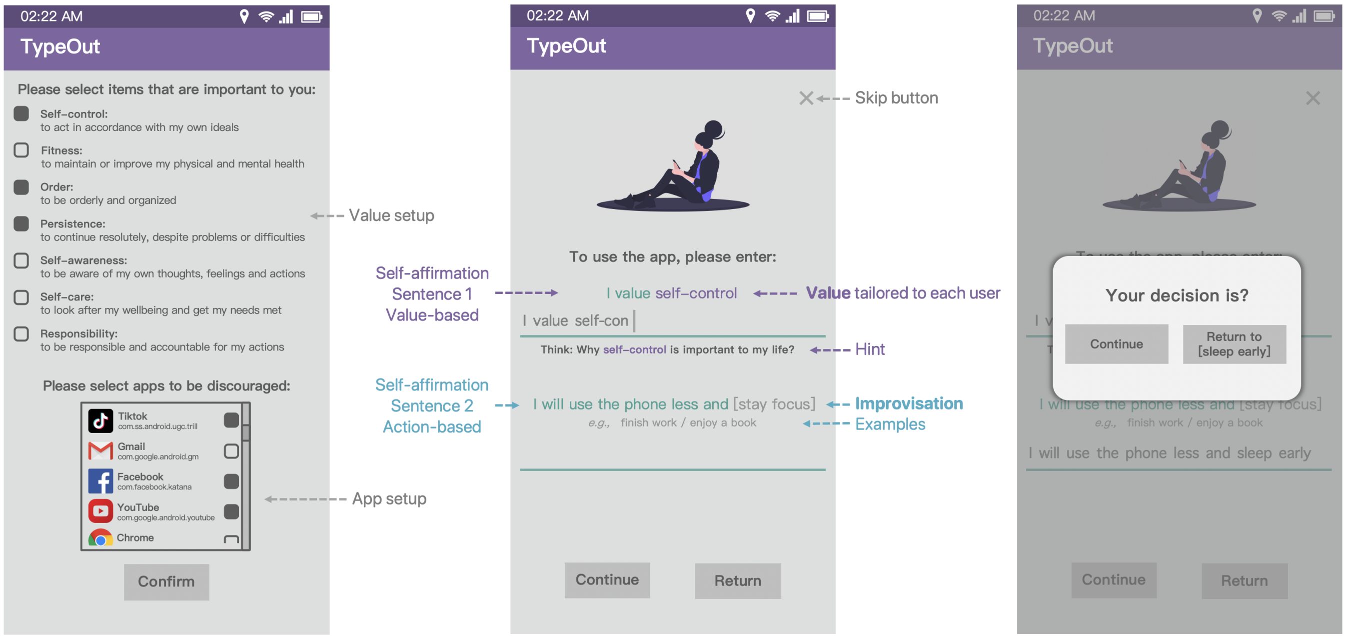


Figure 2: Intervention Design of TypeOut. Users set up their individual values list and select apps for which they want to receive an intervention (left). When an intervention appears, users can leave the app at any stage by clicking the return button or system home button, *e.g.*, before or during typing process (middle), or at the confirmation stage after typing is complete (right). Otherwise, users can enter the app after typing the self-affirmation and clicking the Continue button.

in Table 2. When users go through the content, finish the typing, and click the Continue button, a confirmation dialogue box will pop up asking for users' decision on whether to access the app, in which the Return button's text is replaced by users' improvisation (see the right of Figure 2). During the intervention, users can leave the app at any stage by clicking the return button: 1) before the typing process, 2) after typing some words, or 3) at the confirmation stage when they finish typing.

It is worth noting that users do not always accept or follow an intervention. When they decide not to follow the intervention, such a fact can become a challenge to their belief and sometimes leads to the *backfire effect*: instead of changing their behavior to be consistent with their belief, users would alter their belief and strengthen their original behavior (*i.e.*, phone overuse) [54, 61]. Our personalized value item list and self-improvisation allow users to customize the content themselves, leading to a better consistency between their beliefs and behavior. Moreover, to further reduce the likelihood of the intervention backfiring (and resulting in negative experience, increased app usage frequency or duration), we intentionally frame these sentences in a neutral tone [81], and unbind the value sentence and the action sentence [73]. Specifically, we avoid using verbs that may cause pressure or cognition distortion (*e.g.*, "should", "need" statements) [59, 71]. We also do not add any conjunction (*e.g.*, "so", "and", "thus") between the first and the second sentence, and break them into two separate lines [73]. We do this so that if users cannot achieve the target behavior (*e.g.*, continue to use the app), the neutral tone introduces less threat to users' self-integrity, and the unbinding can loosen the connection between their personal value and their current behavior, thus reducing the likelihood of a backfire.

Combining Section 3.1 and 3.2, we hypothesize that the integration of a typing-based unlock process and self-affirmation-based content can effectively reduce smartphone overuse than each component itself. We verify our hypothesis via a field experiment in Section 4.

3.3 Mobile Application Implementation

We built a mobile application on Android system to instantiate our TypeOut design. We then conducted a one-week pilot field study with five authors of this paper and finalized the design of the application. After the initial self-affirmation exercise, users pick items from the value list that they think are important to themselves. Then, users can select the apps (*i.e.*, target apps) for which they want to receive an intervention. The left of Figure 2 presents the initial setup interface.

We employed the AWARE Framework [24] to detect the screen status and foreground application activities. A typing-based intervention with generated content (as described in Section 3.1 and Section 3.2) will be triggered when one of the target apps is launched. To avoid text auto-completion during typing, we disable any smart typing function during the intervention. Users can press the Return button or system Home button to leave the app at any stage, or finish typing and continue to use the app. Sometimes, users may have an urgent needs to use a target app (*e.g.*, replying to messages). In these cases, users can press a skip button on the right-top corner of the interface to bypass the intervention. To prevent overly

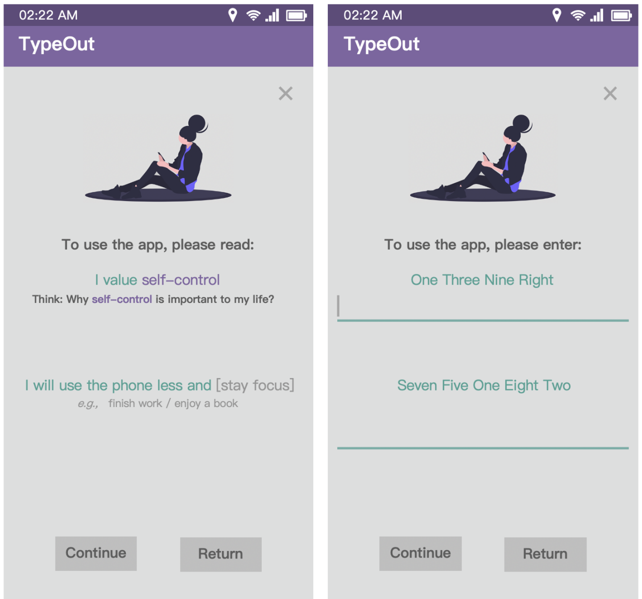


Figure 3: Two Baseline Methods to Compare against TypeOut: Content-Only (left) and Typing-Only (Right). The Content-Only baseline has the same self-affirmation content as TypeOut but not the tying process. The Typing-Only baseline has the same typing process asTypeOut but using random numerals as the typing content.

frequent intervention, when users enter a target app via typing or pressing the skip button, the intervention for this target app will not be triggered in the next five minutes.

4 FIELD EXPERIMENT

We conducted a 10 week field experiment to evaluate the effectiveness of TypeOut and verify our hypothesis. We first introduce our baseline methods (Section 4.1) and experiment design (Section 4.2). Then, we describe our participants (Section 4.3) and study procedure (Section 4.4). Finally, we introduce the results of our experiment (Section 5).

4.1 Baseline Intervention Techniques

We hypothesize that the integration of the two components – the typing process and the self-affirmation content – can effectively reduce phone overuse. To test this hypothesis, we compare TypeOut against two baseline techniques that separate the two components, as shown in Figure 3.

The first baseline only has the self-affirmation content but not the typing process, namely *ContentOnly*. When an intervention is triggered, it displays a pop-up window with the same content as TypeOut. The difference is that users do not need to type to unlock the app (see Figure 3 left). This is similar to a common notification or reminder-based intervention technique [31, 39, 48].

In contrast, the second baseline only has the typing process but not the self-affirmation content, namely *TypingOnly*. When an intervention is triggered, it introduces a JIT typing process similar to TypeOut. However, instead of typing self-affirmation-based content (as introduced in Section 3.2), it presents random numerals that contain no specific meaning (see Figure 3 right). This is a variant of a recent intervention technique LocknType [37]. LocknType uses digits (0-9) while our baseline uses the digits spelled out (one to nine) to maintain a more consistent comparison against TypeOut[2]. Moreover, we set the total character length of numerals close to but shorter than that of TypeOut's content, because the non-semantic contents would slow down the typing. We used eight to ten numeral words based on a pilot study with five users so that the total typing time is similar. [3]

4.2 Experiment Design

We adopt a within-subject design with the intervention techniques as the main independent variable: TypeOut, ContentOnly, and TypingOnly. Users use each intervention technique for two weeks. We counter-balance the order of the intervention to reduce order effect. The first week of the experiment is used for the base measurement and does not have any intervention. Moreover, we add a one-week break after each technique with two purposes: 1) We can measure whether there is any lasting effect (within that break week) when the intervention is removed, *i.e.*, whether users relapse or self-regulate; 2) The break week can serve as a grace period to further reduce the influence of the previous intervention technique on the next one. The total length of the study is 10 weeks (4 base/break weeks + 3 interventions × 2 intervention weeks each).

Our dependent variables include the intervention acceptance rate (when the users accept intervention and leave the target app), the usage duration and frequency of all applications. These variables are logged by our mobile app, stored locally on users' phones, and uploaded to our server automatically once the phone is connected to WiFi. In addition to the objective measurement, we deliver the Smartphone Addiction Scale (SAS) [41] to users at the end of each week to collect subjective feedback. Moreover, the final week's questionnaire also asks users to rank the three techniques based on effectiveness. The experiment ends with a brief exit interview. Figure 4 presents the overall design of the experiment. Our experiment was approved by the university institutional review boards (IRB).

4.3 Participants

We recruited participants from our local community via sending fliers on social platforms (Wechat and Tencent QQ, two most widely used platforms in the local community). We used a screening questionnaire (SAS plus a question about the subjective motivation for their current smartphone usage) to collect basic demographics (gender, age, occupation) and filter out users that either did not have degree of smartphone addiction (SAS < 99.0) [41] or were not

[2] The study was conducted in China, thus all contents are translated into Chinese by authors who are native-speakers. Participants used Pinyin as their text input method. In the result section, the typing length is defined as the character length using Pinyin.

[3] It is worth noting that we did not choose typing non-self-affirmation content as the baseline to keep the baseline consistent with the recent work LocknType [37], as our main purpose is to evaluate the advantage of self-affirmation-based content over the prior work, not to show it is the best. Moreover, the design space of the non-self-affirmation content lacks an established theory like value-based self-affirmation and can be overly large, which is hard to control.

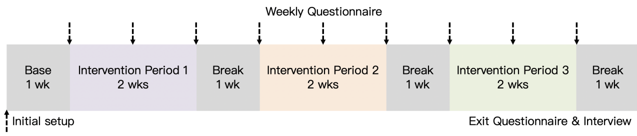


Figure 4: The Design of the 10 week Field Experiment. The order of the three intervention techniques is counter-balanced. We insert the break week after each technique to observe the last effect of each technique, and further reduce its influence on the next technique.

willing to reduce smartphone overuse [4]. We received 123 responses in total. None of participants had experience of using any digital or non-digital smartphone overuse intervention. 56 subjected were filtered with a SAS score lower than the threshold, and two subjected were filtered due to the lack of motivation. We invited 65 participants for the experiment. 5 of them chose to quit during the first two weeks of the study, and 3 of them left between the week 3 and week 5. No more participant left the study after week 5. We also removed 3 users who did not follow the requirement but skipped most of the interventions. Finally, 54 of them completed the experiment (Female = 25, Male = 29, Age = 22.1 ± 5.5). 24 participants were college students, while the rest were working professionals. At the beginning of the study, all participants had a moderate to severe smartphone addiction (SAS = 119.0 ± 20.5).

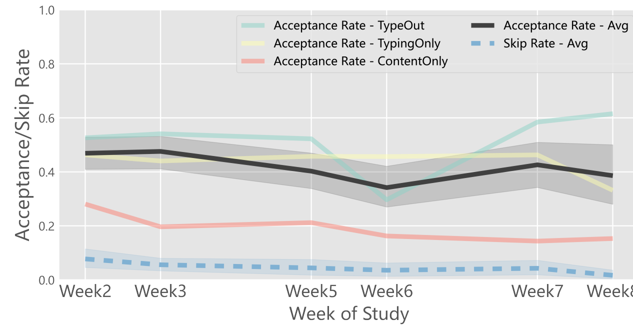
4.4 Procedure

We hosted a 30 minute on-boarding session before the start of the experiment, during which participants familiarized themselves with the study procedure, signed the consent form, installed our application, completed a 10 minute value-based self-affirmation writing exercise, and set up their own value list and target apps accordingly (see Section 3.2). Due to the pandemic, the on-boarding session was virtual. We had six groups (permutations of ordering the three intervention techniques) and randomly assigned participants to one group. Then, participants used the different techniques for 10 weeks, following the procedure shown in Figure 4. By the end of the experiment, we conducted a brief semi-structured interview with participants (20 to 30 minutes) and asked for their comments on the different intervention techniques. Participants were compensated with up to $US100 based on the number of questionnaires they completed and the number of days they uploaded data.

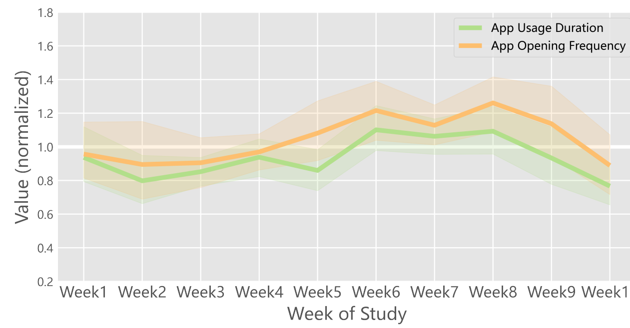
5 RESULTS

We now present the our study results. Over the 10 weeks, we collected 358,138 app opening events, 1,358,064 minutes of app usage duration, and 30,754 intervention encounters (9,837, 11,052, and 9,865 for TypeOut, ContentOnly, and TypingOnly, respectively). We analyzed the quantitative data and the qualitative data collected via questionnaires and interview.

[4]Researchers have found that 58-60% of users with overuse issues want to change [31, 40]. As an initial step of exploring the effectiveness of our new intervention technique, we followed previous research [37] and focused on users with motivations to change their overuse behavior.



(a) Intervention Acceptance Rate. The dashed line shows the rare cases where users click the skip button to bypass interventions.



(b) App Usage Pattern

Figure 5: The Overall Study Compliance over The 10-week Field-Experiment. The shadowed area indicates standard deviation across participants.

5.1 Study Compliance

We first investigate users' compliance during the 10-week period. Figure 5 suggests that participants' behavior fluctuated during the experiment. Therefore, we incorporate order as a main effect in all following analyses. As for skipping interventions, participants were instructed to skip only when necessary in the on-boarding session. The blue line in Figure 5a shows the skip rate during the intervention weeks. The low skip rate indicates that participants did follow our instructions.

5.2 Intervention Workload

We then examined the completion time, number of typing attempts (for TypeOut and TypingOnly), and perceived task workload to understand the interaction cost of each technique. Our results indicated that TypeOut and TypingOnly had similar workload, and ContentOnly had the lowest workload.

5.2.1 Completion Time. Overall, ContentOnly took the shortest time (Mean=2.9±1.9s), while TypeOut and TypingOnly took similar time (Mean=10.8±6.1s and Mean=13.3±7.6s) for participants to complete the typing. The average character length was 51.93±2.88 for TypeOut, which was longer than that of TypingOnly (38.68±1.33). This supports our design choice in Section 4.1 on shorter content for TypingOnly to balance typing time. Figure 6 shows boxplots of

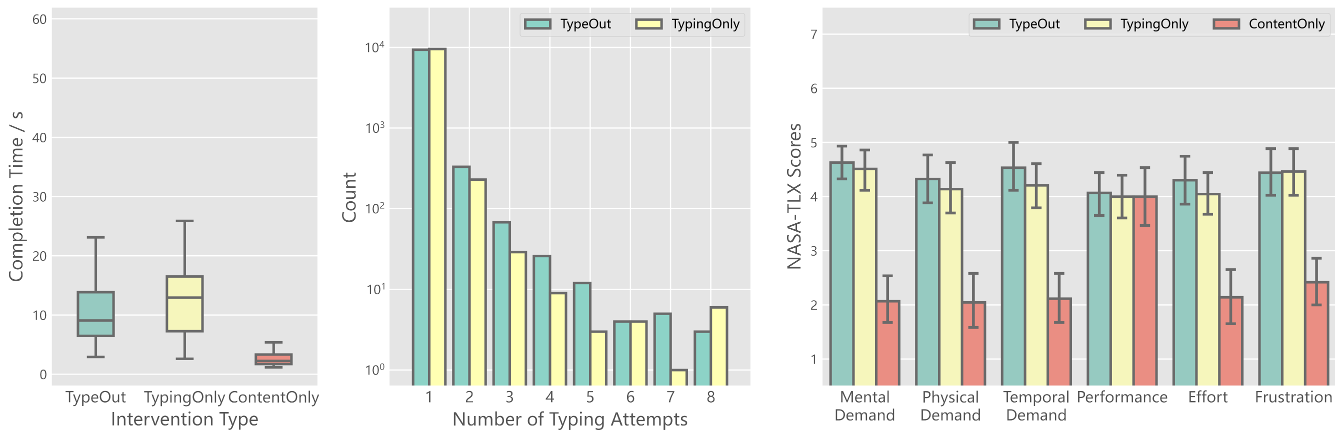


Figure 6: Workload Comparison among The Three Intervention Techniques. (Left) Intervention completion time (Middle) Number of typing attempts for TypeOut and TypingOnly in log-scale. (Right) Perceived workload measured via NASA TLX.

the time distribution around the median. A Shapiro–Wilk normality test showed that the completion time did not follow a normal distribution. Thus we used a Generalized Linear Mixed Model (GLMM) [5] for the statistical analysis [80]. We compared the completion time with *Techniques* as the only main factor ($\chi^2(2) = 225.9, p < 0.001$). In a pairwise post-hoc Tukey's HSD test, we found that TypeOut and TypingOnly required similar times ($p = 0.11$), both more than that of ContentOnly. To comprehensively compare TypeOut and TypingOnly, we ran another GLMM on the data of these two typing *Techniques*, with the *Order* of techniques, their interaction (*Order* × *Techniques*), average *Typing Length*, and *Skip Rate* as additional factors. The results indicate that these two intervention techniques introduced a similar temporal cost, as they did not show significance for any factors ($p_{technique} = 0.79, p_{order} = 0.45, p_{technique \times order} = 0.20, p_{typing\ length} = 0.87, p_{skip\ rate} = 0.12$).

5.2.2 Number of Typing Attempts. We also measured the number of typing attempts during the intervention for TypeOut and TypingOnly (skipped encounters were excluded as they did not involve typing). A number of 1 meant that participants completed the typing task on the first trial. Higher numbers indicate more input errors, which could aggravate the perceived workload from both the input and time perspectives. On average, participants tried similar times: 1.2±0.4 for TypeOut and 1.1±0.2 for TypingOnly (see the middle of Figure 6). We ran a GLMM on the number of attempts, with *Technique*, *Order*, *Technique* × *Order*, and *Typing Length* as factors. The results indicate that the two techniques had similar input costs, as they did not show any significant difference between the two techniques ($p_{technique} = 0.16, p_{order} = 0.22, p_{technique \times order} = 0.70, p_{typing\ length} = 0.19$).

5.2.3 Perceived Workload. We also investigated participants' perceived workload via a NASA TLX assessment (see the right of Figure 6). We compared all three techniques on the six elements of the TLX using a nonparametric ANOVA based on the Aligned Rank Transform and found a significant difference on the techniques ($F(2) = 134.4, p < 0.001$). Post-hoc Wilcoxon signed-rank tests with a Bonferroni correction showed that ContentOnly required significantly lower demand, effort, and frustration, while there was no significant difference between TypeOut and TypingOnly.

In summary, our measure on the workload of the three techniques showed that ContentOnly has the lowest workload, which is not surprising as it only required a single button click to exit the intervention. The two techniques with the typing process introduced higher but similar interaction costs. In the rest of the section, we analyze the effectiveness of each technique in impacting app usage.

5.3 Intervention Acceptance Rate

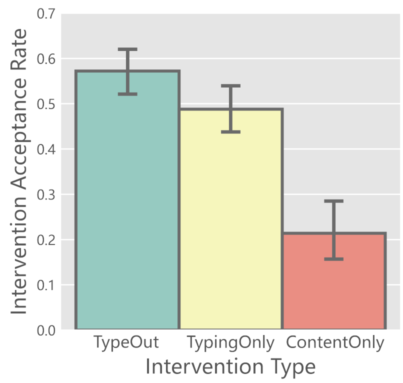
One of the direct indicators of the effectiveness of an intervention is how many times the intervention successfully discourages users from using the target apps. We defined *acceptance rate* as the proportion of times when participants encountered an intervention (the denominator), and decided not to enter the app (the numerator). In general, our results showed that TypeOut achieved a higher acceptance rate.

5.3.1 Intervention Acceptance Rate. We first investigated the overall intervention acceptance rate across all apps, and observed that TypeOut (Mean=57.2±28.5%) had a higher acceptance rate than TypingOnly (Mean=48.8±28.8%) and ContentOnly (Mean=21.3±21.2%), as shown in Figure 7a. Our method outperformed the baselines by at least 8.4% on absolute acceptance rate.

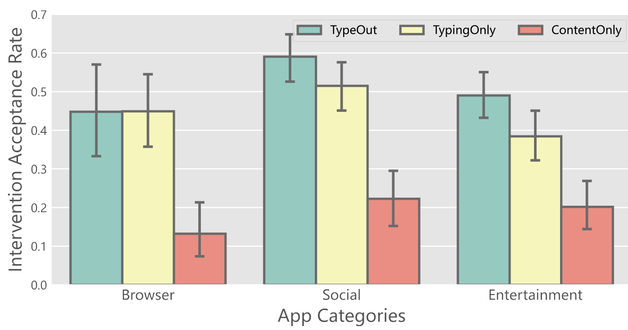
We compared the acceptance rate using a GLMM that included intervention *Technique*, *Order*, *App Category*, *Technique* × *Order*, and *Technique* × *App Category* as factors[6]. The results showed significance for *Technique* ($\chi^2(2) = 127.1, p < 0.001$) *App Category* ($\chi^2(2) = 12.0, p < 0.01$), and *Order* ($\chi^2(2) = 10.2, p < 0.01$), but no interaction effects ($p_{technique \times order} = 0.12, p_{technique \times app\ category} =$

[5]For each model, the link function was chosen from Gaussian, Log-Gaussian, Gamma, and Log-Gamma, based on Kolmogorov–Smirnov testing on the distribution of the outcome variables. Participant ID is controlled as a random effect. For simplicity, we do not repeat this description for the rest of the analysis in this section.

[6]Typing length was excluded as ContentOnly did not involve typing, the same below



(a) Overall Acceptance Rate



(b) Acceptance Rate Broken-down by App Categories

Figure 7: Average Intervention Acceptance Rate of The Three Intervention Techniques.

0.71). A post-hoc Tukey's HSD test on *Technique* showed that TypeOut achieved a higher acceptance rate than TypingOnly ($Z = 13.2, p < 0.001$) and ContentOnly ($Z = 2.4, p < 0.05$).

A post-hoc Tukey's HSD test on *App Category* showed that browser apps had a significantly lower acceptance rate compared to social apps ($Z = 3.2, p < 0.01$) or entertainment apps ($Z = 2.4, p < 0.05$). Figure 7b showed the acceptance rate of different app categories, which indicates that TypeOut outperformed TypingOnly mainly on entertainment apps ($p < 0.05$). Although we observe a difference on social platform apps, the results did not indicate significance ($p = 0.32$). A post-hoc Tukey's HSD test on *Order* showed that the acceptance rate of the first intervention period is higher than the second ($Z = 2.4, p < 0.05$), but other pairs (the first *v.s.* the third, second *v.s.* the third) did not show significant difference, as indicated by the black line in Figure 5a.

5.3.2 Leaving Stage Upon Acceptance. As introduced in Section 3.2, during the intervention of TypeOut, participants could leave the app at different stages. When using TypeOut, about 12.5% of participants left after typing something while this number was around 8.7% for TypingOnly. Participants' longer stay suggested deeper participation in the typing content. More specifically, 85.4±16.8% TypeOut participants left before typing, 12.5±14.6% left after typing a few words, and 2.1±6.2% left at the confirmation stage (after typing is completed, see the right of Figure 2). For TypingOnly, these numbers were 91.2±11.5%, 8.7±11.5%, and 0.1±0.2%, respectively. We ran a GLMM on the ratio of people leaving at each stage, with *Technique*, *Order*, *Leaving Stage*, *Technique* × *Order*, and *Technique* × *Leaving Stage* as the factors. The results showed significant difference on *Leaving Stage* ($\chi^2(2) = 2876.8, p < 0.001$) and an interaction effect of *Technique* × *Leaving Stage* ($\chi^2(2) = 7.3, p < 0.05$), but not others ($p_{technique} = 0.66, p_{order} = 0.82, p_{technique \times order} = 0.71$). A post-hoc Tukey's HSD test on the interaction showed that participants had deeper engagement in the self-affirmation content. TypeOut had marginally higher leaving rate during the typing stage ($Z = 3.6, p = 0.06$) and significantly higher leaving rate during the confirmation stage ($Z = 8.06, p < 0.01$).

5.3.3 User Behavior after Accepting Interventions. We further looked into participants' behavior after acceptance, *i.e.*, the immediate behavior right after users decided to leave the app after encountering the intervention. We measured three post-intervention behavior [37]: 1) turning off the screen, 2) using another target app, and 3) using another non-target app. Results show that participants using all three interventions were most likely to turn off the screen among the three situations, but TypeOut participants were more likely to do so. When using TypeOut, 48.2±13.0% of the time, participants would turn off the screen, compared to 42.3±15.3% for ContentOnly, and 47.5±10.2% for TypingOnly. Moreover, participants had a lower rate of going to another target app when using TypeOut (25.4±12.3%, similar to ContentOnly 25.0±9.9%) than when using TypingOnly (32.1±14.8%). As for non-target apps, the three techniques had similar percentages (26.4±11.6%, 27.4±8.5%, 25.6±12.1% for TypeOut, TypingOnly and ContentOnly, respectively). We ran a GLMM on the post-intervention behavior ratio, with *Technique*, *Order*, the post-intervention *Behavior Type*, *Technique* × *Order*, and *Technique* × *Behavior Type* as the factors. The results showed significance for *Behavior Type* ($\chi^2(2) = 4.1, p < 0.05$) and a marginal interaction effect *Technique* × *Behavior Type* ($\chi^2(4) = 5.8, p = 0.06$), but not others ($p_{technique} = 0.19, p_{order} = 0.78, p_{technique \times order} = 0.27$).

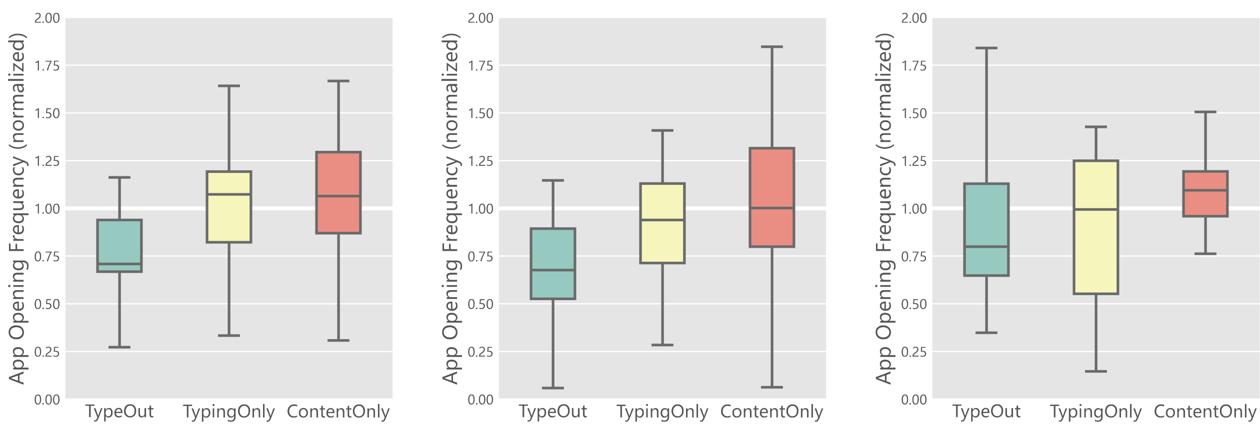
5.4 App Usage Behavior

We then investigated the influence of the intervention on participants' overall app usage behavior. Due to the large app usage variation among individuals, we normalized each participant's data by calculating the ratio against their own data during the base week. A ratio smaller or greater than 1 indicated that participants reduced or increased app usage compared to their ordinary behavior. Overall, participants had a smaller ratio when using TypeOut compared to other intervention weeks.

5.4.1 App Opening Frequency. We counted the number of app opening attempts for both target apps and non-target apps. It is worth noting that the opening counts included *any* attempt to open the app, regardless of users' final decision on whether to continue accessing the app after encountering an intervention. Such a counting method could emphasize the *overall* effect of an intervention instead of its *in-situ* effect (which was already reflected in the intervention acceptance rate results in Section 5.3). A lower value would suggest that participants initiate less app opening. Figure 8 presents the relative opening frequency of all apps (Figure 8a), target apps (Figure 8b), and non-target apps (Figure 8c) during the periods of using the three techniques. In general, participants had the lowest app opening frequency during the weeks of TypeOut (Mean=73.2±26.8% compared to the base week), followed by TypingOnly (Mean=99.8±35.7%), and then ContentOnly (Mean=106.5±40.2%). Although TypingOnly and ContentOnly have the potential to discourage app usage when participants receive that intervention (on the overall acceptance rate metric in Section 5.3.1), participants still maintained a similar app opening frequency as their ordinary behavior without any interventions. We ran a GLMM comparing the opening frequency on all apps. As indicated by Figure 5b, we include *Technique*, *Order*, and *Technique* × *Order* in the model. The results showed significance on *Technique* ($\chi^2(2) = 22.4, p < 0.001$), but not on *Order* ($p = 0.87$) or their interaction ($p = 0.14$). A post-hoc Tukey's HSD test on *Technique* showed that participants had significantly lower app opening frequency during the TypeOut weeks than during the two baseline periods ($Z_{ContentOnly} = 4.0, p < 0.001$ and $Z_{TypingOnly} = 4.3, p < 0.001$), while the ContentOnly-TypingOnly pair did not show a significant difference ($p = 0.99$). We found similar results for another GLMM with the same setup but on the opening frequency on target apps ($\chi^2(2) = 15.5, p < 0.001$, $Z_{ContentOnly} = 3.4, p < 0.01$, and $Z_{TypingOnly} = 3.5, p < 0.01$). As for non-target apps, a GLMM did not indicate significance on all factors ($p_{technique} = 0.11, p_{order} = 0.19, p_{technique \times order} = 0.27$).

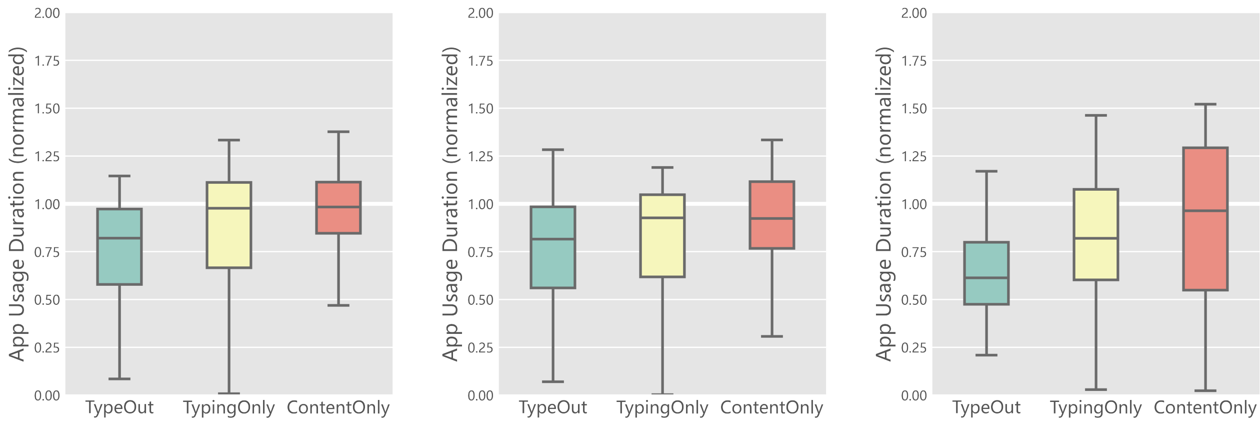
5.4.2 App Usage Duration. In addition to app opening frequency, we also measured app usage duration as it is another important indicator for phone overuse. Similar to Figure 8, Figure 9 presents the relative usage duration of all apps (Figure 9a), target apps (Figure 9b), and non-target apps (Figure 9c). Participants had the lowest app usage duration during the weeks of TypeOut (Mean=74.6±31.0% compared to the base week), followed by TypingOnly (Mean=90.6±27.7%), and ContentOnly (Mean=99.1±28.1%), which is the same order as the results for app opening frequency. When using ContentOnly and TypingOnly, participants still maintained over 90% app usage duration compared to that of the base week. TypeOut can reduce app usage duration more than two baselines. We ran a GLMM with the same setup as those in Section 5.4.1 on all apps usage duration. The results showed significance for *Technique* ($\chi^2(2) = 12.1, p < 0.01$), but not others ($p_{order} = 0.24, p_{technique \times order} = 0.27$). A post-hoc Tukey's HSD test on *Technique* showed that participants had significantly lower app usage duration during the TypeOut weeks ($Z_{ContentOnly} = 3.4, p < 0.01$ and $Z_{TypingOnly} = 2.7, p < 0.05$). Another GLMM on target apps' data showed similar results with significance for *Technique* ($\chi^2(2) = 6.1, p < 0.05$). A post-hoc Tukey's HSD test found significance between TypeOut *v.s.* ContentOnly ($Z = 2.5, p < 0.05$). As for non-target apps, a GLMM on non-target apps' data showed significance for *Technique* ($\chi^2(2) = 6.5, p < 0.05$). A post-hoc Tukey's HSD test found significance between TypeOut *v.s.* ContentOnly ($Z = 2.3, p < 0.05$), and marginal significance between TypeOut *v.s.* TypingOnly ($Z = 2.1, p = 0.08$).

5.4.3 Lasting Effect on App Usage. We used the data during break weeks to measure the lasting effect when the intervention was removed. We calculated the app usage ratio between the break weeks after intervention techniques against the base week. A ratio lower than 1 indicates that users reduced smartphone usage compared to their ordinary behavior. Figure 10 presents the results of opening frequency and usage duration for all apps. Both the frequency and duration during the break weeks were similar among the three interventions. TypeOut had a slightly lower app usage duration and ContentOnly had a slightly lower app opening frequency. The ratios of both app opening frequency and app usage duration are not significantly different from 1. Specifically, for app opening frequency, we ran a GLMM with *Technique* of the previous intervention period, *Order*, and *Technique* × *Order* as factors. The results showed significance for *Technique* ($\chi^2(2) = 11.1, p < 0.01$) and



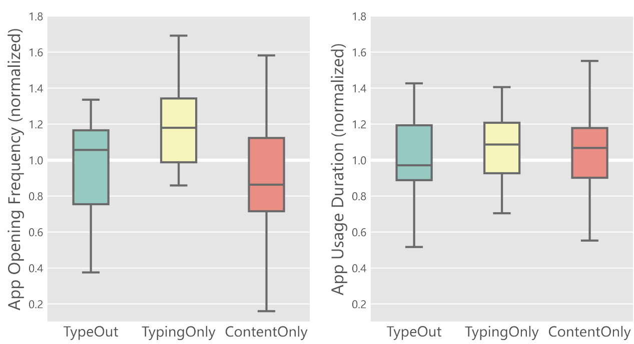
(a) Freq of All Apps **(b) Freq of Target Apps** **(c) Freq of Non-Target Apps**

Figure 8: App Opening Frequency with Three Intervention Techniques. Each participant's data are normalized by calculating the ratio between the frequency of intervention weeks and that of baseline weeks. It is worth noting that the frequency includes *any* attempt to open the app, regardless of the final decision after intervention, thus a lower frequency suggests users initiate less app opening.



(a) Duration of All Apps **(b) Duration of Target Apps** **(c) Duration of Non-Target Apps**

Figure 9: App Usage Duration with Three Intervention Techniques. Similar to Figure 8, data are normalized by calculating the ratio between the duration of intervention weeks and that of baseline weeks. A lower ratio indicates less app usage duration.



(a) Freq of All Apps **(b) Duration of All Apps**

Figure 10: App Usage Frequency and Duration of the break weeks after each intervention techniques. Data are normalized in the same way as Figure 8 and Figure 9.

Order ($\chi^2(2) = 6.5, p < 0.05$), but not their interaction ($p = 0.53$). A post-hoc Tukey's HSD test on *Technique* found that both the opening frequency of TypeOut ($Z = 2.7, p < 0.05$) and ContentOnly ($Z = 2.8, p < 0.05$) were significantly lower than that of TypingOnly, but that of TypeOut and ContentOnly were similar ($p = 0.92$). A post-hoc Tukey's HSD test on *Order* showed significance between the first and the third intervention period ($Z = 2.5, p < 0.05$). As for app usage duration, another GLMM with the same setup only showed significance on *Order* ($\chi^2(2) = 18.23, p < 0.001$). A post-hoc Tukey's HSD test on *Order* showed that the usage duration of the third period was significantly lower than that of the first ($Z = 2.8, p < 0.05$) and the second period ($Z = 4.2, p < 0.001$), as indicated by the lines in Figure 5b. These results indicated that after using them for two weeks, these techniques did not have a strong lasting effect after the intervention was removed. We will further discuss this issue of lasting effect in the Discussion (Section 6).

5.5 Subjective Measure

The weekly questionnaires and summative interviews also provided insights on the effectiveness of the three techniques. We employed Affinity diagramming [62] to analyze the interview data. Two researchers independently made notes based on the recording of interviews, and collaboratively analyzed and categorized the data with several iterations. Overall, our technique showed better acceptance and user experience than baselines.

5.5.1 Smartphone Addiction Scale Scores. Similar to app usage behavior, we also normalized each participants' SAS scores by calculating the ratio against their own scores of the base week. A ratio lower than 1 indicated that users had less smartphone addiction. Figure 11 shows the results of the SAS scores during the intervention weeks (average score of the two weekly questionnaires) and the following break week. We found that TypeOut has the lowest SAS scores during the intervention weeks and the following week. For each period, we ran a GLMM on the SAS scores, with *Technique*, *Order*, and *Technique* × *Order* as factors. The two GLMMs did not show a significant difference among the three techniques ($\chi^2_{Intervention\ Week}(2) = 0.6, p = 0.73$, $\chi^2_{Following\ Week}(2) = 1.2, p = 0.54$), nor other factors (Intervention Week: $p_{order} = 0.13, p_{technique \times order} = 0.29$, Following Week: $p_{order} = 0.36, p_{technique \times order} = 0.90$).

5.5.2 User Reactions. Our interviews helped us to better understand participants' user experience when using the three techniques. Participants could easily ignore the content of ContentOnly. *"Sometimes I completely skip reading the content during the [ContentOnly] weeks, because I just need to click the continue button"* (P17). Compared to TypingOnly, participants found that the content in TypeOut can cause more self-reflection and is more acceptable. *"I have to read the sentence seriously before the typing. After reading them, I often think it is okay to use the phone later"* (P30). *"Typing some random words actually can help. But it is a bit annoying. I prefer the meaningful words as they can remind me of my decision [to reduce*

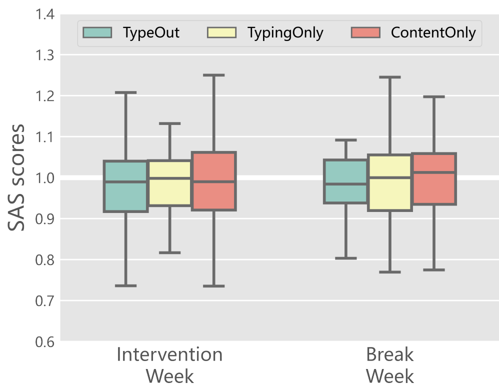


Figure 11: Smartphone Addiction Scale Score during/after using the three intervention techniques. Since each intervention technique period had two weeks, SAS scores during the intervention weeks are the average of the two weekly questionnaires.

usage]" (P5). Participants mentioned that the combination of value affirmation and improvisation was particularly helpful. *"During the typing, I would pause and re-think whether I actually need to use the phone right now... especially at the creation [improvisation] part where I would refer back to the previous [value] sentence and think about what I really need to do"* (P37). Even after typing the content and entering the app, participants could still recall the content. *"When using the app [after finishing typing], sometimes I remembered what I just typed [and leave the app]"* (P19). For some participants, this affirmation content affected their behavior during the break week. *"The content I typed would leave an impression in my mind and it sometimes pop up even when there is no intervention anymore"* (P37). These results indicated the advantages of TypeOut over baselines.

5.5.3 Subjective Effectiveness. Moreover, we also found a surprising finding in users' ranking of the three techniques: an equal number of participants picked TypeOut and TypingOnly (both 41.9%) as the most effective method. This is very interesting since our objective measure showed that TypeOut was significantly more effective than TypingOnly in terms of intervention acceptance rate (Section 5.3), app opening frequency, as well as app usage duration (Section 5.4), but a large proportion of participants thought the opposite. Our interviews revealed that these participants picked the TypingOnly mainly because it was the most "troublesome" technique. *"Compared to the meaningful content, the random content is more difficult to type since I have to type them one by one separately. So I often give up and quit the app. That's why I think [TypingOnly] is more effective."* (P2). *"[TypingOnly] pops up in my mind immediately because this one was so annoying and it intervened me many times. This is the most effective technique."* (P50). TypingOnly did have a fairly high intervention acceptance rate of 48.8% (compared to TypeOut's 57.2%) and this was also reflected by participants' feedback. However, participants did not realize that their overall app opening frequency and usage duration during the weeks of TypingOnly did not decrease compared to those of base week. Meanwhile, during the break week after the TypingOnly weeks, participants had a big relapse on app opening frequency (19.0% more compared to base week). Therefore, there was a clear discrepancy between users' perceived effectiveness and the actual effectiveness of these techniques.

5.6 Results Summary

From the 10-week field experiment, our findings suggest that ContentOnly has the least influence on users' smartphone usage behavior. Our questionnaires and interview results reveals that the low interaction cost and low engagement is the main reason. This finding is supported by prior work [36]. TypingOnly can discourage more smartphone usage than ContentOnly. This indicates that the interaction cost introduced by the JIT typing-based unlock process can reduce overuse, which resonates with the previous study of LocknType [37]. Compared to TypingOnly, TypeOut leverages Self-Affirmation Theory, embeds a cognition-level self-affirmation exercise into the typing content and shows stronger effectiveness, and significantly outperforms the baseline techniques. This illustrates the impact of self-affirmation and verifies our hypothesis that the combination of the two components – the JIT typing process and the self-affirmation-based content – can better reduce phone overuse than either single component alone.

Our finding about the discrepancy between participants' subjective effectiveness and actual effectiveness supports TypeOut from another perspective. The reason behind 41.9% of participants picking TypingOnly as the most effective technique mainly came from the obvious interaction cost introduced by the typing and the frustration it created. Participants' subjective effectiveness can be interpreted as the perceived extent of interference from the intervention. An overly strong interference may cause a negative user experience and reversed results [37], as reflected by the relapse of TypingOnly during the break week. Comparatively, TypeOut, having a similar temporal cost and workload (Section 5.2), did not trigger such a strong reaction from participants, while achieving a stronger intervention effect. This indicates that although self-affirmation influenced participants to reduce overuse, many did not perceive the typing of self-affirmation content to be as strong an interference as TypingOnly, which suggests the potential of our technique for real-life deployment.

6 DISCUSSION

In this section, we discuss the advantage of TypeOut compared to prior intervention techniques, the design space of TypeOut, the potential generalizability to other domains, as well as limitations and future directions to improve the technique.

6.1 From Behavior-level to Cognition-level Intervention

Most of the existing smartphone overuse interaction techniques focus on changing behaviors that are specifically related to the overuse. For example, AppDetox [48] and MyTime [31] let users set their own rules or goals about the smartphone use pattern, and deliver reminders of their rules/goals when appropriate. The intervention contents of these techniques are mainly about users' behavior, such as the time limit of using an app, or the location restriction of using the phone, but do not build a connection with users' cognition. In contrast, TypeOut aims to address the user at a level beneath behavior. Based on self-affirmation content and a cognitive typing task, it connects users' smartphone use behavior with their personal values, which serves as a reminder of their identities and could trigger System 2 style cognitive behavior regulation. Although our experiment was too short to demonstrate longitudinal benefits of TypeOut, it is possible this cognitive/identity based approach will lead to more substantial longitudinal change than behavior-level interventions that mainly focus on momentary decision making. Participants' remarks, such as *"I quickly got myself back to my old habits. I guess I haven't built a new habit yet... I wish I could use the technique longer!"* (P22), suggested that a longer study might lead to greater change. This is also supported by self-affirmation intervention studies in other domains (*e.g.*, social psychological intervention [13]), where the intervention becomes longitudinally effective over multiple years. Despite the short exposure, our intervention was demonstrated to be highly effective at reducing smartphone use during the TypeOut weeks. We encourage other researchers to take cognition-level intervention into account when designing new intervention techniques. This could potentially go beyond a typing process and the smartphone overuse behavior. We have more discussion on the generalizability of TypeOut in the remainder of the discussion.

6.2 Challenges and Takeaways of TypeOut

We share a few challenges encountered during the longitudinal study. First, although we balanced the technique order between participants, there was still a significant order effect, as shown in several statistical results in Section 5. This shows a drawback of the within-subject design in such a longitudinal study: the intervention method used in previous weeks might affect users' reaction towards the next method. Such an effect could be hard to mitigate even with the balanced order design. A potential alternative is using micro-randomization trials [38], where each intervention is sampled randomly from three techniques. However, such a method cannot evaluate the lasting effect because different techniques are mixed. If a larger participant group is available, then a between-subject design could be considered. Second, our current sentence template bank has 13 (value sentences) $\times$12 (action sentence) = 156 templates in total. Many of them have similar structures. Some participants mentioned that they felt the task was tedious after typing a few similar sentences. This indicates that in future studies, intervention content needs to have a larger variance to avoid undermining user experience. Third, in our study, we installed an app on users' phones to track users' behaviors, determine the appropriate intervention moment, and deliver the interventions. If the app were shut down by participants (*e.g.*, by accident, in low-power mode, after rebooting), these functions would not work properly. We established a dashboard to monitor the activeness of the app on participants' phones, and would send a reminder to them if the app stayed inactive for more than 24 hrs. Such a method effectively ensured the user compliance of the study [84]. It is worth noting that these reminders could also act as a different type of intervention. Thus, we kept these reminders as balanced across weeks as possible, and avoided sending frequent reminders. Researchers should also consider such a trade-off between the study compliance and the potential impact on the study.

6.3 Other Intervention Modalities

A self-affirmation task can be conducted via various forms, and typing is only one of them. There are other design choices for TypeOut. For example, users can be prompted to answer a multiple-choice question or solve a word puzzle, in which the target can be to find one of the value items that is important to themselves based on their setup at the beginning. Moreover, together with the many other intervention techniques, the current version of TypeOut also employs a "screen-based" intervention technique (*i.e.*, typing on the screen) to reduce "screen usage". There are other modalities that do not involve the screen directly, thus may provide additional advantages and serve as a complementary alternative. Some work explored using vibration as a secondary modality to reminder users [55]. For TypeOut, one possibility is using voice. Instead of typing sentences on the screen, users can also speak the sentences aloud, and a voice recognition system can be employed to ensure the quality. Speaking would also encourage users to digest the content, which has a similar effect as typing to increase engagement. These are promising directions to explore in the future.

6.4 Towards a Just-In-Time Adaptive Intervention

As a starting point, TypeOut simply triggers an intervention whenever users open a target app (Section 3.1.1) and the content is randomly drawn from a personalized sentence bank (Section 3.2). A deployable system can leverage more advanced methods to make it more adaptive, achieving just-in-time adaptive intervention [52]. From the timing perspective, instead of showing the intervention every time an app is opened, an intelligent system could predict the moment of overuse [46, 67] (*e.g.*, when the app is opened or after it is used for some time). The content of the intervention can also be more context-aware and adaptive to users' in-situ behavior and environment. For example, the action sentence can be different during working hours when users are at the workplace and at night when users are at home. Reinforcement learning techniques such as contextual bandit [25] might be leveraged to make such adaptive models evolve with users' behavior over time.

6.5 Beyond Smartphone Overuse Intervention

In addition, we envision our design could inspire other behavior change intervention domains. There is potential to generalize JIT self-affirmation to a wide range of behavior intervention domains, where an appropriate, engaging JIT mechanism needs to be designed carefully for other target behaviors. For example, the typing mechanism can be easily adapted to other overuse behaviors on digital platforms, such as video game addiction or excessive online shopping. For behaviors that take place in real-life (*e.g.*, excessive smoking [56], unhealthy eating [7], or mental health challenges [82, 83]), after a passive sensing system detects the target behavior, a JIT intervention with self-affirmation-based content can be triggered at an appropriate moment via mobile phones or wearables.

6.6 Limitation and Future Work

Our current study population included mainly young adults with at least moderate smartphone addiction who expressed a willingness to improve their phone usage behavior. Although this group is the major target users of TypeOut, in future work, we will include a wider range of users to evaluate our technique more comprehensively. Additionally, researchers and practitioners have found that sometimes self-affirmation exercises can backfire when people fail to control their behavior, especially for those with low self-esteem: This can lead to disappointment and self-blame, and sometimes cause people give up on their self-regulation, strengthening their original behavior (phone overuse, in our case) [73, 81]. We designed our intervention content with this in mind to leverage personalized value lists, a neutral tone, and a break between the value and action sentences. However, it is still possible for such an intervention to backfire. A promising solution is to design the interactive feedback loop of the intervention to improve self-efficacy when users successfully regulate their behavior [6], or promote acceptance when they fail [30].

7 CONCLUSION

In this paper, we propose a new intervention technique, TypeOut, for reducing problematic smartphone usage. Our design integrates a JIT typing component that requires users to type a few words before accessing apps, and a brief self-affirmation exercise component is embedded in the typing content. We hypothesized that the combination of the two components can introduce more effective intervention than each component alone. We conducted a 10-week field experiment with 54 young adults to evaluate the effectiveness and usability of our technique. Our results indicate that TypeOut discourages 57.2% of app usage, and reduces overall app opening frequency by 26.8% and usage duration by 25.4%, all significantly outperforming baseline techniques. Moreover, our questionnaires and interview reveal that users find TypeOut to be more acceptable and cause more reflection than the baseline techniques. These results verify our hypothesis, though future work may want to consider including a wider sample to replicate the work and help assess generalizability.

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