

# Rotating Online Behavior Change Interventions Increases Effectiveness But Also Increases Attrition

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Behavior change systems help people manage their time online. These systems typically consist of a single static intervention, such as a timer or site blocker, to persuade users to behave in ways consistent with their stated goals. However, static interventions decline in effectiveness over time as users begin to ignore them. In this paper, we compare the effectiveness of static interventions to a rotation strategy, where users experience different interventions over time. We built and deployed a browser extension called HabitLab, which features many interventions that the user can enable across social media and other web sites to control their time spent browsing. We ran three in-the-wild field experiments on HabitLab to compare static interventions to rotated interventions. Rotating between interventions increased effectiveness as measured by time on site, but also increased attrition: more users uninstalled HabitLab. To minimize attrition, we introduced a just-in-time information design about rotation. This design reduced attrition rates by half. With this research, we suggest that interaction design, paired with rotation of behavior change interventions, can help users gain control of their online habits.

CCS Concepts: • **Human-centered computing** → **Empirical studies in collaborative and social computing**; *Collaborative and social computing systems and tools*;

Additional Key Words and Phrases: Social computing; behavior change

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## 1 INTRODUCTION

We wish to spend our time more productively, but we sink hours into social media; we wish to learn new languages, but we get too busy to practice; we wish to be more healthy, but we do not maintain our exercise routines [24]. Inspired by situations like these, *behavior change* systems help people build new habits and retain them [25, 41, 53, 56]. Behavior change systems draw on theories of persuasion and influence [22, 40] to introduce *interventions*: interaction designs that variously inform, nudge, and encourage people to engage in behaviors more in line with their goals.

Behavior change systems today suffer from declining effectiveness as novelty wears off over time. Typically, behavior change systems utilize a *static* design, which never changes. For example, to manage social media browsing time, the three popular options are to block tempting sites [98],

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use a work timer [39], and audit time spent [54, 84]. However, static interventions suffer from high attrition and abandonment rates [23, 36], and interventions decline in effectiveness over time [59]. Habituation eventually drives users to stop paying attention to, or avoid, static interventions—an effect often seen on the web as banner blindness [14]. The end result is that many behavior change systems are tuned out by users, and are unsuccessful at their goals.

If static interventions are tuned out, *rotation* might provide a remedy. Much like a human coach or tutor rotates between different approaches over time, rotation might maintain attention in ways that static interventions cannot. Online behavior change tools could apply similar techniques, for example injecting a visible stopwatch timer into the page on one visit to Facebook, and hiding comments on the next visit. Techniques that personalize interventions via multi-armed bandits show positive treatment effects, suggesting that the approach may hold promise, but this existing work cannot separate the effects of personalization from the effects of rotation [60, 76, 82]. Because rotated interventions continually change the user interface, however, they may frustrate users by violating consistency and a sense of user control, leading to lower effectiveness or higher attrition.

This paper takes up the question: are static or rotated interventions more effective for behavior change? Is it possible to understand the effects of rotation in order to design more effective behavior change systems? We focus specifically on helping users who want to manage their time on social media websites such as Facebook, YouTube, Reddit, and Twitter. We perform a series of field experiments with people who sought out and installed a browser extension that we developed for online behavior change.

Our platform, *HabitLab* (<https://habitlab.stanford.edu>) is a Chrome extension that features a number of online productivity interventions to help users reduce their time spent on sites such as Facebook. We released HabitLab publicly on the Chrome web store, where it has attracted over 8,000 daily active users. This user base allows us to observe real-world usage and attrition patterns over time.

We ran three in-the-wild studies on users who newly installed HabitLab. In Study 1, we compared static interventions to rotation. We measured effectiveness through time on the user's targeted site, and we measured attrition by tracking when users stopped using the extension. Results indicate that rotation is a double-edged sword. Rotating interventions reduced time spent on sites by 34% per day, but at the cost of nearly doubling attrition levels.

Study 2 replicates the first experiment over a longer period of seventy days, and additionally tests whether the number of interventions included in the rotation impacts attrition. The results successfully replicated the original results over a longer 70-day period, and suggested that the larger the set of interventions, the higher the probability of attrition.

To investigate the underlying causes of attrition and mitigate the effects of rotation on attrition, we analyzed user feedback and developed a pair of interface techniques to improve the user experience in the presence of rotation, which we deployed in Study 3. The first technique is informational, aiding people's mental models by reminding them that the system may show a different intervention on each visit. The second technique focuses on user control, providing the same information as well as a just-in-time mechanism for people to opt out of each new intervention as they see it. Results indicated that these interventions reduced attrition by over half, so that 80% of new users were still using the system actively after a week.

In sum, this paper contributes the first comparison of static and rotation intervention strategies in behavior change, a living laboratory system that allows us to deploy this investigation and other field experiments, and interaction design strategies that can help offset increased attrition due to rotation. Its results suggest that people may be more able to control their social media usage more effectively than using today's common techniques such as site blockers. The rest of the paper is organized as follows: we first review studies of behavior change to develop our research question

and hypotheses; we then describe our studies and results; we close with reflections and future design directions.

## 2 BEHAVIOR CHANGE AND MOTIVATION

The field of persuasive technology studies how technology can be used to influence behavior [40]. Persuasive technology systems have been successful in promoting behaviors such as sustainable resource usage [41], fitness [25], sleep [18, 53], healthy eating [32, 74], stress management [2, 90], smoking cessation [75], and productivity [56, 103]. One common framework of behavior change is the B=MAT model [40], which states that desired behaviors result when motivation, ability, and a trigger (a call to action) are all present. Another framework of habit change is the habit loop [35], which tells us that designs can build habits via a repeated process of displaying a trigger, having the user take an action, providing a reward, and having the user invest in the system.

A number of taxonomies characterize the design space of interventions, both general [1, 31, 66, 67] and domain-specific [44, 102]. Michie's behavior change taxonomy lists 93 techniques for behavior change, clustered according to the cognitive phenomenon they target [66]. Systems have investigated effects of these techniques individually, such as using "cheating" to support lapse management [4], using different framings to present results [56], or setting goals and plans [5].

People use a variety of sociotechnical systems to support behavior change, including forums [17, 37], social sharing [21, 57, 77, 78], personal informatics [20, 61], and self-experimentation [52]. People use behavior change forums to gain social support [47] – meeting social needs such as approval and esteem [50]. They do so by providing users with information and advice [47], and establishing norms [17]. They also facilitate social comparisons [28] which influence behaviors, as social comparison theory states that users seek to bring their behaviors in line with norms [38]. Communities also help users find others with similar experiences [48] who can help them through the process of recovering and adapting to changes [71]. Social sharing [78, 85] works by helping users receive support through social interactions, and encouraging accountability [33]. Personal informatics support behavior change through stages of preparation, collection, integration, reflection, and action [61]. The theory of lived informatics [34] adds additional stages where users choose tracking tools, and alternate between lapsing and resuming their tracking behaviors. HabitLab combines personal informatics and self-experimentation to support behavior change. Our study draws on lived informatics by evaluating whether rotating interventions is an effective strategy to combat lapses such as ignoring interventions or uninstalling.

One major topic inspiring our work is users' desires to curb or control their time spent on social media sites. People pressure themselves to, and often do, make efforts to reduce their time spent on social media sites such as Facebook and Twitter [91, 94]. Yet this is difficult because users turn to social media to address their need to belong, the need for self-presentation, the need for self-esteem [69], the need for entertainment and gratification [80], and self-affirmation [97]. Whether social media use improves well-being is a complex question depending on the nature of the engagement [55, 62, 65, 68, 88, 95, 100], but thanks to instant gratification and sites' use of gamification [19, 49, 104] and behavior design techniques [35, 40] to drive engagement, users keep coming back to the point that some consider it an addiction [10, 87, 96, 99].

Much previous work has focused on gamification as an approach to design behavior change systems [30]. Gamification has been shown to have positive effects on engagement and outcomes in behavior-change contexts such as promoting healthy habits [26, 64] and improving educational engagement [8, 9], though effectiveness varies depending on the context and design [43].

Attrition is a major challenge in behavior change systems. Attrition [36], also known as dropout, occurs when participants stop participating, leave, or uninstall the system. Persuasive systems built for weight control and therapy have shown substantial attrition rates in longitudinal studies [15, 76],

and prior work in CSCW has sought to help reduce attrition rates through techniques drawn from dieting and addiction research [4].

A recent trend in behavior change systems has been the concept of personalizing interventions. Such systems explore several possible strategies using techniques such as multi-armed bandits to find the intervention that is most effective for the user [76, 81]. For example, PopTherapy demonstrated personalized messaging could be found through such techniques [76]. Likewise, HeartSteps conducted tens or hundreds of micro-randomized trials on users [29]. When multi-armed bandits are just beginning to get feedback from a user, they will try out several different interventions to see what works. This exploration has the effect of rotation, but the amount of rotation declines as the bandit begins to personalize. In this paper, we examine the contrarian assertion that perhaps rotation should be maintained to sustain novelty even after the multi-armed bandit is aware of which intervention is most effective for the user.

**RESEARCH QUESTION (RQ).** *Can a strategy of rotating interventions produce more effective behavior change systems?*

### 3 ROTATING INTERVENTIONS

In this section, we review literature in behavior change systems and psychology to develop specific testable predictions regarding the research question.

#### 3.1 Effectiveness over time

While behavior change systems can be effective [12, 27, 101], many review papers are more restrained in whether behavior change systems remain effective over long periods of time [16, 42, 70, 73]. The critique holds that behavior changes are long, complex processes, and the effectiveness of a system is hard to maintain indefinitely [79]. Prior work suggests that the effectiveness of showing a static intervention cannot be maintained indefinitely [46, 86]. For example, when a health behavior change system started sending email reminders, the first reminder was successful 28% of the time, but by the fifth reminder it was successful only 18% of the time [51].

A further meta-analysis of 88 computer-tailored interventions for health behavior change suggested that the efficacy of interventions decreases over time [59]. This prompts our first hypothesis:

**HYPOTHESIS 1 (H1).** *Static interventions will suffer from decreased effectiveness over time.*

#### 3.2 The impact of rotation

Novelty can be a driving factor for effectiveness. One study showed that novelty can influence encoding of information into long-term memory, which, in turn, may raise awareness of behavioral changes [58]. Studies of gamification also explore the effect of novelty on user engagement [43].

In web design, people begin ignoring parts of the screen that have little information scent, such as ads. This phenomenon is termed banner blindness, after the commonness of the effect in internet banner advertising [14]. As static interventions remain deployed, they may suffer from the same banner blindness and lack of novelty (wear-out) effects, suggesting a potential mechanism for the decreased effectiveness over time.

Rotating interventions may counter these effects. Different interventions appear in different parts of the interface, making it less likely that the user would ignore them wholesale. Online behavior change systems that use machine learning algorithms such as multi-armed bandits hone in on a small number of interventions to use [76, 81], but during the early exploration phases they are essentially rotating between interventions. Systems that personalize interventions [51] or deploy many micro-studies [29] have generally found positive effects.

Based on these results, non-static interventions may be effective. We hypothesize:

**HYPOTHESIS 2 (H2).** *Rotation will increase effectiveness, compared to static interventions.*

### 3.3 Attrition

Attrition is a major challenge in behavior change systems: a metastudy of eHealth interventions found that an attrition rate around 99% over a 12-week period is normal [36]. Likewise, the number of users in a stress-coping mobile application declined in a steady rate through the study [76].

Though rotating interventions aids novelty, the literature suggests that it may hurt attrition. Rotation violates usability heuristics such as consistency and user control [72]. Specifically, users may perceive a loss of control when they are presented with ever-changing interventions, potentially leading to non-compliance behaviors and a higher attrition rate [45]. Typically, in attrition-risky domains such as education, an effective user-centered design is critical for minimizing attrition [11]. In light of these results, we hypothesize:

**HYPOTHESIS 3 (H3).** *Rotation will increase attrition, compared to static interventions.*

## 4 SYSTEM DESCRIPTION: HABITLAB

Studying behavior change requires in-the-wild intervention and observation [25]. Inspired by previous CSCW tools for naturalistic data collection [83], we developed HabitLab as a living laboratory to help us understand online behavior change and as a platform to explore novel behavior change designs (Figure 1). HabitLab is a Chrome browser extension that aims to help users reduce their time spent online on web pages that the user specifies (e.g., Facebook, Twitter, and Reddit). The system is pitched to end users as a tool that explores various different interventions (referred to as “nudges”) to help them reduce their time on sites.

Users install the extension, and go through an onboarding process where they select sites they wish to reduce their time on (Figure 2). There are predefined options—Facebook and YouTube are selected by default, as they were the most commonly used—but users can also add any custom site. Custom sites are suggested via an analysis of the user’s browsing history. The system

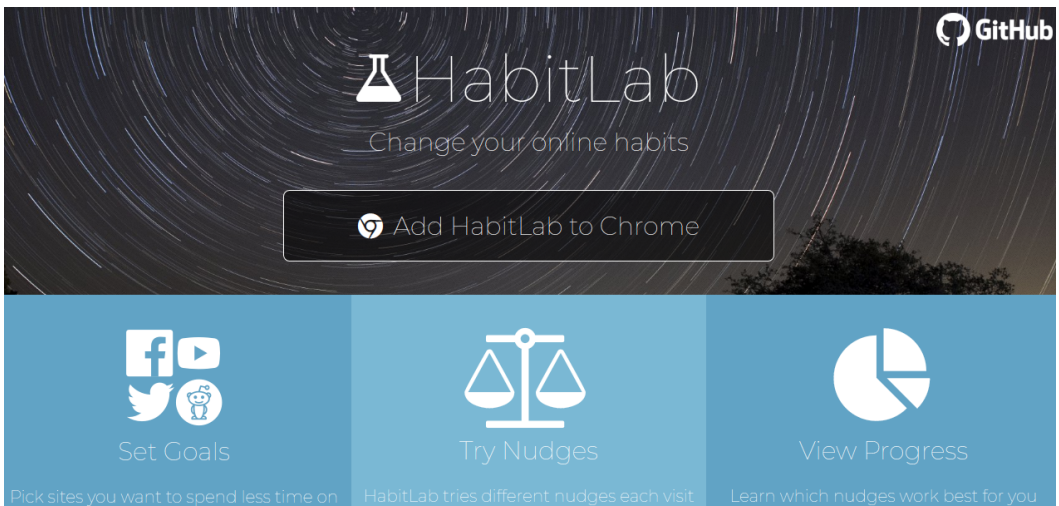


Fig. 1. HabitLab’s homepage describes the browser extension. Users adopt it to try out a large number of different possible interventions, called nudges.

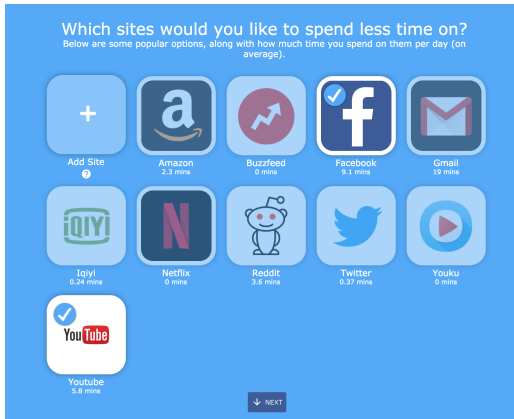


Fig. 2. During onboarding, users choose which sites they want to spend less time on.



Fig. 3. Users are presented with the interventions they will see on each site.

explains to users that they will be shown a variety of interventions (Figure 3), a form of self-experimentation [52], to help them reduce time on that site. These interventions are typically targeted to each site, for example a news feed blocker for Facebook or a related video hider for YouTube. However, some interventions such as a stopwatch timer can be added to any custom site. Users can preview the interventions for the sites they select, and enable or disable each intervention if desired. Users can later enable or disable interventions and sites through a settings page.

HabitLab emphasizes to users the availability of multiple interventions and that it may show users different interventions each time they load a page. This emphasis is made clear on the HabitLab website, Chrome store listing, and through features in the dashboard such as visualizing the relative effectiveness of different interventions. HabitLab implements a multi-armed bandit algorithm to explore and find the interventions that are most effective for each user, optimizing for minimizing time spent on a site. However, in the experiments in this paper, we disabled this functionality and instead used simple random selection so that we can study the effects of rotation in isolation.

#### 4.1 Design of HabitLab Interventions

HabitLab can track time and deploy interventions on all sites, but some interventions are tailored towards specific sites. There are 27 interventions total: seven generic interventions that can be used on all sites, five interventions designed specifically for Facebook, and additional ones designed specifically for YouTube, Reddit, Twitter, Netflix, Gmail, Amazon, iQiyi, and Youku.

Interventions are designed drawing on theories of behavior change—for example, goal setting theory [63], persuasion [22, 40], and gamification [30]. A sample of the interventions available for Facebook, categorized according to underlying strategies and theories, are shown in Table 1. Screenshots of some Facebook interventions are shown in Figure 4.

Not all interventions are enabled by default—this is because some of them have higher attrition rates than others. Non-default interventions can be previewed and enabled by users during onboarding and on the settings page. The interventions enabled by default were the ones we found to have low attrition rates during pilot deployments—we chose this strategy to ensure user retention and growth, which is a prerequisite for gathering data in an in-the-wild experiment setting.

Strategy	Theory	Intervention
Commitment	Self-consistency theory [7, 22, 93]	Ask the user to set a goal for the length of time they will stay on the site (generic)
Enforce default limits	Status quo bias [89]	Automatically close tab after 60 seconds unless the user clicks a button to ask for more time (generic)
Reduce social incentives	Social proof [22, 92]	Hide Facebook comments by default (default)
Delaying Rewards	Operant conditioning [13]	Make the user wait 10 seconds before visiting Facebook (generic)
Removing Rewards	Operant conditioning [13]	Hide the news feed (default)
Inform the user	Theory of reasoned action [6]	Show a counter at the top of the page of how long user has been on Facebook today (default, generic)

Table 1. A subset of the interventions for Facebook, categorized according to persuasion strategy and theory. Interventions that are enabled by default are marked *default*, interventions that are available for all sites are marked *generic*.

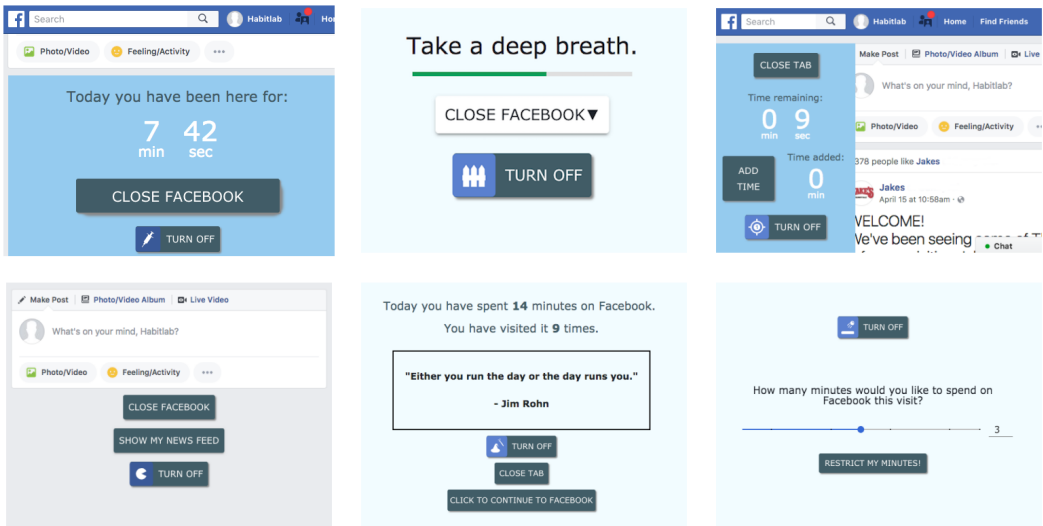


Fig. 4. Examples of interventions available for reducing time on Facebook. From left to right, top to bottom: a timer injected into the news feed; a page before opening Facebook requiring that the user wait a few seconds before visiting; a countdown timer that automatically closes the tab after time elapses; an opt-in required to show the news feed; an interstitial page before opening Facebook with a quote; an interstitial page before opening Facebook that requires the user set a time limit for how long they will spend this session.

#### 4.2 HabitLab adoption and usage

As of writing, HabitLab has over 8,000 daily active users from 85 countries (US, India, Germany, France, and the UK are the top 5), and volunteers have translated it into 9 languages (German, French, Spanish, Dutch, Portuguese, Chinese, Czech, Greek, and Turkish).

Users discover the extension through news articles (it has been mentioned in Wired and the New York Times), the Chrome store, or links from an unrelated open-source project by the author. Users

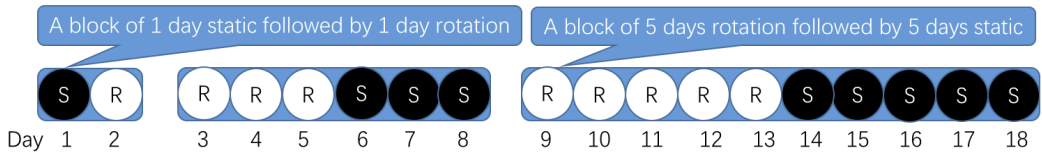


Fig. 5. Example order in which a user might see conditions. Each circle represents a day – on black days the user is in the “static” condition, white is the “rotation” condition. The order of blocks is randomized; here, this participant is seeing blocks in order 1, then 3, then 5, then 7 (omitted in the figure).

are asked to read and provide consent to the research protocol upon installation. They may opt out of data collection if they do not wish to have their data analyzed for research purposes.

## 5 STUDY 1: FIELD STUDY ON THE EFFECT OF ROTATING INTERVENTIONS

Our first study is a within-subjects design run on the HabitLab platform that aims to understand the effects of rotating interventions on effectiveness and attrition.

### 5.1 Participants

Participants in our first study consisted of new HabitLab users installing the system over a period of three weeks in March and April 2018. 692 users installed HabitLab over the course of our experiment and consented to our research protocol. We discarded participants who were not new users of HabitLab, since some users were reinstalls or new devices for existing users. We also discarded participants who did not complete the onboarding process, or who uninstalled the system before they saw their first intervention. This left us with 217 participants.

We do not administer a demographic survey at install time, because long onboarding processes had previously led to high abandonment. Many users find HabitLab through routes other than the web site, but Google Analytics on the web site can provide some window into rough trends. Google Analytics estimates that 89% of visitors to the HabitLab website during the experiment period were male, indicating a male skew. The most common age group was 25–34 (41%), followed by 18–24 (29%), 35–44 (22%), and 45–54 (7%). According to users’ IP addresses, the most highly represented countries were the US (23%), India (12%), Germany (9%), France (5%), and the UK (4%).

Participants agreed to our informed consent protocol during onboarding. This consent protocol indicated that HabitLab would be selecting and rotating between different interventions, but did not mention any specific algorithm or rotation schedule.

### 5.2 Method

Participants used HabitLab in the course of their usual web activity. As they browsed, HabitLab would introduce interventions when appropriate. All interventions were available to all conditions, but the pace at which old interventions were replaced by new ones depended on condition. Users would react to the intervention, or not, as they browsed.

HabitLab operated on all web sites that the user had selected upon installation. However, because users spend differing amounts of time on different domains, and there was a long tail of domains which were set as goal sites by only a few users, we restricted analysis to domains where we had a substantial dataset, specifically: Facebook, Youtube, Reddit, Twitter, VK, and Amazon.

The experimental unit was a participant assigned to a condition for a block of days. Block lengths were randomized between 1 day, 3 days, 5 days, and 7 days, in order to give us insight into the effects of rotation strategy over different time horizons. When participants were randomized to a block,



for example a five-day block, they experienced HabitLab in one condition for five days, then in the other condition for five days, for a total of ten days (Figure 5). Condition order was randomized within each block. At the conclusion of a block, the user was then moved into another block length and the trial repeated. The sequence of block lengths was randomized for each participant. If they kept the system installed, participants would experience all blocks after 32 days.

### 5.3 Conditions

We developed a within-subjects repeated measures design, where users alternated between blocks of time during which they were shown either a static intervention or rotated interventions. A within-subjects design such as this allows us to better control for the large variability across users in how much time they spend on a site.

The static condition captures a typical behavior change design with one strategy. At install time, for each site, the participant is randomly assigned a single intervention among the ones that are enabled for the site. Whenever they visit that site on a day in the static condition, the participant will always see that intervention, i.e. the static intervention is the same across all blocks.

The rotation condition captures a strategy of keeping the interventions changing so that users do not begin ignoring them. Each time a participant in the rotation condition visits a target site (e.g., Facebook), HabitLab picks a random intervention from the enabled set to display.

So, in a five day block, a user might spend five days in the static condition seeing the same intervention each time, then five days in the rotation condition seeing randomly selected interventions each time. They are then moved into another block and the method repeats.

### 5.4 Measures

We measured the *effectiveness* of the system as the number of seconds spent on the target site each day. Time, of course, does not perfectly correspond to attention or engagement behavior, as users can get distracted and not actually attend to a web page. However, prior work has generally found it to be an effective estimate (e.g., [103]). To determine whether the user is actively using a target site, we use Chrome's internal definition of active — the browser window and tab is focused, the computer screen is on, and there has been mouse or keyboard activity on the tab within the past minute. Time on site per day is measured as the aggregated time across sessions from midnight to midnight in the participant's local timezone. There was one data point per user per day per targeted web site. Because time data is not normally distributed, we adopt a common practice of log-transforming the time data prior to analysis.

We measured *attrition* as the number of days the participant kept the extension enabled. We also noted if the extension was still enabled at the conclusion of our study. The browser does not send a notification to our server if a user disables the extension, so we coded instances of attrition when the server stopped receiving data from the user for over two days, with no later resumption.

As with many online field experiments, effective data cleaning is essential to accurate analysis. We excluded users who had HabitLab installed on multiple devices, to focus on site usage on a single device. We discarded days on which the target site was never visited, as in neither condition would the intervention have been shown. We also discarded the first day because participants installed the extension midway through the day, resulting in an underestimate at the day level; we likewise discarded any days on which the user uninstalled or disabled the extension, as this would again cause the measured time to be an underestimate of the actual time spent on site that day.

### 5.5 Method of Analysis

For analyzing effectiveness at both the day and session level, we used a linear mixed model (LMM). We used an LMM because we have multiple samples from each user, but the number of samples

from each user and in each condition is variable (because attrition may occur before they completed all conditions, or they may not visit a site on a particular day), which violates the assumptions of the repeated-measures ANOVA.

To test whether interventions decrease in effectiveness over time (H1), we focused on just data points from the static condition. The model included a term for the number of days that particular intervention had previously been seen,<sup>1</sup> a random effect for the participant, and a random effect for domain. To test linear mixed models for significance, we used a likelihood ratio test to compare a reduced model without the number of days predictor to the full model. A significant test indicates that the number of days has statistically significant explanatory power, analogous to a significant beta coefficient in a traditional regression.

To test whether static or rotated interventions increase effectiveness (H2), we used data from both the static and rotation conditions. This second LMM, predicting log time spent on the site each day, included a random effect for participant, a random effect for domain, a fixed effect for block length, and a fixed effect for condition. A likelihood ratio test compared to a reduced model without the condition variable.

To analyze whether static or rotated interventions increase attrition (H3), we used a Cox proportional hazards regression. Cox proportional hazards models predict the relative “hazard” (i.e. risk) of attrition given each predictor. This is used in the health sciences for estimating expected lifetimes when we may have differing durations of observations for each participant, and may have observed deaths (which correspond to attrition) for some participants but not others. Each data point consists of a point of observation, and whether the participant had experienced attrition at that point or was still active. To avoid crossing conditions in this analysis, we focus the Cox analysis on just each user’s first assigned block and condition, for example a seven-day rotation block or three-day static block. Each observation consists of the length of block, and whether the user had experienced attrition by the end of the first condition for their first block. The Cox model used a single predictor: condition. The output of a Cox proportional hazards model is similar to a regression, with a significance value and estimate attached to the predictor.

## 5.6 Results

In this study, participants had an average of 3.0 target sites enabled. They visited at least one target site 67% of days on average. On each of those days, participants experienced interventions an average of 3.6 times. We did not receive any feedback indicating that participants were aware of patterns in how HabitLab was rotating interventions.

*5.6.1 Effectiveness of interventions over time.* First we examine whether interventions decrease in effectiveness over time within the static condition. If so, rotation may be a viable strategy.

The likelihood ratio test confirms that the number of days the user had seen the static intervention affected the log of time spent on a domain per day ( $\chi^2(1) = 4.69, p < 0.05$ ), supporting H1. Each day the intervention has been previously seen increased the log time spent by 0.225 (Table 2). By exponentiating the log estimates, this translates into an increase of 25% on top of a baseline 117 seconds per day for each additional day the user were exposed to the static intervention.

*5.6.2 Effectiveness of rotation and static intervention strategies.* Next, we compare whether the daily time spent on domains differs between days when participants were in the rotation and static conditions.

The likelihood ratio test found a significance difference between the full and reduced models predicting effectiveness ( $\chi^2(1) = 4.88, p < 0.01$ ), indicating that condition significantly impacted

<sup>1</sup>Repeating the analysis using the number of times the intervention had been seen yields the same conclusions.

Table 2. Within the static condition, interventions decline in effectiveness. Longer visit lengths increase with the number of days seeing the same static intervention.

	<i>Dependent variable:</i>
	Log time spent per day
Number of days the user had seen the static intervention	0.225* (0.097)
(Intercept)	4.759*** (0.392)
Observations	124
<i>Note:</i>	*p<0.05; **p<0.01; ***p<0.001

Table 3. Daily time spent on sites in the static and rotation conditions. Users spend less time per day on sites in the rotation condition.

	<i>Dependent variable:</i>
	Log time spent per day
Rotation (baseline: static)	-0.417* (0.190)
Block length	0.018 (0.048)
(Intercept)	4.981*** (0.346)
Observations	370
<i>Note:</i>	*p<0.05; **p<0.01; ***p<0.001

effectiveness. Relative to the static condition, rotating interventions decreased the log time spent on domains per day by 0.417 (Table 3), supporting H2. Exponentiating the coefficients for descriptive purposes, this translates into a shift from an estimated 146 seconds per day in the static condition to 96 seconds per day in the rotation condition, a decrease of 50 seconds (34%) per day.

**5.6.3 Attrition due to rotation and static intervention strategies.** The Cox proportional hazard regression model comparing the static and rotation conditions found that attrition rates are significantly higher with the rotation condition (Figure 6, Table 4). After 2 days, 78% of users remain in the static condition, while only 71% remain in the rotation condition. After 7 days – the duration of the longest experiment block – 68% of users remain in the static condition, while only 39% of users remain in the rotation condition. These results support H3.

We considered the possibility that switching between static and rotated interventions contributes to attrition beyond simply rotating them. We analyzed this by comparing the probability of attrition on days where the condition remains the same as the previous day, to days where the condition changes – either from static to rotated, or from rotated to static. The baseline daily attrition

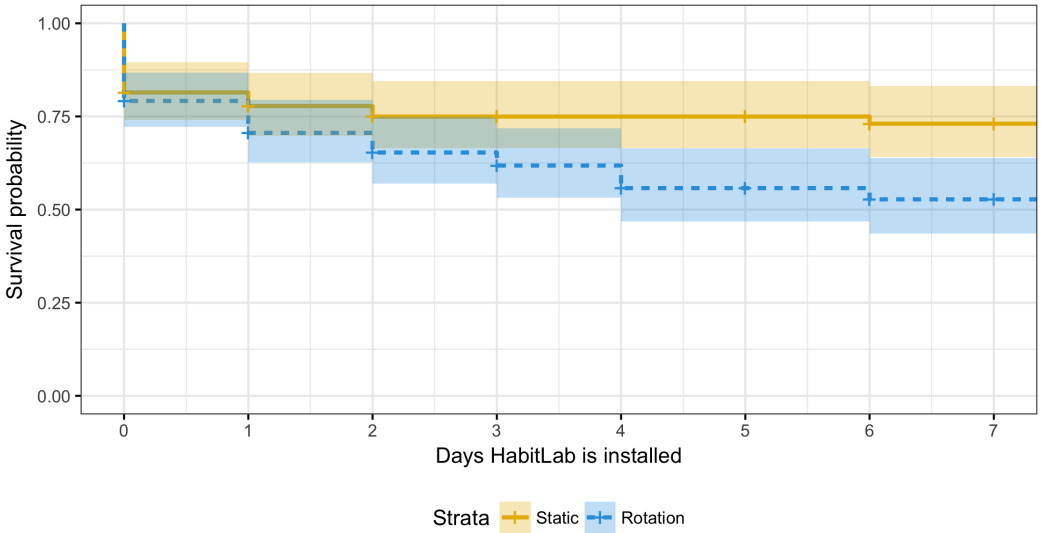


Fig. 6. Rotating interventions increases attrition among users.

Table 4. A Cox proportional hazards analysis suggests that the rotation condition substantially increases the hazard of attrition. Coefficients are log hazard ratio, so positive values indicate increased hazard and negative values indicate decreased hazard.

<i>Dependent variable:</i>	
Log hazard ratio	
Rotation (baseline: static)	0.544* (0.249)
Observations	217

Note: \*p<0.05; \*\*p<0.01; \*\*\*p<0.001

rate is 18% when staying within the same experimental condition – 14% when staying within the static condition, and 20% when staying within the rotation condition. On the first day after switching from static interventions to rotated interventions, the attrition rate is 36% – a significant increase compared to remaining within the same condition (Fisher’s exact test,  $p < 0.001$ ). However, switching from rotated interventions to static interventions does not increase the attrition rate – it remains at 18%. So we believe these effects are not due to the changes between conditions, but due to the conditions themselves – switching from static to rotated is experiencing the first instance of a rotation, and it is not surprising that the effect may be larger with the first change.

## 6 STUDY 2: LONGER-TERM EFFECTS OF ROTATION ON ATTRITION

Study 1 found that compared to static interventions, rotation increases effectiveness but also increases attrition. To provide additional support for our findings in Study 1 and motivate our design experiment, we present a second field study that seeks to answer the question: Does the

number of interventions in the rotation affect the level of attrition? This study occurs over a longer period – ten weeks – allowing us to examine these effects in a more longitudinal setting.

### 6.1 Participants

Our participants were HabitLab users who installed over a 5 week period in January–February 2018 and consented to our experiment protocol. 680 users who agreed to participate. After excluding users with multiple devices, users who did not complete the onboarding process, and users who had less than two sessions on Facebook where they saw interventions – we restricted analysis in this study to users who were using Facebook because it had the most number of default interventions available – we were left with 409 participants. Demographics were similar to Study 1.

### 6.2 Method

This was a between-subjects study where users' default settings for the number of enabled interventions varied depending on their condition: some users only had one default enabled intervention, and others had more. Interventions were then selected randomly from the enabled set. Among users who did not change these defaults, this enabled a between-subjects comparison of the effects of the number of interventions a user was rotating between, on retention rates.

In practice, we found that many users changed the set of interventions – 78% of participants in this study changed them over the course of using HabitLab, most often during onboarding. We wanted to retain a good user experience, but this muddied the experimental manipulation. So, we restricted analysis to the 91 users who did not change defaults. A  $\chi^2$  test found there was no significant effect of condition on whether users changed defaults ( $\chi^2(2) = 0.4671, p=0.8$ ), suggesting that randomization remained effective even after this filter.

Unlike Study 1, this was a between subjects experiment, so there were no time blocks: participants were assigned to the condition for the duration of the study.

### 6.3 Conditions

Participants were randomized into three conditions. In the one intervention condition, for every site the user enabled HabitLab on, only one intervention was enabled by default. The intervention was randomly chosen among the set of default interventions for that site. This is equivalent to the static condition from Study 1.

In the all interventions condition, for every site the user enabled, all interventions that are default for that site were enabled by default. This is equivalent to the rotation condition from Study 1. In the half interventions condition, for every site the user enabled, half of all interventions that are default for that site were enabled by default. The subset was chosen randomly.

### 6.4 Measures

We measured attrition, using the same procedures as those described in Study 1.

### 6.5 Method of Analysis

Like Study 1, we applied a Cox proportional hazards regression model to compare attrition rates.

### 6.6 Results

In this study, participants had an average of 3.3 target sites enabled. They visited at least one target site 64% of days on average. On each of those days, participants experienced interventions an average of 6.8 times.

In this longer, between-subjects experiment, attrition rates were significantly higher in the all interventions condition (Figure 7, Table 5). This agrees with the analogous result from Study 1

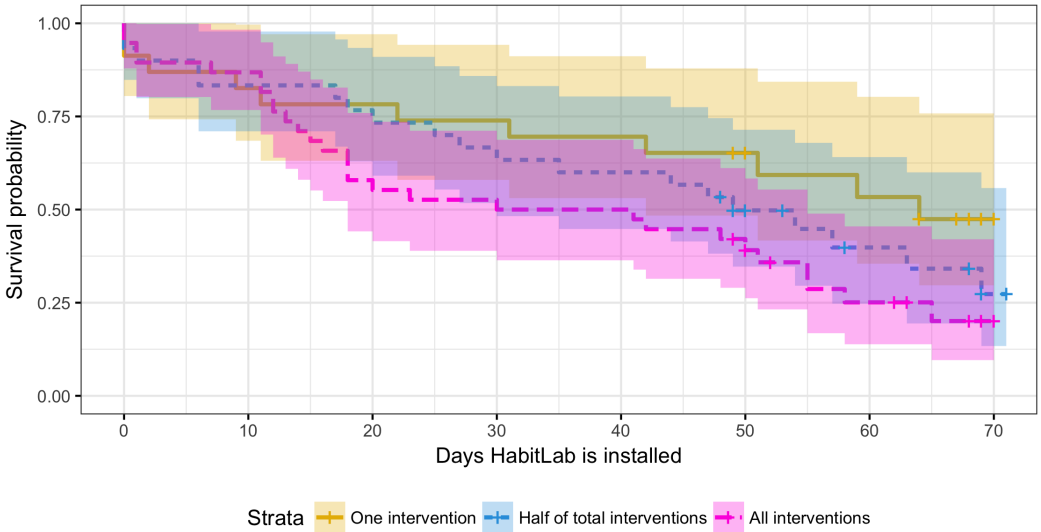


Fig. 7. Including all interventions resulted in significantly more attrition than just one intervention.

Table 5. A Cox proportional hazards analysis over a longer period suggests that rotating with more interventions increases the hazard of attrition.

	<i>Dependent variable:</i>
	Log hazard ratio
Half of total interventions (baseline: one intervention)	0.395 (0.380)
All interventions	0.711* (0.358)
Observations	91

*Note:* \*p<0.05; \*\*p<0.01; \*\*\*p<0.001

showing a higher attrition rate for the rotation condition. The half of total interventions survival curve falls in between that of the one intervention and all interventions conditions, but does not have a statistically significant difference.

### 7 STUDY 3: DESIGN INTERVENTIONS TO REDUCE ATTRITION

Study 1 and Study 2 collectively demonstrated that rotation increases effectiveness but also increases attrition. Why does rotation increase attrition? To understand this, we needed to understand why users uninstalled in the first place.

We performed a qualitative content analysis on the uninstall feedback left to us by users. This feedback was collected in a tab that opened automatically when users uninstalled HabitLab. The page stated that feedback would be used for research purposes. Users had the option to check boxes to agree with a set of predefined reasons they why they were uninstalling, and leave free-text

feedback. We performed an inductive analysis of the free-text feedback, grouping responses by themes, reflecting on our themes, and refining our groupings until convergence.

A total of 782 users submitted the uninstall feedback form. This data represents all past users of HabitLab, and includes users outside studies 1 and 2. We use this larger dataset because only 8 participants from Study 1, and 39 from Study 2, filled out the feedback form. 751 users who submitted the form checked at least one of our predefined reasons. 274 users (36%) uninstalled because “Interventions were annoying”, 248 users (33%) uninstalled because HabitLab “Did not feel effective”, 100 users (13%) uninstalled because HabitLab “Was causing lag”, 75 (10%) uninstalled due to “Privacy concerns”, and 202 (27%) cited “Other reasons”. The total sums to more than 100% because users could check more than one reason.

A total 155 users submitted free-form textual feedback. Some users began with an incorrect mental model and uninstalled after they learned what it was doing:

- *Didn't seem what I was expected. Installed two minutes ago and removed it*
- *I just didn't understand the concept before downloading*

Some users indicated they wanted more control over the intervention that was shown to them, or were simply looking for a time tracker and were not interested in interventions at all:

- *I wanted a timer for every “domain”, it can be good for statistics of time*
- *I was interested in tracking my usage to start, instead of setting interventions that I may not actually be concerned about*

Some users indicated dissatisfaction with particular interventions:

- *Mostly it was the bar covering up facebook message indicators*
- *it was just annoying you out of not using sites, not convincing you to. It became like ads, they are always there. But you don't like them and turn them off with ad-block.*

Some users wished interventions would be more forceful, or less intrusive:

- *Interventions are not forceful enough. They are too easy to click around or disable*
- *I liked the interventions but not on every page change or load, that was just a bit too much*

Finally, some users decided they simply did not want or need interventions:

- *Made me realize I don't have Facebook addiction, spending less than 30 minutes [...] per day*
- *I'm weak...*

Other themes included localization issues, performance issues, privacy concerns, accidental installations, and misattribution of other issues to HabitLab.

## 7.1 Design interventions

Based on the qualitative feedback on reasons for uninstalling, we drew on two of the most consistent themes to hypothesize why rotation may be increasing attrition:

**HYPOTHESIS 4 (H4).** *Violation of mental model: Users may have sped through onboarding and not understood that HabitLab rotates interventions. So, when they experience a new intervention, the system violates their mental model and they disable it in confusion or frustration.*

**HYPOTHESIS 5 (H5).** *User control: Users may be aware that the system is choosing interventions for them, but are frustrated by a lack of control over the system's behavior. They may dislike one or more of the interventions but not realize how to turn them off.*

These two hypotheses could feasibly be addressed through design interventions. Other pieces of feedback, for example how aggressive the interventions were, we judged as out of scope of the current study on rotation strategies and will pursue as future work. We developed two different interfaces, one to address mental model violation and the other to address a perceived lack of control. They are shown to users when they see a new intervention for the first time.

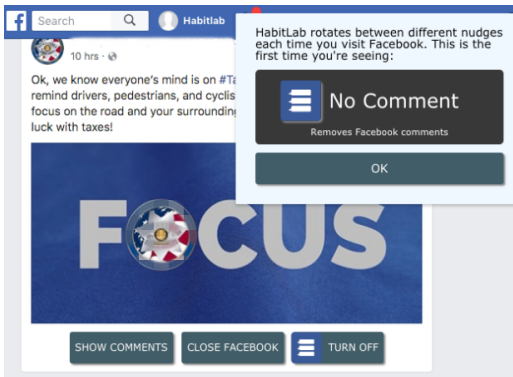


Fig. 8. Mental model interface: each time the user sees a new intervention, HabitLab names it and explains about rotation.

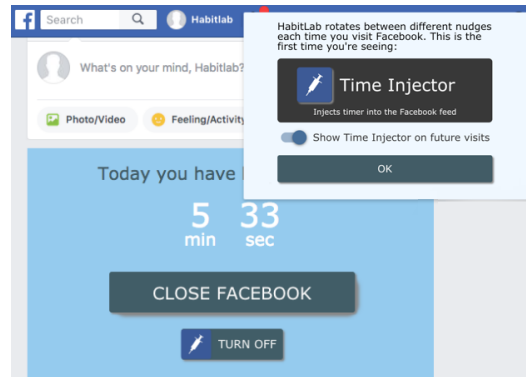


Fig. 9. User control interface: in addition to the mental model information, HabitLab gives users a direct interface to disable the new intervention.

The first design, which we will call *mental model* (Figure 8), is inspired by H4: it reminds the user that HabitLab has rotated to a new intervention and gives the name of the intervention. If mental model misalignment was the issue, this design might help explain to the user what the system is doing and why. The second design, which we will call *user control* (Figure 9), is inspired by H5: it includes the message in the information design but also adds a toggle option to allow the user to turn off the new intervention for future visits without needing to visit HabitLab's settings. If lack of control was the issue, this design may give sufficient control so that users keep HabitLab enabled.

## 7.2 Experiment Design

We ran a between-subjects design where we randomized the design shown to new users of HabitLab and tested whether it impacted attrition over a period of one week, similar to Study 1.

## 7.3 Participants

Our participants were HabitLab users who installed over a 10 day period in April 2018. There were a total of 282 users who installed and agreed to participate. We removed users who were not new users (e.g. an existing user installing on a new device, or a former user reinstalling the system), and users who left before they saw their first intervention. This leaves us with data from 93 participants. Demographics, estimated by Google Analytics, were similar to Study 1.

## 7.4 Method

Participants installed HabitLab and set it up as described in the Study 1 and Study 2. They used HabitLab in the course of their normal web browsing activity. HabitLab rotated between randomly chosen interventions on each visit to the chosen web page for all users, equivalent to the rotation condition in Study 1. Each time the user experienced a new intervention that they had not seen before, however, HabitLab might show an explanation design in the corner of the browser.

## 7.5 Conditions

There were three conditions for this study. In the no design condition, users saw no message, equivalent to the rotation condition from Study 1. In the mental model condition, users were shown the informational intervention (Figure 8) to remind them that the system rotates interventions. In



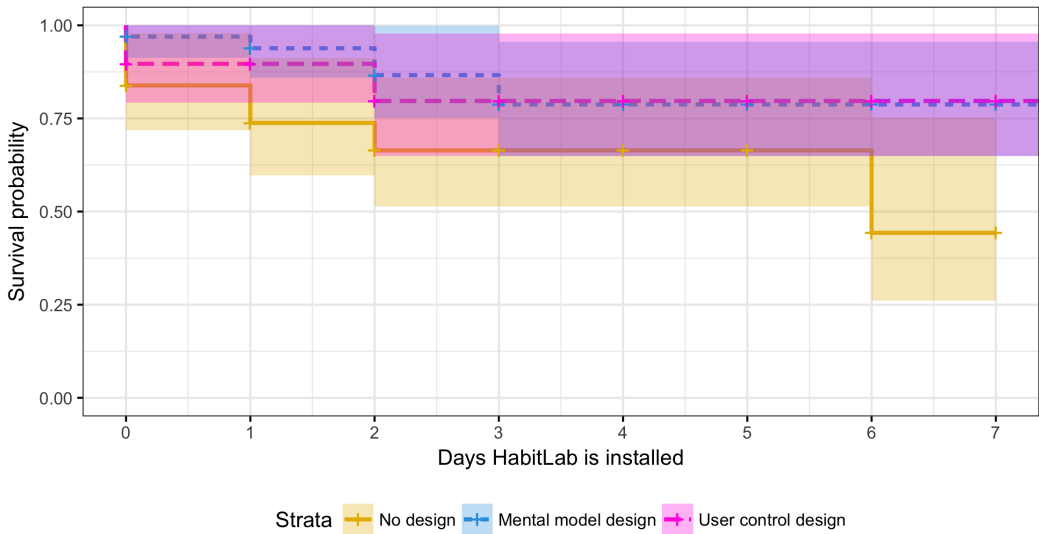


Fig. 10. Reminding users about how the rotations worked every time a new intervention was introduced significantly reduced attrition rates.

the user control condition, users were additionally given control over whether to turn off each new intervention without needing to visit the settings screen (Figure 9).

## 7.6 Measures

Our main dependent variable was attrition—how many days users kept the system installed by the end of the study, seven days after installation. The measure of attrition was the same as in Study 1 and Study 2. We also measured effectiveness, using the same method as Study 1.

## 7.7 Method of Analysis

To analyze attrition, we again used a Cox proportional hazards regression model, similar to Study 1, using interaction design as the predictor variable. To analyze effectiveness, we used a LMM predicting log time on site per day, with a fixed effect for condition, and random effects for participant and domain. Data cleaning followed the same procedures as Study 1.

## 7.8 Results

In this study, participants had an average of 2.9 target sites enabled. They visited at least one target site 71% of days on average. On each of those days, participants experienced interventions an average of 6.6 times.

The Cox proportional hazard regression indicates that the mental model design significantly reduces attrition rates relative to no design ( $p < 0.05$ , Figure 10, Table 6). This result supports H4. After seven days, 79% of participants in the mental model condition remain, while 80% remain in the user control condition and only 44% remain in the no design (control) condition. In other words, the intervention conditions more than halved the attrition rate, from 56% to 21% attrition. Adding the additional option to permanently turn off the intervention the first time it is seen is not significantly different from no design given our sample size.

Table 6. A Cox proportional hazards analysis suggests that the informational intervention that corrected users' mental models was successful in reducing attrition due to rotation. Coefficients are log hazard ratio.

<i>Dependent variable:</i>	
Log hazard ratio	
Mental model design	-1.015* (0.494)
User control design	-0.869 (0.527)
Observations	93
<i>Note:</i> * $p < 0.05$ ; ** $p < 0.01$ ; *** $p < 0.001$	

There was no effect of condition on effectiveness: the full model was not significantly more explanatory than the reduced model without the condition variable ( $\chi^2(2) = 1.46, n.s.$ ). So, these interventions did not reduce effectiveness while they were improving attrition.

## 8 DISCUSSION

Our findings suggest that changing behavioral interventions can be beneficial from the perspective of efficacy, but detrimental to retention. By showing simple messages when presenting new interventions, we can improve users' mental models, and reduce attrition from changing interventions.

In addition to the interface-based techniques we have presented to combat detrimental effects of changing interventions, algorithmic techniques can also help. For example, in the context of a multi-armed bandit, potential algorithmic techniques include:

- (1) Limiting the exploration speed such that users are not overwhelmed by the rate at which they are seeing new interventions.
- (2) Modeling individual interventions' likelihood of attrition, and favoring algorithms which are less likely to cause attrition if needed to keep the user around longer.

There are also additional interface-based techniques that may be helpful in reducing attrition from changing interventions, but that we have not tested, such as:

- (1) Making how new interventions are introduced predictable and known to the user.
- (2) Allowing users a choice of intervention when we introduce new interventions.

### 8.1 Limitations

This work featured deployment periods of a few weeks. This may not be enough time to observe some very long-term effects: for example, some changes in intervention effectiveness set in only after months or years [59]. That said, given the fast turnover rate which is observed with behavior-change software, even short-term effects of changing interventions on attrition can be important.

While we believe our general finding about the double-edged nature of changing interventions may apply to other behavior-change contexts, particular parameters—such as speed at which users grow blind to an intervention, may be domain-specific.

One shortcoming of our Study 1 design is that we cannot rule out the possibility that our observed increase in effectiveness is due to selective attrition, rather than due to benefits from the rotation. Namely, it is possible that observing rotation may selectively lead to uninstallation for users for whom interventions are ineffective. To rule out this possibility, we will need to investigate ways to

maintain retention in the presence of rotation, and see whether the improvement in effectiveness relative to a static intervention still remains. It may also be possible to design intention-to-treat analyses that discount attrition in measures of effectiveness. Furthermore, while we observed that the first visit is longer than subsequent visits when users visit sites multiple times per day, but this effect may be due to temporal usage patterns rather than intervention effectiveness.

Because users have differing preferences, interventions may have differing rates of attrition for each user. An ideal retention-maximizing system would not assign interventions randomly, but would personalize interventions to each user. Assuming there is a novelty component to attrition — i.e., users quit because they grow bored of the same intervention — then a system which intelligently times interventions to minimize attrition can in theory have lower attrition than even the best static intervention. There are 2 difficulties in making this a reality: first is needing to learn to correctly predict which intervention would minimize attrition for a user at a given time, a reinforcement learning problem. Second, as shown by the increase in attrition when using a naïve rotation strategy, a system that switches between interventions also needs to overcome the barriers of needing users to develop more complex mental models, and ensuring that users feel in control.

## 8.2 Design reflections on social computing and behavior change

Social systems are inherently tied to behavior change and retention. Social networks and other social apps and services make heavy use of gamification and behavior change techniques to drive engagement and boost retention [19, 35]. A system like HabitLab that helps users use these services less thus occupies an interesting space: it is modifying the service to hide the features that serve to boost engagement, helping users break away from their addiction to the site.

But we tread a fine line: behavior change systems themselves suffer from attrition, so we may sometimes need to make tradeoffs between better retaining users and helping them regulate their behaviors. For example, the Facebook interventions in HabitLab with the lowest attrition—those that passively show time spent—are among the least effective. Is telling users that the system is helping them more than it actually is a form of benevolent deception [3] that would ultimately help boost retention and help users achieve their goals? Would gamifying the system with social features, making users connect with friends and keep tabs on their friends' social media usage, help boost retention and effectiveness—even though users may lose time engaging with social features?

## 9 CONCLUSION

Behavior change intervention effectiveness declines as interventions are repeatedly shown to the user. This decline can be combated by rotating between a stable set of different interventions. Rotating interventions increases attrition, but user interface changes can ameliorate the issue. Taken together, these results suggest opportunities to build behavior change systems that operate more like coaches and tutors: they might explore different strategies to find what works well, and then occasionally rotate to keep things fresh.

More broadly, there is a large opportunity for behavior change research through big data and crowdsourcing that has been under-explored due to the paucity of large-scale deployments of research systems. Could we predict which interventions will work well for a new user, before they even start using the system? Could we automatically deploy and test modified versions of interventions, to hill-climb our way to more effective ones? Could we enlist an engaged user community to come up with, generate, and test new interventions for the long-tail of behavior change goals that designers had never even thought of? These can be realized with machine learning and crowdsourcing techniques, but there have not been appropriate communities for an in-the-wild deployment. We hope HabitLab will provide such a platform to realize this vision of community-driven behavior change research in the wild.

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## A APPENDIX: LIST OF INTERVENTIONS

The following is the list of interventions used for this study, showing the intervention name and description as seen by the end user.

Generic interventions that can be used on all sites:

- Minute Watch: Notifies you of time spent every minute
- Supervisor: Shows time spent on site at the top of screen
- Scroll Freezer: Freezes scrolling after a certain amount of scrolls
- Stat Whiz: Show time spent and visit count each visit
- GateKeeper: Makes you wait a few seconds before visiting
- 1Min Assassin: Closes tab after 60 seconds
- Bouncer: Asks how long you want to spend on site this visit

Facebook-specific interventions:

- Time Injector: Injects timer into the Facebook feed
- Feed Eater: Removes the Facebook news feed
- TimeKeeper: Notifies you of time spent in the corner of your desktop
- No Comment: Removes Facebook comments
- Clickbait Mosaic: Removes clickbait from the news feed

Youtube-specific interventions:

- Sidekicker: Remove sidebar links
- Think Twice: Prompt the user before watching a video
- No Comment: Removes comment section

Netflix-specific interventions:

- Fun Facts: Gives you a fact and links an article on the effect of TV
- Alarm Clock: Asks the user to set an alarm before watching a show
- Stop Autoplay: Stops the site from automatically playing the next video

Reddit-specific interventions:

- Comment Remover: Removes Reddit comments
- Mission Objective: Asks what you aim to do this visit and puts a reminder up

Youku-specific interventions

- Think Twice: Prompt the user before watching a video
- Sidekicker: Remove sidebar links

iQiyi-specific interventions

- Think Twice: Prompt the user before watching a video
- Sidekicker: Remove sidebar links

Twitter-specific interventions:

- Feed Eater: Removes the Twitter news feed

Amazon-specific interventions:

- No Recs: Hides recommendations

Gmail-specific interventions

- Speedbump: Delays the arrival of new emails

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