Understanding Disengagement in Just-in-Time Mobile Health Interventions

JOONYOUNG PARK, KAIST, Republic of Korea
UICHIN LEE*, KAIST, Republic of Korea

Just-in-time (JIT) intervention aims to proactively detect a user's problematic behaviors and deliver interventions at an opportune moment to facilitate target behaviors. However, prior studies have shown that JIT intervention may suffer from user disengagement, a phenomenon in which a user's level of engagement with intervention apps and target behaviors declines over time. In this study, we aimed to deepen our understanding of disengagement in a mobile JIT intervention system. As a case study, we conducted a user study with college students (n = 54) for eight weeks to understand how disengagement appears over time and what factors influence user disengagement. Our findings reveal that personal traits, such as boredom proneness and self-control issues, are closely related to disengagement, with key factors including 1) boredom and habituation related to repetitive and monotonous JIT interventions, 2) inopportune alarm, 3) distrust for the JIT feedback mechanism, and 4) a lack of motivation due to low rewards. We provide theoretical and practical design guidelines for follow-up studies on JIT intervention system design.

CCS Concepts: • **Human-centered computing** → **Empirical studies in ubiquitous and mobile computing**.

Additional Key Words and Phrases: JIT interventions, user engagement, DBCI

ACM Reference Format:
Joonyoung Park and Uichin Lee. 2023. Understanding Disengagement in Just-in-Time Mobile Health Interventions. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 7, 2, Article 72 (June 2023), 27 pages. https://doi.org/10.1145/3596240

1 INTRODUCTION

Digital behavioral change intervention (DBCI) uses behavioral intervention technology (BIT) to provide behavioral and psychological interventions to promote the health and well-being of a variety of individuals [91]. To do this, a variety of mobile-based DBCI applications now leverage advanced sensing technologies that precisely detect and track the user's current contexts and behaviors. Such features are key to the design of Just-in-Time (JIT) interventions for the sake of timely feedback delivery [32]. JIT interventions were utilized to address a variety of health-related issues, such as physical activity promotion [7], stress management [76], smoking cessation [69], and eating disorder mitigation [81].

Health behavior change through DBCI typically begins with user engagement with the intervention technology. In a DBCI context that requires constant interaction with users for health promotion, user engagement is a key factor for successful DBCI [70]. Prior studies on DBCI tried to conceptualize user engagement for DBCI by considering two aspects of engagement; i.e., DBCI app engagement and behavioral engagement [107]. DBCI app engagement focuses on how users use the technologies and functions provided by DBCI to change their behavior.

*The corresponding author

Authors' addresses: Joonyoung Park, jypark@kse.kaist.ac.kr, KAIST, Daejeon, Republic of Korea; Uichin Lee, uclee@kaist.ac.kr, KAIST, Daejeon, Republic of Korea.

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than the author(s) must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.
© 2023 Copyright held by the owner/author(s). Publication rights licensed to ACM.
2474-9567/2023/6-ART72 $15.00
https://doi.org/10.1145/3596240

Behavioral engagement focuses on how the user undertakes and sustains behavioral changes in order to achieve a targeted goal. Previous research considered engagement with DBCI as a dynamic process involving two types of engagement [107]. They emphasized that a comprehensive understanding of the engagement process for DBCI can be obtained by separately analyzing the two aspects of engagement.

User engagement is essential for a successful DBCI. However, previous studies warned of an "attrition" phenomenon in which user engagement with DBCI stops over time [25]. In particular, they defined "non-usage" as one of the attrition types that stopped using the DBCI app during the treatment period. In traditional DBCI, engagement with intervention is primarily achieved with *pull-based interaction* [16]. Since users initiate intervention by launching a DBCI app based on their needs, in pull-based DBCI, the non-usage of the DBCI app plays an important role in analyzing engagement with DBCI. Pull-based engagement can be easily measured through metrics representing usage for DBCI applications; e.g., how long or how often DBCI is used. However, user engagement analysis is not straightforward with JIT DBCI, which provides intervention in a push-based manner such as delivering notifications. Since push-based DBCI proactively intervenes in the user's problematic situation, the user is likely to be exposed to the intervention. To get a comprehensive understanding of engagement with JIT DBCI, therefore, it is important to take a close look at the process of user engagement with an intervention.

However, there has been a lack of exploratory studies that have comprehensively observed and analyzed user engagement over time in JIT DBCI. The purpose of this study is to observe and analyze the patterns of the app and behavioral engagement in the JIT DBCI. Intervention receptivity is largely influenced by personal and contextual factors [67]. Since users are repeatedly exposed to JIT interventions in problematic situations, requiring immediate behavior adherence, this study analyzes the influences of two traits (i.e., boredom proneness and self-control) along with contextual factors on engagement with JIT intervention over time.

This study aims to deepen our understanding of the disengagement process in JIT interventions. Toward this goal, we employed a simple health intervention app that aims to prevent prolonged sedentary behaviors (e.g., delivering stand-up requests if sitting time reaches 50 minutes). We conducted an eight-week field study with 54 college students and collected log and subjective data for further analyses.

Through the analyses, we investigated the factors that influence disengagement and the user experience of JIT interventions over time. Our results show that participants with high boredom proneness or low self-control faced stronger disengagement tendencies than those with low boredom proneness or high levels of self-control. Our qualitative analysis revealed detailed disengagement and re-engagement processes. The re-engagement cycle was triggered by positive experiences with JIT interventions, such as rewards, opportune alarming, and self-reflection. In contrast, the disengagement cycle was mainly affected by boredom and habituation (related to repetitive and monotonous JIT interventions), inopportune alarm, distrust for the JIT feedback mechanism, and a lack of motivation due to low rewards.

2 BACKGROUND AND RELATED WORK

2.1 User Engagement in Digital Behavior Change Intervention

Prior studies (e.g., HCI, education) involving user interaction with technology have emphasized the importance of user engagement for successful technology adoption [70]. Interests in "Design for more engaging experiences" [35, 38] naturally led to research looking into defining and conceptualizing engagement [70]. Prior studies in different fields defined engagement by means of various factors or components such as attention [13], enjoyment [80], and motivation [70]. Although agreement on the definition of engagement and its components has not yet been reached [107], many studies considered user interaction with technology as an important component for conceptualizing engagement [70, 88].

The importance of user engagement has also been noted throughout Digital Behavior Change Intervention (DBCI) studies [2, 107], where health behavior changes must be achieved through continuous interaction with

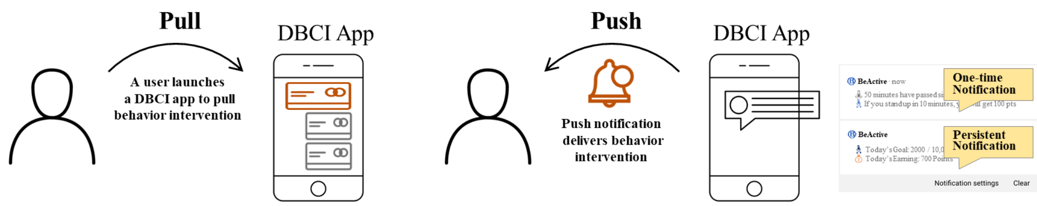


Fig. 1. Two Types of User Engagement in DBCI: Push-based and Pull-based

users. Given that engagement with intervention is a process of interaction with users for the sake of achieving behavioral goals, prior studies emphasized that it is necessary to analyze not only the use of the intervention system (i.e., app usage), but also the performance of the target behavior through intervention (i.e., adherence) [2]. Similarly, Yardley et al. emphasized that "engagement with DBCI (i.e., app use)" and "engagement with behavior change" should be analyzed separately to understand the relationship between engagement with technology and behavior change [107]. In other words, "effective engagement" with intervention covers DBCI and behavior intervention [2, 107].

2.1.1 Types of User Interaction with DBCI: Push-based vs. Pull-based. User engagement with DBCI can be driven either pull-based or push-based [100]. Pull-based engagement is user-driven based on user needs [62]. The user launches the DBCI application to obtain or check the necessary information.

Pull-based engagements can be observed in traditional DBCIs that provide users with therapeutic programs such as Cognitive Behavioral Therapy (CBT) [27]. In CBT-based DBCI, two types of engagements can occur together through DBCI application usage [22]. For example, a user can launch a DBCI application to monitor their current health status (i.e., app engagement) [16] or use self-help content (i.e., behavioral engagement) [27].

Push-based engagement is driven by the DBCI system. DBCI systems send signals (e.g., alarms or push notifications) to users whenever intervention is required to engage users [72]. Push-based engagement is mainly observed in JIT DBCI, which proactively delivers interventions at problematic situations [44, 73]. This means that users can engage with intervention behavior without launching a DBCI app. Due to these characteristics, push-based JIT DBCI has been widely utilized in various health fields where disease prevention is required through proactive intervention [7, 76].

2.1.2 Attrition, Abandonment, and Disengagement Concepts in DBCI. Previous studies on DBCI warned of an "attrition" phenomenon in which user engagement with DBCI is discontinued [25]. Attrition is prevalent; in one study, approximately 99% of users ended participation within 12 weeks [27], and in another study, more than half of the participants quit within three months [105]. According to a recent survey [55], low completion rates of less than 50% are relatively common in digital mental health interventions.

In previous studies, attrition was conceptualized in two forms; "dropout" and "non-usage" [25]. The difference between dropout and non-usage concepts can be understood through the treatment process using DBCI. In general, the treatment process of traditional DBCI can be divided into 1) participation enrollment for treatment, 2) assessment before treatment, 3) treatment period (or session), and 4) assessment after treatment [11, 47, 92]. Non-usage refers to a phenomenon in which the user stops using the provided DBCI application during the treatment period [25]. This can be caused by various factors, such as forgetfulness of use [43], inconsistency between system operation and user expectations [24], and decreased interest [82]. Dropout has been conceptualized as a phenomenon in which users stop participating or do not complete the treatment process [40, 58]; for example, a case in which an assessment of treatment is not performed after the treatment period. Although the definition of

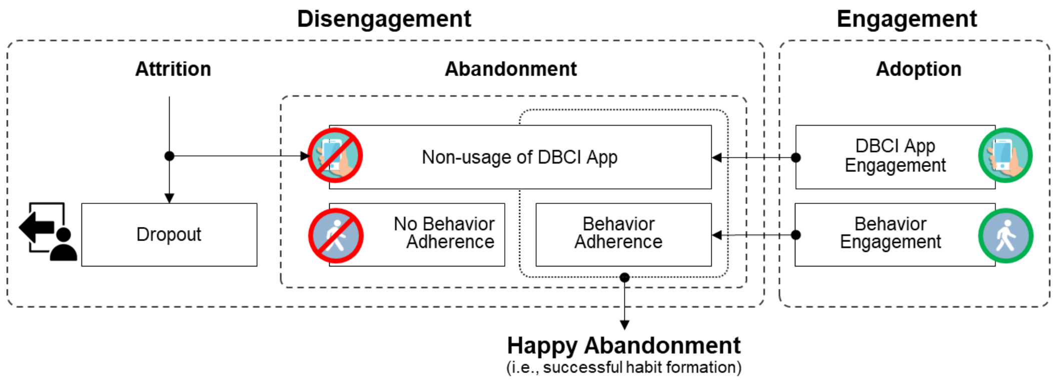


Fig. 2. Attrition, Abandonment,and Disengagement Concepts in DBCI

dropout was different in previous studies [60], it commonly referred to the phenomenon of users leaving the treatment process.

Attrition for DBCI is similar to the concept of "abandonment" described in research on personal informatics (PI) systems. In a study on the PI system, abandonment was defined as a state of "discontinued tracking" [3]. The PI system provides the ability to collect personal information and monitor it to support the self-tracking of an individual's specific behaviors or habits [54]. Therefore, "discontinued tracking" from the PI system means disengagement of both self-tracking and self-monitoring activities. In this respect, abandonment is integrated with disengagement with DBCI. Some studies on PI systems have revealed "happy abandonment" [15], where users stop using the tracker by reaching a goal. In terms of engagement, "happy abandonment" should be distinguished from other abandonment states, as it is considered a state in which the user stops using the app but sustains the target behavior, i.e., maintains adherence to the target behavior. In summary, attrition and abandonment are described as subconcepts of disengagement for DBCI, as shown in the figure.

2.1.3 User Engagement Process in Just-in-Time DBCI. For health promotion, JIT-based mHealth interventions require behavior engagement separate from app engagement. Therefore, it is essential to investigate behavioral engagement processes in the context of JIT interventions for a comprehensive understanding of engagement with JIT interventions.

Behavioral engagement through JIT interventions can be described through a multi-stage receptivity model [14]. The multi-stage receptivity model describes the behavioral engagement process for a single JIT intervention. According to the model, behavioral engagement begins with awareness of a JIT intervention signal. Behavioral engagement is fundamentally impossible if the user does not recognize the alarm in the perception stage. After recognizing the signal, the user decides whether or not to perform an intervention behavior in the given context. Such a decision-making process can be influenced by various personal and contextual factors. Once the user decides to adhere to the intervention, behavioral engagement occurs in the action stage.

Extending the multi-stage receptivity model allows for consideration of behavioral engagement processes over time. For proactive and iterative JIT interventions, users repeatedly recognize intervention signals and decide whether or not to engage in action.

Repetitive perception of JIT intervention signals is related to the "habituation" phenomenon mentioned in previous studies [45, 67]. Habituation is a non-associative learning process of behaviorism, in which a response decreases to the same single stimulus provided repeatedly [63]. Due to the repetitive nature of JIT interventions,

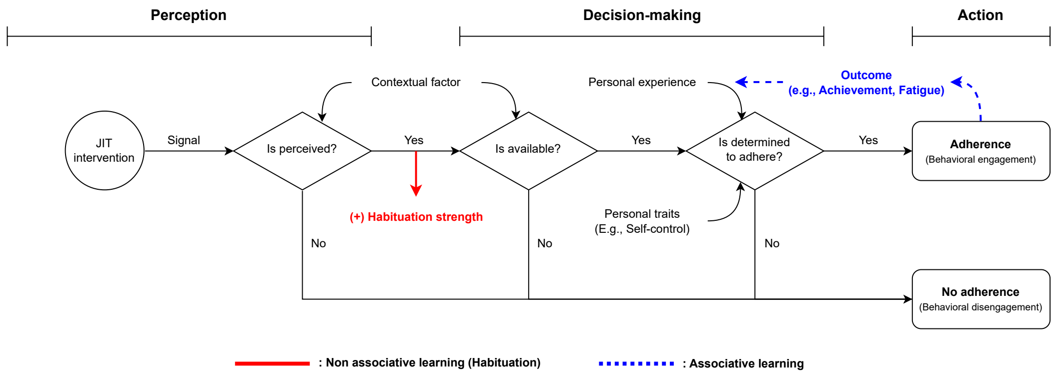


Fig. 3. User Engagement and Disengagement Process in JIT DBCI

users may lose their awareness of intervention signals over time. For example, users may become accustomed to the same recurring intervening alarm sound or message and ignore the cue over time. Thus, in the long term, behavioral engagement with JIT intervention is first affected by an individual's habituation level to the intervention signal in the perception stage.

The decision-making process of behavioral engagement in the context of repeated JIT interventions is described as an associative learning process. Associative learning in behaviorism refers to learning the relationship between a stimulus and an action [63]. In a JIT intervention scenario, a user can repeatedly receive JIT intervention signals (i.e., stimulus) and perform intervention behaviors (i.e., action). In this process, the user can learn a positive relationship between the intervention signal (i.e., stimulus) and the behavior (i.e., action) through the sense of achievement obtained by repeating the intervention behaviors. Here, the sense of achievement is the outcome of associative learning, which reinforces subsequent behavioral engagement.

2.2 Influence of Personal Traits on Disengagement of JIT Intervention

According to the study on JIT interventions, engagement with the interventions is influenced by the user's context and receptivity [67]. Therefore, exploring the factors and contexts influencing user receptivity can play an important role in deepening our understanding of disengagement from JIT interventions.

Prior studies demonstrated that boredom can be attributed to repetitive and predictable experiences [26]. Repetitive and proactive JIT intervention delivery can cause boredom, and users with a higher trait of boredom (or boredom proneness) may feel it more strongly. Furthermore, perceived boredom could be amplified due to repeated intervention messages and recommended behaviors. Prior studies identified that an individual's boredom proneness is associated with a low level of attention [18, 23] and low power of execution [64]. An empirical study analyzing the relationship between trait boredom and adherence to behavioral guidelines (e.g., social distancing in the COVID-19 pandemic) revealed that trait boredom could be an indirect factor inhibiting adherence [102]. We hypothesized that those with higher than average boredom proneness are more likely to suffer from disengagement and may show different trends concerning adherence to interventions.

JIT interventions ask users to perform a target behavior when the intervention is delivered (for example, within 10 minutes). Therefore, successful engagement with the intervention is closely related to how well an individual manages the personal contexts in which the intervention takes place. This individual capability could be well captured by the trait of self-control, an individual's capability to perform a desirable behavior by controlling their immediate environments [4]. Prior studies on self-control showed that the trait self-control was mainly described as control power [4, 65], and it was emphasized as an important resource for achieving goal behavior [85]. People with high self-control have better control over their thoughts, emotions, and impulses than people with low self-control [65]. A variety of studies on user behavior have shown that people with high self-control perform more successfully in health-related behaviors and activities [19]. In contrast, low self-control has been found to be associated with procrastination [30]. Since JIT interventions require *timely self-control* in a given context to achieve goals with deadlines, we hypothesize that trait self-control may be closely related to disengagement with JIT intervention.

Prior studies on DBCI have warned of the attrition of user engagement with interventions over time. Despite a common recognition of the importance of the issues, in-depth explorations of the disengagement process of JIT interventions are lacking in the field of HCI. In this study, we use a simple mobile intervention and conduct a field study to investigate disengagement in JIT interventions. We analyze how traits of boredom and self-control are related to disengagement and identify the contextual factors affecting the disengagement and re-engagement processes of JIT interventions. Thus, we set out the following research questions:

- **RQ1**: How does JIT intervention disengagement appear over time?
- **RQ2**: Do personal traits such as self-control and boredom proneness influence disengagement and user experience for JIT intervention over time?
- **RQ3**: What factors influence a user's disengagement and re-engagement processes in the context of JIT interventions?

3 SYSTEM DESIGN

To explore disengagement with JIT interventions, we designed a JIT intervention system to improve users' prolonged sedentary lifestyles. The purpose of the system was to discourage prolonged sedentary lifestyles and increase the amount of physical activity in daily life through JIT intervention. Considering the ease and simplicity of tracking step counts and measuring prolonged sedentary behavior using current smartphone sensing technologies (e.g., Google Activity Recognition), we designed a smartphone-based intervention system.

3.1 Intervention System Design

Our intervention system tracks both step counts and prolonged sedentary behavior to encourage physical activity. As in typical pedometer applications, we provided step count tracking and goal setting as baseline interventions. The mechanism consists of JIT intervention and feedback under prolonged sedentary behavior, as shown in Figure 4.

3.1.1 JIT Intervention System Design. In this section, we describe our JIT intervention system design.

JIT Intervention Timing. Prior studies on JIT-based DBCI have provided important clues regarding the design of the JIT intervention timing. In a prior study on JIT intervention, several researchers described JIT intervention as an intervention delivered at the onset of a target behavior [44, 83]. They emphasized the importance of breaking impulses in moments of problematic behavior. This is because once a problematic behavior occurs, it can be reinforced. For example, a first smoking failure leads to a full relapse [86]. According to the studies [44, 83], the optimal moment for JIT intervention could be before problematic behavior occurs. Therefore, JIT interventions must be designed to deliver interventions for problematic behaviors proactively. Regarding the design of intervention content and delivery frequency for mitigating prolonged sedentary behavior, prior observational studies have explained the importance of the pattern in which sedentary behavior accumulates. These studies suggested that short periods of light-intensity active rest may lower health problems such as cardiometabolic risk [36] and obesity [6]. Based on the studies [6, 36], we designed a JIT intervention system that proactively provides short periods of light-intensity active rest for prolonged sedentary behavior. We considered an intervention scenario discouraging prolonged sedentary behavior, as in prior studies [95].

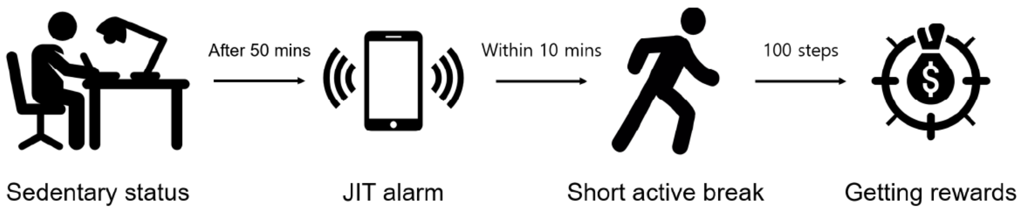


Fig. 4. Intervention Mechanisms

JIT Intervention Operation. A system-driven JIT alarm is delivered to encourage users to take a "short active break" (called a mission), which involves stopping sedentary behavior, getting up, and walking for a short period of time. As a system-driven operation similar to that in a prior study [72], the alarm is proactively delivered to the user whenever their sitting state lasts 50 minutes. The mission directed the user to stand up and walk 100 steps in 10 min after receiving the alarm; this activity usually takes less than 2 min.

In order to maximize the effect of JIT intervention, an alarm sound was played during the intervention delivery process. According to prior research [71], the alarm sound (or vibration) was accompanied by a message to maximize the effect of the intervention. The sound/vibration patterns were slightly varied to distinguish them from other regular notifications.

To avoid possible disturbance, the system allows users to choose one of the three-time frame options for alarm delivery; 1) from 9 AM to 6 PM, 2) from 10 AM to 7 PM, and 3) from 11 AM to 8 PM, respectively. Based on the user's selection, the system only rings the alarm during the chosen period.

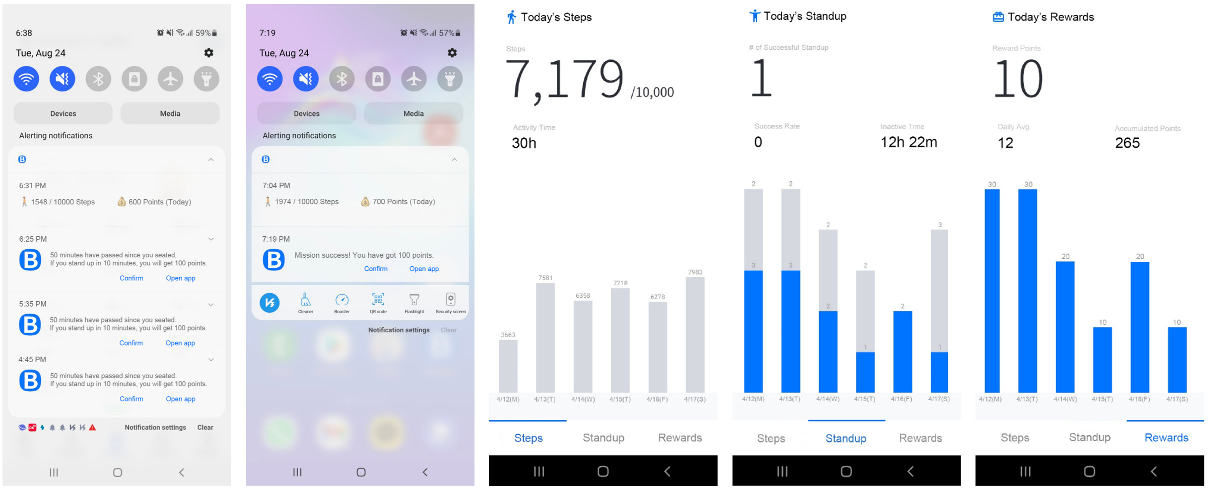
3.1.2 Intervention Feedback Design. In this section, we describe our JIT intervention feedback design.

Reward Feedback. As mentioned in Section 2.1.3, engagement with JIT interventions can be understood as an associative learning process accompanied by reinforcement. Reinforcement in associative learning is related to positive reinforcement, a type of operant conditioning in behaviorist theories [89]. Positive reinforcement is a learning process that increases the frequency of occurrence of a target behavior through a reinforcer. According to this process, users can form a positive habit (i.e., quitting prolonged sedentary behavior) for the target behavior. In this study, the proposed JIT intervention system was designed to trigger a user to perform a target behavior through a JIT signal and provide a reward (i.e., reinforcement) for behavioral adherence.

Prior studies in behavioral psychology have evaluated the effectiveness of various behavior reinforcement strategies, such as badges [29], levels [31], and points/rewards [10]. Among these, monetary rewards have been used as the most representative and effective reinforcement strategy in studies that leverage behaviorism [39]. Reinforcement strategies using monetary rewards have been used in various psychological-based behavioral change studies (e.g., smoking cessation [99] and physical activity [74], and have proven to be effective as a behavioral change strategy (BCT) in DBCI studies [61]. In addition, a previous study showed that monetary rewards increase experimental compliance [66]. Accordingly, in this study, we adopted monetary rewards to maximize the effects of the reinforcement of intervention behavior.

If the user successfully performs the target behavior, the system provides a micro-incentive for behavioral reinforcement; i.e., 100 points (approximately 0.1 USD). Since our intervention system runs 9 hours a day, users can earn up to 0.9 USD per day if they adhere to all intervention behaviors.

Notification Feedback. The system maintains unchecked JIT alarm messages in the notification drawer (i.e., Android OS notification drawer) as intervention feedback. This operation allows the user to check the notifications later when they check other notifications. Aligned with the prior study [17, 33], such notifications



(a) JIT Alarm (b) Persistent Display (c) Steps Dashboard (d) Standup Dashboard (e) Rewards Dashboard

Fig. 5. Intervention Components

provide feedback and help users to reflect on their activities (e.g., adherence failures). We provide additional feedback through a "persistent notification" in the notification drawer—here, persistence means that a given notification is always displayed in the notification drawer. This provides additional opportunities for users to check their activity history and progress. Since the "persistent notification" stays in the notification drawer, users can opportunistically check it whenever they check received notifications, which frequently happen throughout the day. As in an "always-on display", this kind of piggybacked notification served as a constant reminder to achieve goals by supporting convenient self-tracking [17, 33, 101]. Furthermore, opportunistic checking lowers a user's time pressure for decision making caused by "sudden appearance" [101] such as a push-based prompt.

3.2 System Component Description

Our intervention system component is composed of 1) JIT Alarm and Message (Push-based Component), 2) Activity Statistics Dashboard (Pull-based Component), and 3) Always-On Display. The system runs on Android phones with an operating system version 10.0.0 (Queen Cake) or higher. All component screenshots are shown in Figure 5.

3.2.1 JIT Alarm and Message. The JIT alarm message includes a suggestion for a mission (i.e., active break), along with a warning sound on prolonged sedentary behavior. The message delivers the specific actions to be performed and offers reward information to encourage the activity; *"50 minutes have passed since you were seated. If you stand up in 10 minutes, you will get 100 points."*

3.2.2 Activity Statistics Dashboard. The Activity Statistics Dashboard is designed as a pull-based intervention component. It provides a visualization interface for tracking and monitoring activity and intervention adherence records when the user launches the app. The dashboard consists of a Steps Dashboard, a Standup Dashboard, and a Rewards Dashboard. Users are rewarded only when they adhere to the push-based JIT interventions only (i.e., having an active break after a 50 minute seating). We do not reward users for engaging in pull-based components (e.g., checking dashboards).

Steps Dashboard. The Steps Dashboard visualizes the user's daily step count. The left-right sliding function is used to observe and check a user's past step records and overall trends. In addition, the dashboard shows the weekly activity time.

Standup Dashboard. In addition, Standup Dashboard shows the daily adherence rate for the JIT intervention. The adherence rate is calculated by the ratio of the daily number of successful missions and the JIT alarms received. This achievement rate is displayed to the user along with the weekly inactivity time.

Rewards Dashboard. The Rewards Dashboard displays the points acquired daily and the total points accumulated to date. In addition, the dashboard shows the average points acquired daily. The daily average points acquired are calculated by dividing the total points acquired by the number of days of participation to date.

3.2.3 Persistent Notification Display. Users can directly launch the Activity Statistics Dashboard by touching the Persistent Notification Display as shown in Figure 5b. In the notification drawer, the Persistent Notification Display updates the user's step record and rewards them in real-time.

4 USER STUDY DESIGN

We conducted an 8-week in-the-wild field study with 54 college students to investigate how the intervention app influences disengagement.

4.1 Methods

Through a user study, we attempted to explore how disengagement with JIT intervention emerges over time. To that end, we designed a within-group study with 54 participants. The study was conducted for eight weeks with a full intervention period. All participants experienced the JIT intervention mechanisms in their daily routines during the study period. Our study was approved by the university's Institutional Review Board (IRB) and was conducted with the participant's written consent.

4.2 Participants

For the selection of study participants, we referred to previous studies on sedentary lifestyles. Prior studies have emphasized the importance of interventions for prolonged sedentary lifestyles among college students [49, 106]. According to a study [90], most adults' physical activity and sedentary behavior habits are strongly influenced by habits formulated while in college. It was found that 82% of college students who lacked physical activity in college maintained their inactive habits into adulthood [90]. In addition, prolonged sedentary behavior among college students was significantly associated with health problems such as stress, anxiety, and depression [49, 106]. Accordingly, we decided to recruit college students who wish to improve long-term sedentary habits.

We recruited participants through online communities and portals from two large universities in Korea. During the recruitment process, a questionnaire was used to investigate the suitability of applicants to participate in the study. The questionnaire asked 1) whether participants had serious health problems related to physical activity (e.g., heart disease), 2) whether they were willing to improve their prolonged sedentary habits, and 3) using an Android mobile phone with an operating system version 10 or higher.

To select participants with a willingness to improve prolonged sedentary habits, we created a questionnaire leveraging a transtheoretical model (TTM) [77] that describes the stage of behavior change. We selected applicants who chose one of two items. The two items were *"I intend to begin regularly engaging in physical activity to improve prolonged sedentary habits in the next six months."* and *"I intend to begin regularly engaging in physical activity to improve prolonged sedentary habits in the next 30 days."* In terms of the TTM model, these were applicants with TTM level 2 (i.e., getting ready) or 3 (i.e., ready). After the initial screening of 75 volunteers, we selected 54 (38 males and 16 females, age: M = 25.83, SD = 4.09).

4.3 Procedure

The study procedure consists of three stages: (1) orientation pre-survey, (2) 8-week data collection and bi-weekly surveys, and (3) post-interview. Each participant received 70 USD for participation in the experiment. Participants who conducted post-interviews received an additional 10 USD.

4.3.1 Orientation & Pre-Survey. We conducted an online orientation to explain how the study would proceed. Participants attended the orientation and were briefed on the experimental guidelines, including a description of the data to be collected during the study. Subsequently, we helped participants install the app by providing online guides for installing the app.

Before the study, all participants participated in a pre-survey to check their personal traits 1) Boredom and 2) Self-control. For boredom trait measurement, we used a short-scale version of the Boredom Proneness Scale (BPS) questionnaire [97]. The questionnaire consisted of six sub-items measuring intrinsic factors of boredom and six sub-items measuring extrinsic factors. This was developed by the confirmatory factor analysis for the original questionnaires [26].

In addition, we measured the self-control trait using the questionnaire referred to in a prior study on sedentary behavior [56]. The questionnaire comprises six sub-items selected from the Self-Regulation Questionnaire (SRQ) [8]. The SRQ has been widely used in previous studies to assess individual self-control in various behaviors, including physical activity and sedentary behavior [9, 56].

4.3.2 8-week Data Collection. During the entire study period, we collected user activity records and survey responses on user experience with the app.

Activity Log. To track disengagement patterns, we collected participants' physical activity logs (e.g., steps) and records of interactions with intervention during all periods. We checked the data collection status via server storage and dashboard in real-time to ensure that there was no problem with data collection for all participants. We communicated with participants who had challenges via email or message. In total, 12,042 JIT alarm interaction datasets and 3,024 daily steps were collected from 54 participants during the 8-week study.

Bi-weekly Survey. Through a bi-weekly survey conducted every other week, we collected changes in user experience using the intervention over time. We used the hedonic quality and boredom associated with using the app. These two factors are related in that users are less bored with products they perceive as having high hedonic quality [34]. By measuring the hedonic quality of a DBCI, therefore, we can evaluate its usability and observe the related user experience. In addition, this study used financial incentives to promote adherence to intervention behaviors. In previous studies, incentives were used as an extrinsic motivator to achieve goals (e.g., promoting phone usage regulation [72]). An important issue regarding extrinsic motivation is the "crowding out effect" [28]: extrinsic motivation undermines intrinsic motivation. Likewise, the financial incentives in our study may weaken the intrinsic motivation for behavioral engagement. Accordingly, we collected survey responses to investigate a user's intrinsic motivation for behavioral engagement.

To measure hedonic quality, the User Experience Questionnaire (UEQ) sub-items "Stimulation" and "Novelty" were utilized [84]. Stimulation and Novelty have been widely used as metrics to evaluate the hedonic quality of products in prior studies [34].

To evaluate the boredom associated with using the app, we utilized a questionnaire adopted in a previous study [104]. The questionnaire was used to collect users' evaluations of their boredom with the brand. We modified the questionnaire to investigate the boredom of using the app using questions such as "I'm tired of interventions provided by the system."

To measure intrinsic motivation to engage with JIT interventions, we used the Intrinsic Motivation Inventory (IMI) questionnaire [20]. We revised the existing IMI questionnaire to measure the motivation for using the app by including the application contexts, e.g., "I enjoy the active break provided by the system."

4.3.3 Post Interview. After the main study period, we performed a semi-structured online interview with 30 participants to understand participants' experiences on the intervention app related to disengagement. The interview questionnaire was focused on investigating the influences of JIT components (e.g., JIT alarm) on disengagement (or re-engagement) and its reasons.

4.4 Data Analysis Methods

To answer our research questions, we analyzed the collected data. First, we analyzed the changes in user engagement with the intervention to find out how disengagement with JIT interventions emerges over time. As mentioned in Section 2.1, prior studies on DBCI emphasized the importance of a comprehensive metric for measuring "effective engagement" for intervention [2, 107]. Based on the results of the study, we analyzed user engagement in terms of 1) app usage frequency (i.e., technology engagement) and 2) adherence to target behavior (i.e., behavior engagement). To quantitatively analyze adherence, we measured the daily adherence rate of the JIT intervention. Specifically, the daily adherence rate was calculated as the ratio of the number of daily successful missions to the number of received alarms. Using one-way repeated measures Analysis of Variance (ANOVA), we analyzed whether there was a significant change over time in engagement.

Second, to investigate the effect of personal traits (i.e., trait boredom and self-control) on disengagement and user experience for JIT intervention, we first analyzed the distribution of each personal trait using a histogram and the correlation between two personal traits. We clustered participants using the K-means clustering algorithm based on the correlation analysis. In this process, we used the elbow method to select an optimal number of clusters. In addition, we labeled each cluster according to the level of both personal traits. After clustering participants, we compared how engagement and user experience for JIT intervention differed between groups (i.e., clusters) over time. Before analyzing the interaction effect, we investigated whether the collected data for each group followed a normal distribution. We performed the Kolmogorov-Smirnov normality and Shapiro–Wilk test, which showed that our data do not follow an approximately normal distribution. Thus, we used a semi-parametric approach of generalized estimating equations (GEE) that can model possible temporal correlations common in long-term data analysis. Furthermore, this method allows us to analyze the interaction effects between the group and time.

A thematic analysis was conducted on the interview data to investigate which factors influence disengagement and re-engagement processes for JIT interventions [94]. All interview sessions were recorded and transcribed. Each author labeled and annotated words, phrases, or sentences related to engagement and disengagement factors. Based on the work, we grouped the labeled codes into groups with similar themes. After creating the initial theme, the labeled code and theme were repeatedly reviewed and re-grouped. This work was performed iteratively until consensus was reached by all authors.

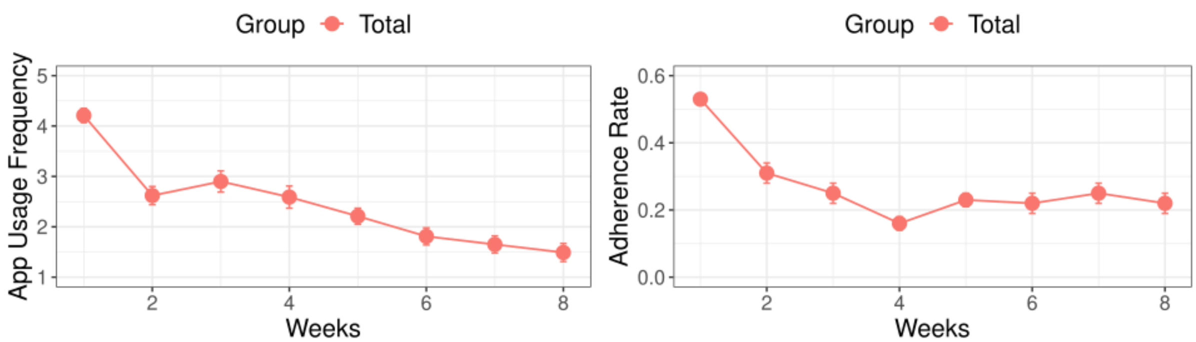
5 RESULTS

We describe the data analysis results to answer my research questions: *RQ1: How does user disengagement with JIT interventions appear over time? RQ2: Do personal traits such as self-control and boredom proneness influence disengagement and user experience for JIT intervention over time?* and *RQ3: What factors influence a user's disengagement and re-engagement process in the context of JIT interventions?*

5.1 Disengagement Trend Analysis (RQ1)

First, we analyzed changes in engagement over time for all participants. The daily average app usage frequency and adherence rate of intervention behavior analyzed on a weekly basis are shown in Figure 6 and Table 1.

5.1.1 Daily Average App Usage Frequency. We observed an overall decrease in the daily average app usage frequency over the study periods as shown in Figure 6a and Table 1. One-way repeated measures ANOVA with



(a) Daily Average App Usage Frequency

(b) Daily Average Adherence Rate

Fig. 6. Changes in User Engagement with JIT Interventions

Table 1. Descriptive Statistics of Changes in User Engagement with JIT Interventions

Variable	*N*	Mean (SD)							
		1W	2W	3W	4W	5W	6W	7W	8W
App Usage Frequency	54	4.21 (1.04)	2.62 (1.32)	2.90 (1.53)	2.59 (1.61)	2.21 (1.14)	1.81 (1.22)	1.65 (1.27)	1.49 (1.29)
Adherence Rate	54	.53 (.10)	.31 (.24)	.25 (.20)	.16 (.17)	.23 (.18)	.22 (.21)	.25 (.22)	.22 (.25)

N = The number of participants

a Bonferroni correction determined that there was a significant effect of the period (i.e., week) on app usage frequency, Wilks's Lambda = .19, F(7,47) = 29.24, p < .001, η^2 = .81

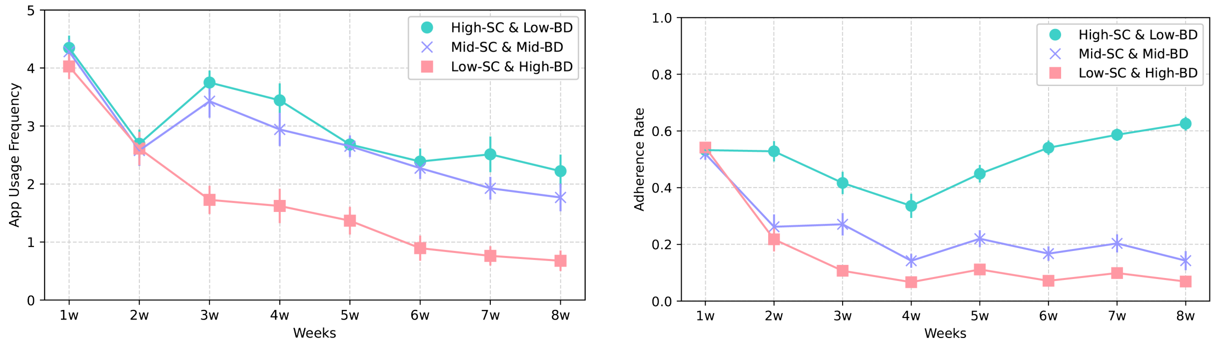
5.1.2 Daily Average Adherence Rate. In the analysis of adherence rates of intervention behavior, descriptive statistics showed that the adherence rate overall decreased over the 8 weeks as shown in Figure 6b and Table 1. One-way repeated measure ANOVA with a Bonferroni correction showed that there was a significant effect of the period (i.e., week) on adherence rates, Wilks's Lambda = .16, F(7,47) = 34.89, p < .001, η^2 = .84

5.2 Influence of Personal Traits on Engagement and User Experience (RQ2)

We analyzed whether trait boredom and self-control influence engagement and user experience for JIT interventions.

5.2.1 Correlation between Traits of Boredom and Self-Control. To figure out how the participants' personal traits differ, we analyzed the distribution of scores for each trait using a histogram, as shown in Figure 9 (See Appendix). The maximum score of trait self-control is 84 and that of trait boredom is 42. The results showed that the average scores for traits of self-control and boredom were 25.04 (SD = 7.08) and 36.78 (SD = 12.02), respectively.

We investigated the relationship between the two traits. A Shapiro-Wilk test showed a significant departure from normality for trait self-control; W(54) = .96, p = .074, and trait boredom; W(54) = .97, p = .15. A Pearson correlation result showed that there was a negative correlation between the two variables; r(52) = -.56, p < .001.



(a) Daily Average App Usage Frequency (b) Daily Average Adherence Rate

Fig. 7. Changes in User Engagement with JIT Interventions by Traits

We then clustered participants to understand better the influence of personal traits on user experience and engagement for JIT intervention. Using the K-means clustering algorithm, we determine the optimal number of clusters using the Elbow method by considering the minimum number of users per cluster (at least 10 users). The result showed that three clusters were the most appropriate regarding the number of users per cluster (See Figure 10 in Appendix). We name these clusters as follows: (1) high trait self-control and low trait boredom (High-SC & Low-BD), (2) middle trait self-control and boredom (Mid-SC & Mid-BD), and (3) low trait self-control and high trait boredom (Low-SC & High-BD).

5.2.2 Influence of Personal Traits on Engagement. To investigate the influence of personal traits on engagement, we analyzed how engagement with JIT interventions in each group changed over time (See Figure 7 and Table 2)

App Usage Frequency. Overall, app usage frequency decreased in all groups over eight weeks (See Figure 7a). We analyzed the interaction effect using generalized estimating equations to investigate the influence of personal traits on engagement with JIT intervention. In the analysis, we set the Middle-SC & BD as a reference variable and observed the engagement trend of the other two groups over time. The results showed that there was a significant change in app usage frequency over time; $\chi^2(1, N = 54) = 188.36$, $p < .001$. The interaction effect between time and group was significant; $\chi^2(2, N = 54) = 10.36$, $p < .001$, which means that there was a significant difference in the change in app usage frequency over time corresponding to the level of personal trait. The Low-SC & High-BD group was significantly different from the other groups.

Adherence Rate. Descriptive statistics showed that the adherence rates were similar in the beginning (i.e., the first week), but they quickly dropped over time (in the first four weeks). The adherence rates of those who have low/mid self-control levels maintained low adherence rates. However, the High-SC & Low-BD group gradually recovered the adherence rates for the rest of the four weeks (See Figure 7b). In the analysis of the main effect, the results showed that there were significant differences in adherence rate across the eight weeks (time); $\chi^2(1, N = 54) = 112.29$, $p < .001$. We did not find significant effects on groups, but there was also a significant interaction effect between period and group, $\chi^2(2, N = 54) = 156.74$, $p < .001$. We found that the High-SC & Low-BD group was significantly different from the other groups.

5.2.3 Influence of Personal Traits on User Experience. We investigated the influence of personal traits on engagement with JIT intervention. To analyze how engagement with JIT interventions between groups changed over time, we compared the changes in scores of hedonic quality, boredom (i.e., the boredom of app usage), and intrinsic motivation between groups on a bi-weekly basis. In order to distinguish between boredom (i.e., the trait

Table 2. Descriptive Statistics of Changes in User Engagement with JIT Interventions by Traits

Variable	N	Mean (SD) 1W	2W	3W	4W	5W	6W	7W	8W
App Usage Frequency									
High-SC & Low-BD	12	4.35 (1.06)	2.70 (1.22)	3.75 (1.03)	3.44 (1.46)	2.68 (.59)	2.39 (1.12)	2.51 (1.53)	2.22 (1.42)
Mid-SC & Mid-BD	23	4.28 (1.04)	2.58 (1.33)	3.43 (1.41)	2.94 (1.43)	2.65 (.93)	2.27 (.92)	1.93 (.98)	1.77 (1.19)
Low-SC & High-BD	19	4.03 (1.07)	2.61 (1.44)	1.73 (1.21)	1.62 (1.48)	1.37 (1.19)	.89 (1.09)	.76 (.83)	.68 (.88)
Adherence Rate									
High-SC & Low-BD	12	.53 (.11)	.53 (.18)	.42 (.20)	.34 (.21)	.45 (.15)	.54 (.13)	.59 (.11)	.63 (.12)
Mid-SC & Mid-BD	19	.52 (.10)	.26 (.22)	.27 (.20)	.14 (.12)	.22 (.15)	.17 (.13)	.20 (.16)	.14 (.17)
Low-SC & High-BD	23	.54 (.10)	.22 (.21)	.11 (.10)	.07 (.07)	.11 (.06)	.07 (.06)	.10 (.06)	.07 (.06)

N = The number of participants

of boredom) as a personal trait and boredom in app usage experience, we marked all the metrics related to user experience distinctly; 1) UX-HedonicQuality, 2) UX-Boredom, and 3) Intrinsic Motivation.

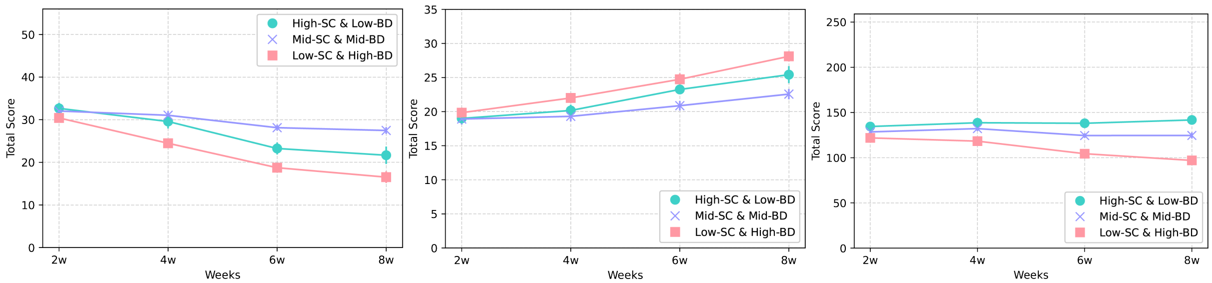
UX-HedonicQuality. Over eight weeks, UX-HedonicQuality scores of all groups overall decreased, as shown in Figure 8a and Table 3. Through a semi-parametric analysis using GEE, we showed that there was a significant main effect related to the period, $\chi^2(1, N = 54) = 109.19$, $p < .001$, and an interaction effect between group and period: $\chi^2(2, N = 54) = 28.48$, $p < .001$.

UX-Boredom. As shown in Table 3, in the UX-Boredom score analysis, we observed that the score increased in all groups over time. An analysis of the main effect showed that there was a significant effect related to the period, $\chi^2(1, N = 54) = 70.53$, $p < .001$. In addition, there was a significant interaction effect, $\chi^2(1, N = 54) = 8.49$, $p < .014$.

Intrinsic Motivation. In Figure 8c, we found that the change patterns of the Low-SC & High-BD group were different from those of the other groups. The motivation in the Low-SC & High-BD groups decreased over time; however, other groups showed a tendency to maintain their motivation for eight weeks. In addition, we observed that there was a significant main effect related to the period, $\chi^2(1, N = 54) = 18.76$, $p < .001$, and an interaction effect, $\chi^2(1, N = 54) = 55.72$, $p < .001$.

5.3 Contextual Factors Influencing Disengagement and Re-engagement Processes (RQ3)

In this subsection, we describe the factors influencing engagement with JIT interventions derived from qualitative analysis. Through the data analysis for RQ2, we observed two patterns of engagement with JIT intervention. One



(a) UX-HedonicQuality Score (b) UX-Boredom Score (c) Intrinsic Motivation Score

Fig. 8. Changes in User Experience on JIT Interventions by Level of Traits

Table 3. Descriptive Statistics of Changes in User Experiences for JIT Interventions by Traits

Variable	*N*	Mean (SD)			
		2W	4W	6W	8W
UX-HedonicQuality					
High-SC & Low-BD	12	32.67 (6.41)	29.58 (8.14)	23.25 (7.06)	21.67 (1.20)
Mid-SC & Mid-BD	23	32.04 (3.88)	31.04 (4.98)	28.13 (3.55)	27.48 (3.96)
Low-SC & High-BD	19	30.42 (4.32)	24.47 (4.73)	18.74 (5.70)	16.53 (6.86)
UX-Boredom					
High-SC & Low-BD	12	19.00 (4.41)	20.17 (4.26)	23.25 (3.52)	25.42 (6.23)
Mid-SC & Mid-BD	23	18.91 (3.93)	19.30 (3.71)	20.87 (3.45)	22.57 (3.78)
Low-SC & High-BD	19	19.84 (3.69)	22.00 (3.68)	24.74 (4.32)	28.11 (3.73)
Intrinsic Motivation					
High-SC & Low-BD	12	134.50 (12.10)	138.67 (12.46)	138.08 (10.96)	141.75 (6.98)
Mid-SC & Mid-BD	23	128.52 (13.26)	132.17 (13.61)	124.52 (12.78)	124.60 (17.23)
Low-SC & High-BD	19	121.89 (12.55)	118.32 (10.63)	104.42 (12.27)	97.00 (9.04)

N = The number of participants

was the "Disengagement" cycle in which the response to JIT intervention decreased over time, and the other was the "Re-engagement" cycle to adapt to JIT intervention. Here, we defined the "Re-engagement" cycle as consciously and adaptively following the JIT intervention away from disengagement. Our qualitative analysis revealed the detailed factors of two opposing behavioral processes: "Disengagement' and "Re-engagement" cycles. Here, we set out the following sub-RQs:

- **RQ3-1**: What factors formulate the "Disengagement" cycle?
- **RQ3-2**: What factors formulate the "Re-engagement" cycle?

5.3.1 RQ3-1: Disengagement Process Factors. We analyzed factors that influence the "Disengagement" cycle in JIT intervention. We found different factors: (1) Boredom and habituation to repeated and same JIT interventions, (2) Inopportune alarm, (3) Distrust for JIT intervention operations, (4) lack of self-efficacy in adherence, and (5) low motivation in adherence.

Boredom and Habituation to Repeated and Same JIT Interventions. Boredom and habituation were major factors influencing the disengagement cycle. Both factors were caused by repeated delivery of the same JIT intervention. Participants developed habituation to the same and repeated JIT intervention over time. P20 stated, *"The missions were interesting at first, but later I became numb to the alarms. Because there is nothing new. It was just the same sound and message."* Participants reported feeling bored with repeated and the same JIT intervention alarm sounds and messages. P2 used the Korean slang "No Jam" (meaning no fun) to express boredom with repeated JIT interventions.

Boredom with the intervention was strongly observed in the Low-SC & High-BD group. They showed a tendency to quickly get bored with the intervention behavior. One participant in the group said, *"I usually feel more bored than others. After using it once or twice, it quickly became stale as I realized it was no different from other health apps. After then, I felt mission activity was trivial and gradually ignored it."* As a result, boredom with repeated interventions led to the devaluation of interventions and reduced adherence to the JIT intervention over time.

Inopportune Alarm. Disturbance to the main task due to the JIT alarm was another factor that influenced disengagement cycles. The JIT alarm sound or vibration was a major factor that interrupted concentration on the main task (e.g., studying) and incurred resumption costs for returns to the task. P38 mentioned that *"I was very focused on taking a trial exam, but when an alarm arrived, my concentration broke. Once I lost my concentration, returning to the task was difficult. After repeating the same experience several times, I became irritated and annoyed by the alarm. Eventually, I ended up ignoring the alarm over time."* As a result, repeated inopportune alarms increased participants' irritation with JIT alarms and decreased their response to JIT interventions over time.

Distrust for JIT Feedback Mechanism. The distrust of the JIT feedback mechanism affects the disengagement cycles. The main distrust of the JIT feedback mechanism was related to "tracking activities." Some participants (n = 9, 17%) noted that the amount of activity (i.e., the number of steps) tracked by the system depended on the situation. For example, P44 mentioned *"I walked the same distance yesterday and today, but today, the mission success alarm did not arrive on time."* This issue appeared at the stage of performing a mission, because of a "mismatch" between the amount of activity perceived by the participants and the amount of activity tracked by the system. Our extensive pilot test validated the tracking accuracy of the system; however, the tracking accuracy may also be affected by real-world user contexts.

In addition, several participants (n = 6, 11%) mentioned experiencing other tracking issues; 1) "untracked adherence" (i.e., true-negative case of adherence), and 2) "accidental adherence" (i.e., false-positive case of adherence). Regarding experience related to "untracked adherence," P11 stated *"Occasionally, an alarm would arrive while I had gone to drink water. When I saw the missed alarm after returning, I realized there was a limit to following the app's mission. In this situation, I did not do so even if there was still enough time to complete the mission. Because I have already been walking."* For "accidental adherence," P3 stated *"It was accidentally recorded as a mission success, but I was uncomfortable because I did not do it voluntarily."* Participants who repeatedly experienced tracking activity issues became distrustful of the JIT feedback mechanism over time. Consequently, their distrust increased their disappointment with the system, leading to decreased responses to the JIT interventions.

Lack of Motivation Due to Low Rewards. Reduced motivation for adherence due to "small incentives" influenced disengagement cycles. The reduced motivation was mainly because small financial rewards crowded out participants' motivation to engage in healthy behaviors. Participants mentioned that their motivation for adherence decreased when they perceived that the accumulated rewards were lower than their expectations. P22 said *"It was very disappointing when I checked the status bar and realized that the accumulated rewards were not much. And my motivation (for adherence) dropped significantly as well. Attitudes have changed over time. Anyway, it was hard to collect a lot of money because it was too tiny. If I succeeded at any time, I could get points, so I stopped paying attention to mission failures."* In terms of interaction with JIT interventions, we noted that reduced motivation could be triggered by the process of checking the rewards displayed in the persistent notification display. Consequently, dissatisfaction with the accumulated rewards contributed to the devaluation of adherence and decreased responses to the JIT intervention over time.

5.3.2 RQ3-2: Re-engagement Process Factors. We analyzed factors that influence the "Re-engagement" cycle in JIT intervention. We found different factors: (1) rewards for adherence, (2) opportunistic alarm usage, and (3) self-reflection for non-adherence.

Sense of Achievement for Rewards. Most participants (n = 23, 43%) reported a reward for adherence as a re-engagement factor. The sense of achievement felt by increasing rewards reinforced their motivation to perform the target behavior. P17 mentioned that *"I was proud to see an increase in rewards. It was an opportunity to take care of my health and earn money. There was nothing bad, so I tried to keep going.'* In particular, some participants (n = 8, 15%) reported that the persistent notification display helped them continuously maintain their motivation for adherence. P18 mentioned that *"Every time I pulled down the notification drawer, I could see the accumulated rewards and thought I had to work much harder. It was nice to see the increased rewards (after completing the mission) and to be confident that I could make them."* The sense of achievement through rewards strengthened adherence, which in turn increased the self-efficacy of the target behavior. Consequently, this cycle positively affected the effort to adapt to the JIT intervention, leading to adherence retention over time.

Opportune Alarming and Routine Adjustment. Opportune alarming is an important re-engagement factor for JIT interventions. Participants reported that an opportune alarm helped them escape situations in which they lost concentration on the primary tasks. Specifically, JIT alarms helped them take active rest, which positively affected their work productivity through refreshments. P51 said *"I was not concentrating on my studies. At that time, an alarm arrived, and I decided to go outside for a while. After getting back, I definitely felt my improved efficiency."* As a result, the experience of repeated refreshments helped some participants adjust and align their daily routines with the JIT alarm cycle over time.

This trend was clearly observed in the interview responses of the High-SC & Low-BD groups. Over time, they made a conscious effort to adhere to the intervention behavior. P19 stated, *"After trying it a few times, I felt my work efficiency had improved. Therefore, I became more interested in alarms than before. Later, I utilized the alarm, just like a school bell. I had scheduled daily work like 1st class, 2nd class, etc. After getting used to it, I felt my time efficiency was improving."* Opportune alarming helped increase work productivity by providing an opportunity for refreshment and adjusting a work routine based on JIT alarms over time.

Self-Reflection for Non-Adherence. Self-reflection on intervention behavior failure was another re-engagement factor. Through interview analysis, we observed that self-reflection was triggered when checking unconfirmed messages stacked on the persistent notification display. P1 mentioned *"Whenever pulling down the notification drawer, I often saw (unchecked) alarm messages. I was ashamed when I saw so many messages. It made me reflect on my past failed behaviors due to my laziness."* Repetitive self-reflection experiences can be an important factor that changes the disengagement cycle for JIT intervention into a re-engagement cycle. P8 said, *"After failing (adherence) several times, I gradually stopped participating in the mission. However, whenever I pulled down the notification drawer, I was repeatedly forced to see the unchecked alarm messages. This experience was engraved in my memory. As I continued to reflect on this, at some point, I decided to change my mind and perform missions much better. Although the mission failures continued, I felt that I was adjusting well, and the number of successes increased little by little."* The self-reflection experience triggered by checking the notification drawer positively affects the effort to continuously adapt to the JIT intervention over time, thereby leading to adherence retention. Overall, repeated self-reflection triggered by the persistent notification display positively affected adherence retention by breaking the disengagement cycle for JIT intervention over time.

6 DISCUSSION

We discuss our results regarding the disengagement process of JIT interventions and provide theoretical and design implications for JIT intervention design.

6.1 Influence of Personal Traits on Engagement

Our activity log analysis showed that participants experienced a disengagement process on JIT interventions in the 8-week experiment. Disengagement was observed through an overall decrease in app usage frequency and adherence rate for eight weeks.

Trait boredom and trait self-control affected disengagement in terms of the adherence rate over time. The High-SC & Low-BD group showed a tendency to re-engage with the intervention behavior, whereas the Low-SC & High-BD showed a marked disengagement trend over time. A qualitative analysis of interview responses allowed us to understand different trends. Low-SC & High-BD experienced strong boredom with repetitive JIT interventions, resulting in disengagement tendencies from the early period of study. This boredom proneness was revealed through the hedonic quality score over time. In contrast, High-SC & Low-BD tended to cope consciously and adaptively to the intervention over time.

Differences between the two groups were also revealed from the user experience of app use over time. The High-SC & Low-BD groups continuously experienced self-reflection for adherence failures with the Persistent Notification check in the notification drawer. In contrast, the Low-SC & High-BD group experienced demotivation to adhere when they perceived a cumulative incentive amount was less than they had expected in the process of checking the Persistent Notification. Such differences in experiences were shown through changes in intrinsic motivation scores over time. The intrinsic motivation score of the High-SC & Low-BD group tended to be overall maintained during the study period, whereas that of the Low-SC & High-BD group decreased significantly over time.

We observed that the re-engagement cycle was triggered through positive experiences with JIT interventions such as rewards, opportune alarming, and self-reflection. In contrast, the disengagement cycle was affected by habituation, boredom, distrust, interruption, and motivational crowding out on JIT interventions. Our findings showed that engagement with the JIT intervention was formed through the iterative process of 'disengagement', 're-engagement', or a mixture of both cycles, which were experienced differently according to personal traits and user contexts.

6.2 Influence of Micro-Financial Incentives on Engagement

Our study results showed that micro-financial incentives (MFI) in the context of JIT interventions for health promotion are effective in reinforcing positive behavioral change. In the interviews, participants reported that the sense of accomplishment gained from earning rewards encourages them to adhere to active breaks. This result aligns with various behavioral change studies using financial incentives [61, 66, 74]. Previous studies on financial incentives have discussed the effectiveness of incentives as a behavioral change strategy. In addition, the result can be interpreted as an associative learning outcome for JIT intervention alarms [63]. MFI and a sense of achievement through behavioral adherence positively associate the JIT intervention signal with the intervention behavior. When the JIT engagement signal is delivered, MFI and a sense of achievement are reminded, leading to adherence to the intervention behavior.

However, some participants reported negative experiences with MFI over time. They noted that their motivation for adherence weakened when they saw a cumulative incentive amount was less than they had expected while checking the persistent notification. In addition, as there was no penalty for failure to adhere, they showed a tendency of self-rationalization to failure over time. Such experiences eventually led to a disengagement cycle. Our results showed that, depending on the context, participants performed the intervention behavior for reward acquisition rather than for health promotion purpose itself. This can be seen as the "motivation crowding out effect" in which extrinsic motivation inhibits intrinsic motivation as discussed in the theory of motivation [28]. Future work should carefully investigate this tradeoff when leveraging MFI for behavior change, as discussed in our design implications below.

6.3 Seeking Deeper Understanding of Disengagement with JIT Interventions

We analyzed the disengagement process of JIT intervention by conducting an in-the-wild study. Our analysis is based on insights from prior studies [2, 93, 107] where engagement should be measured by analyzing both *application usage* (i.e., app engagement) and *behavior adherence* (i.e., behavioral engagement). The results revealed that disengagement occurred in intervention adherence and app usage over time, and that personal traits such as boredom proneness and self-control were closely related to disengagement. Our qualitative analysis was conducted based on the receptivity model [14], detailing the disengagement or re-engagement process of JIT intervention.

Our findings highlight the need to better operationalize "app engagement" in JIT intervention contexts. JIT interventions often use push notifications and opportunistic displays (e.g., notification drawers or persistent displays). These features are the main departure from traditional pull-based interventions, where users should launch an app and navigate through the intervention content. Defining "app engagement" for JIT interventions is closely related to how users interact with JIT interventions. Conceptualizing user interactions with JIT interventions requires the development of a detailed user interaction model, as in the receptivity model [14], for each component constituting the JIT intervention system, for example, the interaction sequences of each push- or pull-based intervention element.

Our results further highlight the necessity of redefining the concept of disengagement with JIT interventions. The results showed that owing to push notifications and false positives of behavior adherence, user engagement tended to exist. Rarely engaging with the app can be treated as non-usage, but this does not always indicate complete non-adherence due to push notifications and false positives.

One approach that can overcome this is Micro-Randomized Trial (MRT) experimental design. Given that false positive cases are considered user engagement, they affect the analysis of intervention effectiveness. Since the MRT design enables the analysis of the effects of specific intervention components over time in JITAI, the noise that affects the effect analysis can be minimized by using the weighted and centered least-squares technique, which considers covariates in the analysis process [79].

An alternative approach would be to use the multistage receptivity model [14], which allows us to formulate attrition with a conditional probability. We can define that attrition occurs if the user's engagement with the behavioral intervention disappears even though the user perceives the intervention delivery (i.e., intentionally ignoring messages). One strategy to measure such disengagement is to track adherence time series and treat the tail part as a stationary random process, in which the mean and variance do not vary over time. If these statistics do not differ from the baseline period (without intervention), we can say that attrition has occurred.[1] Further conceptualization and modeling of JIT disengagement based on log data analytics [51, 53] could be conducted to deepen our understanding of JIT disengagement and attrition.

6.4 Design Implications

Our study revealed how the disengagement and re-engagement cycles were formed in JIT intervention. We presented practical design guidelines to help achieve effective engagement with JIT interventions.

6.4.1 Design Strategies for Mitigating Disengagement. Based on our results, we provide design guidelines for mitigating disengagement from JIT interventions.

Mitigating Boredom. Users experienced boredom and fatigue owing to the repetition of the same JIT intervention mechanism. This demonstrates the need for a system design that can avoid the delivery of repetitive interventions. One strategy could be to increase novelty by introducing uncertainty with variations in the type

[1]Although interventions are not delivered, users' physical activity data can be used to simulate interventions. With that strategy, we can calculate adherence rates in the baseline period.

of target behavior and in the messages delivered during the intervention process. For example, based on the CASA paradigm [52, 68], the strategy of using random, funny nicknames or phrases (with context adaptation) can be used to mitigate boredom. Alternatively, we can introduce humorous design factors [108] or leverage gamification elements [21]. There are also several directions for manipulating micro-financial incentives for boredom mitigation. While the current approach is limited to a fixed amount per intervention, we can offer variable incentive amounts to break away from such monotonous incentivization. For example, we could consider an incentive mechanism that schedules an escalating reward amount based on successive goal achievements or a mechanism that schedules lottery based random incentives [48, 57, 98].

Mitigating Interruption. Inopportune interruptions in JIT alarms are a major factor. One easy mitigation strategy is to provide autonomy by offering a feature that allows users to configure opportune alarms to suit their daily life patterns. Alternatively, prior studies on opportune moment detection based on a user's context can be used as well [12, 42, 75].

Mitigating Distrust. A user's distrust stems largely from the lack of a mental model of JIT intervention (e.g., low perceived tracking accuracy and a lack of knowledge on how JIT intervention works). Ensuring transparency on how JIT intervention works (i.e., when alarms are delivered, how behavior tracking is captured, and when possible errors can happen) helps users anticipate the impact of the system's decisions, thus developing trust [37]. When supporting transparency, designers should consider the trade-off between soundness and completeness, as shown in a prior mental model study [46].

Mitigating Self-Efficacy Loss. Our results show that the accumulated intervention messages on the persistent notification display were a double-edged sword for disengagement. Depending on the user's context and traits, the messages induced the user's self-reflection to improve or lower the self-efficacy of adherence. This result implies the need for a system design to adaptively interact with users based on their current state of engagement (e.g., the number of failures today). For example, the system may use different messaging strategies [59] such as encouragement or warning or goal setting strategies [41, 50], depending on the level of engagement, which may lead to sustained user engagement.

Mitigating Demotivation. Our study results show that perceived financial incentives can cause disengagement by lowering the motivation for adherence. This suggests the need for a micro-incentive system design that can overcome the crowding-out effect of financial compensation [78]. The goal of financial incentives is to reinforce behavior learning (i.e., becoming less sedentary whenever a user perceives a 50-min warning notification). We can leverage time-varying incentive schedules that can possibly minimize crowding-out effects (e.g., gradually reducing incentive amounts or using loss-based incentive framing).

6.4.2 Design Strategies for Facilitating Engagement. We observed that participants experienced a cycle of disengagement by incorporating JIT intervention as part of their everyday routines. This suggests the importance of a system design that supports users in adapting to JIT interventions by helping them create their behavioral routines. A promising strategy is to promote self-reflection by providing an analytics interface with visualization of a daily timeline for intervention activities [103]. Through the visualization interface, the system can induce the user to review their daily intervention activity history, which provides users with actionable insights for adjusting JIT interventions [5, 103]. An alternative strategy would be to incorporate time-management strategies such as Pomodoro into the system design as in prior studies [43, 72]. By integrating intervention mechanisms with time management strategies, users can manage intervention activities and time management in an integrated manner in their daily lives. Furthermore, given that interventions are offered via mobile applications, we can consider incorporating inconvenience in mobile interactions where users must engage in behavior intervention in order to unlock their phones [73, 87]. The system can then proactively support users in creating and adjusting their behavioral routines to adhere to JIT interventions successfully.

6.5 Limitation and Future Work

This study did not control for exogenous variables that could affect disengagement. In the comparative analysis of disengagement by personal traits, we confirmed that there was no significant difference in the daily average number of alarms received in each group. However, because our study was designed without randomization, it was difficult to confirm that all confounding variables were controlled. Further randomized controlled trials (RCTs) should be conducted to understand the effects of user traits and intervention variations.

There could be various other personal traits that influence the disengagement process of JIT interventions. For example, prior studies have shown that personality constructs (e.g., agreeableness and extraversion) are associated with work engagement [1]. In addition, behavior engagement is also related to habit strength that indicates how easily an individual can change that behavior [96]. Further exploration of the effects of various personal traits on disengagement from JIT interventions is needed.

Our field trial was conducted at a large university, and the participants were largely university students who used Android smartphones. JIT interventions will be delivered as mobile applications and tech-savvy students can be early adopters. Since tech-savvy users experienced various disengagement factors, we expect that such factors are likely to appear in less tech-savvy users. To increase the generalizability of this study, follow-up studies with users of more diverse occupations, ages, and other mobile platforms (e.g., iPhones) are needed.

The generalizability of our study is limited because our results may have included incentive effects. Prior studies on incentives have revealed that monetary incentives may lower intrinsic motivation for behavior engagement [78]. In our experimental design, monetary incentives may have accelerated disengagement by reducing intrinsic motivation to adhere to the JIT intervention. To increase the generalizability of this study, a controlled study could be performed to find out how the JIT disengagement process differs with and without monetary incentives. In addition, further studies are required to analyze the impact of other types of reinforcers such as ranking and badges that are often used in behavior change technologies.

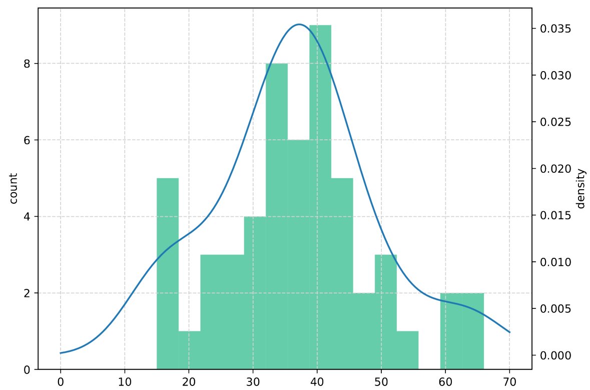
7 CONCLUSION

We explored how disengagement with JIT intervention systems changes over time. An 8-week user study (n = 54) showed that participants experienced disengagement in terms of the usage frequency of the JIT system and adherence to intervention behaviors. In a comparative analysis between groups based on personality traits, trait boredom and self-control affected disengagement by decreasing the adherence rate over time. In addition, disengagement has a negative effect on user experience factors such as hedonic quality. Our qualitative analysis revealed the disengagement and re-engagement cycles of JIT interventions. Re-engagement cycles were triggered by positive experiences with JIT interventions, e.g., self-reflection, whereas disengagement cycles were affected by boredom and interruption. Engagement with JIT interventions is formed through the iterative process of disengagement, re-engagement, or a mixture of both cycles, which are experienced differently according to personality traits and user contexts. Our findings provide theoretical and practical design guidelines for JIT intervention design. We hope that our study on the disengagement process of JIT interventions will be considered in a variety of behavioral change domains utilizing JIT interventions.

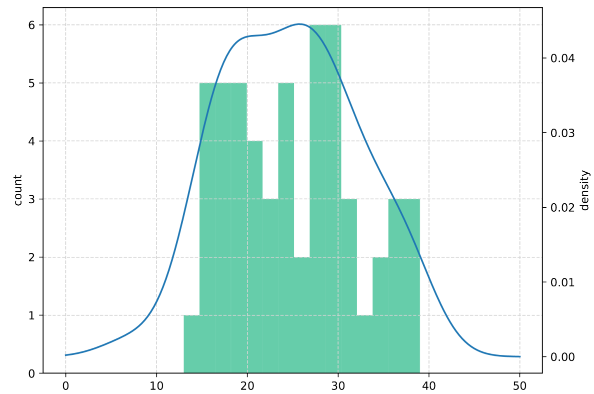
ACKNOWLEDGMENTS

This research was supported by the Bio & Medical Technology Development Program of the National Research Foundation (NRF) funded by the Korean government (MSIT) (No. 2021M3A9E4080780) and by the Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Korean government (MSIT) (2022R1A2C2011536).

8 HISTOGRAM OF TWO PERSONAL TRAITS



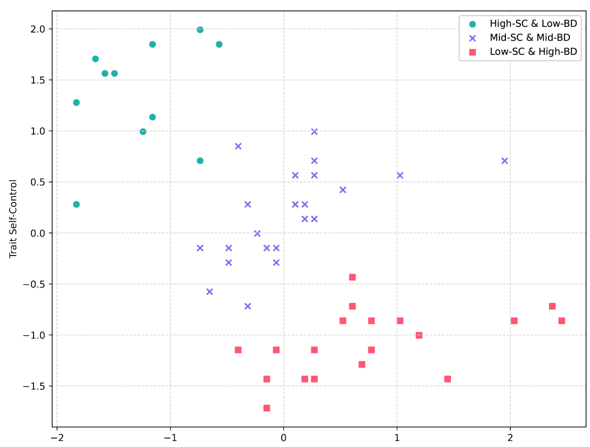
(a) Distribution of Trait Boredom Scores



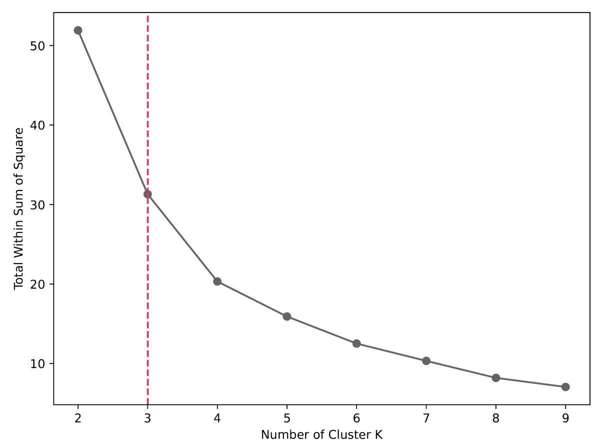
(b) Distribution of Trait Self-Control Scores

Fig. 9. Histogram by Two Personal Traits. The x-axis represents the scores for each trait and the y-axis represents the number of participants and density or each sum of scores.

9 CLUSTERING RESULTS BY K-MEANS AND ELBOW METHODS



(a) Scatter Plot of Two Traits



(b) Optimal Number of Clusters

Fig. 10. Clustering Results by K-means and Elbow Methods

REFERENCES

[1] Reece Akhtar, Lara Boustani, Dimitrios Tsivrikos, and Tomas Chamorro-Premuzic. 2015. The engageable personality: Personality and trait EI as predictors of work engagement. *Personality and Individual Differences* 73 (2015), 44–49.

[2] Nabil Alshurafa, Jayalakshmi Jain, Rawan Alharbi, Gleb Iakovlev, Bonnie Spring, and Angela Pfammatter. 2018. Is More Always Better? Discovering Incentivized MHealth Intervention Engagement Related to Health Behavior Trends. *Proceedings of the ACM on interactive, mobile, wearable and ubiquitous technologies* 2, 4 (2018), 1–26.

[3] Christiane Attig and Thomas Franke. 2020. Abandonment of personal quantification: A review and empirical study investigating reasons for wearable activity tracking attrition. *Computers in Human Behavior* 102 (2020), 223–237.
[4] Roy F Baumeister, Kathleen D Vohs, and Dianne M Tice. 2007. The strength model of self-control. *Current directions in psychological science* 16, 6 (2007), 351–355.
[5] Frank Bentley, Konrad Tollmar, Peter Stephenson, Laura Levy, Brian Jones, Scott Robertson, Ed Price, Richard Catrambone, and Jeff Wilson. 2013. Health Mashups: Presenting statistical patterns between wellbeing data and context in natural language to promote behavior change. *ACM Transactions on Computer-Human Interaction (TOCHI)* 20, 5 (2013), 1–27.
[6] Dale S Bond, J Graham Thomas, Hollie A Raynor, Jon Moon, Jared Sieling, Jennifer Trautvetter, Tiffany Leblond, and Rena R Wing. 2014. B-MOBILE-a smartphone-based intervention to reduce sedentary time in overweight/obese individuals: a within-subjects experimental trial. *PloS one* 9, 6 (2014), e100821.
[7] Andreas Braun, Ingrid Schembri, and Sebastian Frank. 2015. Exerseat-Sensor-supported exercise system for ergonomic microbreaks. In *European Conference on Ambient Intelligence*. Springer, 236–251.
[8] Janice M Brown, William R Miller, and Lauren A Lawendowski. 1999. The self-regulation questionnaire. 1999.
[9] Jude Buckley, Jason D Cohen, Arthur F Kramer, Edward McAuley, and Sean P Mullen. 2014. Cognitive control in the self-regulation of physical activity and sedentary behavior. *Frontiers in human neuroscience* 8 (2014), 747.
[10] Joseph A Cafazzo, Mark Casselman, Nathaniel Hamming, Debra K Katzman, and Mark R Palmert. 2012. Design of an mHealth app for the self-management of adolescent type 1 diabetes: a pilot study. *Journal of medical Internet research* 14, 3 (2012), e2058.
[11] Per Carlbring, Bengt E Westling, Peter Ljungstrand, Lisa Ekselius, and Gerhard Andersson. 2001. Treatment of panic disorder via the Internet: A randomized trial of a self-help program. *Behavior Therapy* 32, 4 (2001), 751–764.
[12] Narae Cha, Auk Kim, Cheul Young Park, Soowon Kang, Mingyu Park, Jae-Gil Lee, Sangsu Lee, and Uichin Lee. 2020. Hello There! Is Now a Good Time to Talk? Opportune Moments for Proactive Interactions with Smart Speakers. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 4, 3, Article 74 (sep 2020), 28 pages.
[13] Peter McFaul Chapman. 1997. *Models of engagement: Intrinsically motivated interaction with multimedia learning software.* Ph. D. Dissertation. University of Waterloo.
[14] Woohyeok Choi, Sangkeun Park, Duyeon Kim, Youn-kyung Lim, and Uichin Lee. 2019. Multi-stage receptivity model for mobile just-in-time health intervention. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 3, 2 (2019), 1–26.
[15] James Clawson, Jessica A Pater, Andrew D Miller, Elizabeth D Mynatt, and Lena Mamykina. 2015. No longer wearing: investigating the abandonment of personal health-tracking technologies on craigslist. In *Proceedings of the 2015 ACM international joint conference on pervasive and ubiquitous computing*. 647–658.
[16] Emily IM Collins, Anna L Cox, Jon Bird, and Cassie Cornish-Tresstail. 2014. Barriers to engagement with a personal informatics productivity tool. In *Proceedings of the 26th Australian Computer-Human interaction Conference on Designing futures: The future of design*. 370–379.
[17] Sunny Consolvo, David W McDonald, Tammy Toscos, Mike Y Chen, Jon Froehlich, Beverly Harrison, Predrag Klasnja, Anthony LaMarca, Louis LeGrand, Ryan Libby, et al. 2008. Activity sensing in the wild: a field trial of ubifit garden. In *Proceedings of the SIGCHI conference on human factors in computing systems*. 1797–1806.
[18] Robin Damrad-Frye and James D Laird. 1989. The experience of boredom: The role of the self-perception of attention. *Journal of Personality and Social Psychology* 57, 2 (1989), 315.
[19] Denise TD De Ridder, Gerty Lensvelt-Mulders, Catrin Finkenauer, F Marijn Stok, and Roy F Baumeister. 2012. Taking stock of self-control: A meta-analysis of how trait self-control relates to a wide range of behaviors. *Personality and Social Psychology Review* 16, 1 (2012), 76–99.
[20] Edward L Deci, Haleh Eghrari, Brian C Patrick, and Dean R Leone. 1994. Facilitating internalization: The self-determination theory perspective. *Journal of personality* 62, 1 (1994), 119–142.
[21] Sebastian Deterding, Dan Dixon, Rilla Khaled, and Lennart Nacke. 2011. From game design elements to gamefulness: defining" gamification". In *Proceedings of the 15th international academic MindTrek conference: Envisioning future media environments*. 9–15.
[22] Julie Doyle, Lorcan Walsh, Antonella Sassu, and Teresa McDonagh. 2014. Designing a wellness self-management tool for older adults: results from a field trial of YourWellness. In *Proceedings of the 8th international conference on pervasive computing technologies for healthcare*. 134–141.
[23] John D Eastwood, Alexandra Frischen, Mark J Fenske, and Daniel Smilek. 2012. The unengaged mind: Defining boredom in terms of attention. *Perspectives on Psychological Science* 7, 5 (2012), 482–495.
[24] Daniel A Epstein, Monica Caraway, Chuck Johnston, An Ping, James Fogarty, and Sean A Munson. 2016. Beyond abandonment to next steps: understanding and designing for life after personal informatics tool use. In *Proceedings of the 2016 CHI conference on human factors in computing systems*. 1109–1113.
[25] Gunther Eysenbach. 2005. The law of attrition. *Journal of medical Internet research* 7, 1 (2005), e402.
[26] Richard Farmer and Norman D Sundberg. 1986. Boredom proneness–the development and correlates of a new scale. *Journal of personality assessment* 50, 1 (1986), 4–17.

[27] Peter Farvolden, Eilenna Denisoff, Peter Selby, R Michael Bagby, and Laura Rudy. 2005. Usage and longitudinal effectiveness of a Web-based self-help cognitive behavioral therapy program for panic disorder. *Journal of medical Internet research* 7, 1 (2005), e129.
[28] Bruno S Frey and Reto Jegen. 2001. Motivation crowding theory. *Journal of economic surveys* 15, 5 (2001), 589–611.
[29] David Gibson, Nathaniel Ostashewski, Kim Flintoff, Sheryl Grant, and Erin Knight. 2015. Digital badges in education. *Education and Information Technologies* 20, 2 (2015), 403–410.
[30] Zeynep Şimşir Gökalp, Mustafa Saritepeci, and Hatice Yildiz Durak. 2022. The relationship between self-control and procrastination among adolescent: The mediating role of multi screen addiction. *Current Psychology* (2022), 1–12.
[31] Juho Hamari and Jonna Koivisto. 2015. "Working out for likes": An empirical study on social influence in exercise gamification. *Computers in Human Behavior* 50 (2015), 333–347.
[32] Wendy Hardeman, Julie Houghton, Kathleen Lane, Andy Jones, and Felix Naughton. 2019. A systematic review of just-in-time adaptive interventions (JITAIs) to promote physical activity. *International Journal of Behavioral Nutrition and Physical Activity* 16, 1 (2019), 1–21.
[33] Tim Harries, Parisa Eslambolchilar, Chris Stride, Ruth Rettie, and Simon Walton. 2013. Walking in the wild–Using an always-on smartphone application to increase physical activity. In *Human-Computer Interaction–INTERACT 2013: 14th IFIP TC 13 International Conference, Cape Town, South Africa, September 2-6, 2013, Proceedings, Part IV 14.* Springer, 19–36.
[34] Marc Hassenzahl. 2001. The effect of perceived hedonic quality on product appealingness. *International Journal of Human-Computer Interaction* 13, 4 (2001), 481–499.
[35] Marc Hassenzahl and Noam Tractinsky. 2006. User experience-a research agenda. *Behaviour & information technology* 25, 2 (2006), 91–97.
[36] Genevieve N Healy, David W Dunstan, Jo Salmon, Ester Cerin, Jonathan E Shaw, Paul Z Zimmet, and Neville Owen. 2008. Breaks in sedentary time: beneficial associations with metabolic risk. *Diabetes care* 31, 4 (2008), 661–666.
[37] Alon Jacovi, Ana Marasović, Tim Miller, and Yoav Goldberg. 2021. Formalizing trust in artificial intelligence: Prerequisites, causes and goals of human trust in ai. In *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency.* 624–635.
[38] Richard Jacques. 1995. Engagement as a design concept for multimedia. *Canadian Journal of Educational Communication* 24, 1 (1995), 49–59.
[39] Haemi Jee. 2017. Review of researches on smartphone applications for physical activity promotion in healthy adults. *Journal of exercise rehabilitation* 13, 1 (2017), 3.
[40] Eunice Jun, Gary Hsieh, and Katharina Reinecke. 2017. Types of motivation affect study selection, attention, and dropouts in online experiments. *Proceedings of the ACM on Human-Computer Interaction* 1, CSCW (2017), 1–15.
[41] Gyuwon Jung, Jio Oh, Youjin Jung, Juho Sun, Ha-Kyung Kong, and Uichin Lee. 2021. "Good Enough!": Flexible Goal Achievement with Margin-Based Outcome Evaluation. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems* (Yokohama, Japan) *(CHI '21)*. Association for Computing Machinery, New York, NY, USA, Article 222, 15 pages.
[42] Auk Kim, Woohyeok Choi, Jungmi Park, Kyeyoon Kim, and Uichin Lee. 2018. Interrupting Drivers for Interactions: Predicting Opportune Moments for In-Vehicle Proactive Auditory-Verbal Tasks. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 2, 4, Article 175 (dec 2018), 28 pages.
[43] Jaejeung Kim, Chiwoo Cho, and Uichin Lee. 2017. Technology supported behavior restriction for mitigating self-interruptions in multi-device environments. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 1, 3 (2017), 1–21.
[44] Jaejeung Kim, Joonyoung Park, Hyunsoo Lee, Minsam Ko, and Uichin Lee. 2019. LocknType: Lockout task intervention for discouraging smartphone app use. In *Proceedings of the 2019 CHI conference on human factors in computing systems.* 1–12.
[45] Predrag Klasnja, Shawna Smith, Nicholas J Seewald, Andy Lee, Kelly Hall, Brook Luers, Eric B Hekler, and Susan A Murphy. 2019. Efficacy of contextually tailored suggestions for physical activity: A micro-randomized optimization trial of HeartSteps. *Annals of Behavioral Medicine* 53, 6 (2019), 573–582.
[46] Todd Kulesza, Simone Stumpf, Margaret Burnett, Sherry Yang, Irwin Kwan, and Weng-Keen Wong. 2013. Too much, too little, or just right? Ways explanations impact end users' mental models. In *2013 IEEE Symposium on visual languages and human centric computing.* IEEE, 3–10.
[47] Alfred Lange, Bart Schrieken, Jean-Pierre van de Ven, Bert Bredeweg, Paul MG Emmelkamp, Joisel Van Der Kolk, Linda Lydsdottir, Marina Massaro, and Anneke Reuvers. 2000. "Interapy": The effects of a short protocolled treatment of posttraumatic stress and pathological grief through the Internet. *Behavioural and Cognitive Psychotherapy* 28, 2 (2000), 175–192.
[48] Kennon A Lattal and Nancy A Neef. 1996. Recent reinforcement-schedule research and applied behavior analysis. *Journal of Applied Behavior Analysis* 29, 2 (1996), 213–230.
[49] Eunmi Lee and Yujeong Kim. 2019. Effect of university students' sedentary behavior on stress, anxiety, and depression. *Perspectives in psychiatric care* 55, 2 (2019), 164.
[50] Hyunsoo Lee, Auk Kim, Hwajung Hong, and Uichin Lee. 2021. Sticky Goals: Understanding Goal Commitments for Behavioral Changes in the Wild. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems* (Yokohama, Japan) *(CHI '21)*. Association for Computing Machinery, New York, NY, USA, Article 230, 16 pages.

[51] Hansoo Lee, Joonyoung Park, and Uichin Lee. 2022. A Systematic Survey on Android API Usage for Data-Driven Analytics with Smartphones. *Comput. Surveys* 55, 5, Article 104 (dec 2022), 38 pages.
[52] Jong-Eun Roselyn Lee and Clifford I Nass. 2010. Trust in computers: The computers-are-social-actors (CASA) paradigm and trustworthiness perception in human-computer communication. In *Trust and technology in a ubiquitous modern environment: Theoretical and methodological perspectives*. IGI Global, 1–15.
[53] Uichin Lee, Gyuwon Jung, Eun-Yeol Ma, Jin San Kim, Heepyung Kim, Jumabek Alikhanov, Youngtae Noh, and Heeyoung Kim. 2023. Toward Data-Driven Digital Therapeutics Analytics: Literature Review and Research Directions. *IEEE/CAA Journal of Automatica Sinica* 10, 1 (2023), 42–66.
[54] Ian Li, Anind Dey, and Jodi Forlizzi. 2010. A stage-based model of personal informatics systems. In *Proceedings of the SIGCHI conference on human factors in computing systems*. 557–566.
[55] Jessica M Lipschitz, Rachel Van Boxtel, John Torous, Joseph Firth, Julia G Lebovitz, Katherine E Burdick, and Timothy P Hogan. 2022. Digital Mental Health Interventions for Depression: Scoping Review of User Engagement. *Journal of Medical Internet Research* 24, 10 (2022), e39204.
[56] Yuhan Luo, Bongshin Lee, Donghee Yvette Wohn, Amanda L Rebar, David E Conroy, and Eun Kyoung Choe. 2018. Time for break: Understanding information workers' sedentary behavior through a break prompting system. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*. 1–14.
[57] Amanda Mahoney. 2017. A comparison of escalating versus fixed reinforcement schedules on undergraduate quiz taking. *Journal of Behavioral Education* 26 (2017), 264–276.
[58] Katherine M Melville, Leanne M Casey, and David J Kavanagh. 2010. Dropout from Internet-based treatment for psychological disorders. *British Journal of Clinical Psychology* 49, 4 (2010), 455–471.
[59] Beth E Meyerowitz and Shelly Chaiken. 1987. The effect of message framing on breast self-examination attitudes, intentions, and behavior. *Journal of personality and social psychology* 52, 3 (1987), 500.
[60] Gideon Meyerowitz-Katz, Sumathy Ravi, Leonard Arnolda, Xiaoqi Feng, Glen Maberly, Thomas Astell-Burt, et al. 2020. Rates of attrition and dropout in app-based interventions for chronic disease: systematic review and meta-analysis. *Journal of Medical Internet Research* 22, 9 (2020), e20283.
[61] Susan Michie, Michelle Richardson, Marie Johnston, Charles Abraham, Jill Francis, Wendy Hardeman, Martin P Eccles, James Cane, and Caroline E Wood. 2013. The behavior change technique taxonomy (v1) of 93 hierarchically clustered techniques: building an international consensus for the reporting of behavior change interventions. *Annals of behavioral medicine* 46, 1 (2013), 81–95.
[62] Helen Monkman, Andre Kushniruk, Elizabeth Borycki, Debra Sheets, Jeff Barnett, and Christian Nøhr. 2020. The medium is the message: How do canadian university students want digital medication information? *Life* 10, 12 (2020), 339.
[63] Bruce R Moore. 2004. The evolution of learning. *Biological Reviews* 79, 2 (2004), 301–335.
[64] Jhotisha Mugon, Andriy Struk, and James Danckert. 2018. A failure to launch: Regulatory modes and boredom proneness. *Frontiers in Psychology* 9 (2018), 1126.
[65] Mark Muraven, Dianne M Tice, and Roy F Baumeister. 1998. Self-control as a limited resource: regulatory depletion patterns. *Journal of personality and social psychology* 74, 3 (1998), 774.
[66] Mohamed Musthag, Andrew Raij, Deepak Ganesan, Santosh Kumar, and Saul Shiffman. 2011. Exploring micro-incentive strategies for participant compensation in high-burden studies. In *Proceedings of the 13th international conference on Ubiquitous computing*. 435–444.
[67] Inbal Nahum-Shani, Shawna N Smith, Bonnie J Spring, Linda M Collins, Katie Witkiewitz, Ambuj Tewari, and Susan A Murphy. 2018. Just-in-time adaptive interventions (JITAIs) in mobile health: key components and design principles for ongoing health behavior support. *Annals of Behavioral Medicine* 52, 6 (2018), 446–462.
[68] Clifford Nass, Jonathan Steuer, and Ellen R Tauber. 1994. Computers are social actors. In *Proceedings of the SIGCHI conference on Human factors in computing systems*. 72–78.
[69] Felix Naughton, Sarah Hopewell, Neal Lathia, Rik Schalbroeck, Chloë Brown, Cecilia Mascolo, Andy McEwen, and Stephen Sutton. 2016. A context-sensing mobile phone app (Q sense) for smoking cessation: a mixed-methods study. *JMIR mHealth and uHealth* 4, 3 (2016), e5787.
[70] Heather L O'Brien and Elaine G Toms. 2008. What is user engagement? A conceptual framework for defining user engagement with technology. *Journal of the American society for Information Science and Technology* 59, 6 (2008), 938–955.
[71] Fabian Okeke, Michael Sobolev, Nicola Dell, and Deborah Estrin. 2018. Good vibrations: can a digital nudge reduce digital overload?. In *Proceedings of the 20th international conference on human-computer interaction with mobile devices and services*. 1–12.
[72] Joonyoung Park, Hyunsoo Lee, Sangkeun Park, Kyong-Mee Chung, and Uichin Lee. 2021. GoldenTime: Exploring System-Driven Timeboxing and Micro-Financial Incentives for Self-Regulated Phone Use. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*. 1–17.
[73] Joonyoung Park, Jin Yong Sim, Jaejeung Kim, Mun Yong Yi, and Uichin Lee. 2018. Interaction restraint: Enforcing adaptive cognitive tasks to restrain problematic user interaction. In *Extended Abstracts of the 2018 CHI Conference on Human Factors in Computing Systems*. 1–6.

[74] Mitesh S Patel, David A Asch, Roy Rosin, Dylan S Small, Scarlett L Bellamy, Jack Heuer, Susan Sproat, Chris Hyson, Nancy Haff, Samantha M Lee, et al. 2016. Framing financial incentives to increase physical activity among overweight and obese adults: a randomized, controlled trial. *Annals of internal medicine* 164, 6 (2016), 385–394.
[75] Veljko Pejovic and Mirco Musolesi. 2014. InterruptMe: designing intelligent prompting mechanisms for pervasive applications. In *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing*. 897–908.
[76] Laura Pina, Kael Rowan, Asta Roseway, Paul Johns, Gillian R Hayes, and Mary Czerwinski. 2014. In situ cues for ADHD parenting strategies using mobile technology. In *Proceedings of the 8th International Conference on Pervasive Computing Technologies for Healthcare*. 17–24.
[77] James O Prochaska, Colleen A Redding, and Kerry E Evers. 1997. The transtheoretical model and stages of change. *Health behavior* (1997), 97.
[78] Marianne Promberger and Theresa M Marteau. 2013. When do financial incentives reduce intrinsic motivation? comparing behaviors studied in psychological and economic literatures. *Health Psychology* 32, 9 (2013), 950.
[79] Tianchen Qian, Ashley E Walton, Linda M Collins, Predrag Klasnja, Stephanie T Lanza, Inbal Nahum-Shani, Mashfiqui Rabbi, Michael A Russell, Maureen A Walton, Hyesun Yoo, et al. 2022. The microrandomized trial for developing digital interventions: Experimental design and data analysis considerations. *Psychological methods* (2022).
[80] Whitney Quesenbery and Whitney Interactive Design. 2003. Dimensions of usability: Defining the conversation, driving the process. In *UPA 2003 Conference*. 23–27.
[81] Tauhidur Rahman, Mary Czerwinski, Ran Gilad-Bachrach, and Paul Johns. 2016. Predicting" about-to-eat" moments for just-in-time eating intervention. In *Proceedings of the 6th International Conference on Digital Health Conference*. 141–150.
[82] Amon Rapp and Federica Cena. 2016. Personal informatics for everyday life: How users without prior self-tracking experience engage with personal data. *International Journal of Human-Computer Studies* 94 (2016), 1–17.
[83] Hillol Sarker, Moushumi Sharmin, Amin Ahsan Ali, Md Mahbubur Rahman, Rummana Bari, Syed Monowar Hossain, and Santosh Kumar. 2014. Assessing the availability of users to engage in just-in-time intervention in the natural environment. In *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing*. 909–920.
[84] Martin Schrepp, Andreas Hinderks, and Jörg Thomaschewski. 2014. Applying the user experience questionnaire (UEQ) in different evaluation scenarios. In *International Conference of Design, User Experience, and Usability*. Springer, 383–392.
[85] Amitai Shenhav, Matthew M Botvinick, and Jonathan D Cohen. 2013. The expected value of control: an integrative theory of anterior cingulate cortex function. *Neuron* 79, 2 (2013), 217–240.
[86] Saul Shiffman, Jean A Paty, Maryann Gnys, Jon A Kassel, and Mary Hickcox. 1996. First lapses to smoking: within-subjects analysis of real-time reports. *Journal of consulting and clinical psychology* 64, 2 (1996), 366.
[87] Jaemyung Shin, Bumsoo Kang, Taiwoo Park, Jina Huh, Jinhan Kim, and Junehwa Song. 2016. BeUpright: Posture Correction Using Relational Norm Intervention. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems* (San Jose, California, USA) *(CHI '16)*. Association for Computing Machinery, New York, NY, USA, 6040–6052.
[88] Candace L Sidner, Cory D Kidd, Christopher Lee, and Neal Lesh. 2004. Where to look: a study of human-robot engagement. In *Proceedings of the 9th international conference on Intelligent user interfaces*. 78–84.
[89] Burrhus F Skinner. 1963. Operant behavior. *American psychologist* 18, 8 (1963).
[90] Phillip B Sparling and Teresa K Snow. 2002. Physical activity patterns in recent college alumni. *Research quarterly for exercise and sport* 73, 2 (2002), 200–205.
[91] Stephanie Stockwell, Patricia Schofield, Abi Fisher, Joseph Firth, Sarah E Jackson, Brendon Stubbs, and Lee Smith. 2019. Digital behavior change interventions to promote physical activity and/or reduce sedentary behavior in older adults: A systematic review and meta-analysis. *Experimental gerontology* 120 (2019), 68–87.
[92] Lars Ström, Richard Pettersson, and Gerhard Andersson. 2004. Internet-based treatment for insomnia: a controlled evaluation. *Journal of consulting and clinical psychology* 72, 1 (2004), 113.
[93] Sarah Taki, Sharyn Lymer, Catherine Georgina Russell, Karen Campbell, Rachel Laws, Kok-Leong Ong, Rosalind Elliott, and Elizabeth Denney-Wilson. 2017. Assessing user engagement of an mHealth intervention: development and implementation of the growing healthy app engagement index. *JMIR mHealth and uHealth* 5, 6 (2017), e7236.
[94] Mojtaba Vaismoradi, Hannele Turunen, and Terese Bondas. 2013. Content analysis and thematic analysis: Implications for conducting a qualitative descriptive study. *Nursing & health sciences* 15, 3 (2013), 398–405.
[95] Saskia Van Dantzig, Gijs Geleijnse, and Aart Tijmen Van Halteren. 2013. Toward a persuasive mobile application to reduce sedentary behavior. *Personal and ubiquitous computing* 17, 6 (2013), 1237–1246.
[96] Bas Verplanken and Sheina Orbell. 2003. Reflections on past behavior: a self-report index of habit strength 1. *Journal of applied social psychology* 33, 6 (2003), 1313–1330.
[97] Stephen J Vodanovich, J Craig Wallace, and Steven J Kass. 2005. A confirmatory approach to the factor structure of the Boredom Proneness Scale: Evidence for a two-factor short form. *Journal of personality assessment* 85, 3 (2005), 295–303.

[98] Kevin G Volpp, George Loewenstein, Andrea B Troxel, Jalpa Doshi, Maureen Price, Mitchell Laskin, and Stephen E Kimmel. 2008. A test of financial incentives to improve warfarin adherence. *BMC health services research* 8, 1 (2008), 1–6.

[99] Kevin G Volpp, Andrea B Troxel, Mark V Pauly, Henry A Glick, Andrea Puig, David A Asch, Robert Galvin, Jingsan Zhu, Fei Wan, Jill DeGuzman, et al. 2009. A randomized, controlled trial of financial incentives for smoking cessation. *N Engl J Med* 360 (2009), 699–709.

[100] Ashley Walton, Inbal Nahum-Shani, Lori Crosby, Predrag Klasnja, and Susan Murphy. 2018. Optimizing digital integrated care via micro-randomized trials. *Clinical Pharmacology & Therapeutics* 104, 1 (2018), 53–58.

[101] Yunlong Wang and Harald Reiterer. 2019. The point-of-choice prompt or the always-on progress bar? A pilot study of reminders for prolonged sedentary behavior change. In *Extended Abstracts of the 2019 CHI Conference on Human Factors in Computing Systems*. 1–6.

[102] Wanja Wolff, Corinna S Martarelli, Julia Schüler, and Maik Bieleke. 2020. High boredom proneness and low trait self-control impair adherence to social distancing guidelines during the COVID-19 pandemic. *International journal of environmental research and public health* 17, 15 (2020), 5420.

[103] Jong-bum Woo and Youn-kyung Lim. 2020. Routinoscope: Collaborative routine reflection for routine-driven do-it-yourself smart homes. *International Journal of Design* 14, 3 (2020), 19.

[104] Jane E Workman and Cathryn M Studak. 2007. Relationships among fashion consumer groups, locus of control, boredom proneness, boredom coping and intrinsic enjoyment. *International Journal of Consumer Studies* 31, 1 (2007), 66–75.

[105] Robert C Wu, Diego Delgado, Jeannine Costigan, and JANE MacIver. 2006. Pilot study of an internet patient-physician communication tool for heart failure disease management. *World Hospitals and Health Services* 42, 3 (2006), 32.

[106] Zhen Xu, Qiuxia Xu, Yifan Wang, Jielu Zhang, Jiapei Liu, and Fei Xu. 2020. Association of sedentary behavior and depression among college students majoring in design. *International journal of environmental research and public health* 17, 10 (2020), 3545.

[107] Lucy Yardley, Bonnie J Spring, Heleen Riper, Leanne G Morrison, David H Crane, Kristina Curtis, Gina C Merchant, Felix Naughton, and Ann Blandford. 2016. Understanding and promoting effective engagement with digital behavior change interventions. *American journal of preventive medicine* 51, 5 (2016), 833–842.

[108] Yeonsu Yu and Tek-Jin Nam. 2014. Let's giggle! design principles for humorous products. In *Proceedings of the 2014 conference on Designing interactive systems*. 275–284.