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Understanding Disengagement in AI-based Just-in-Time Mobile Health Interventions

Excerpted from "Understanding Disengagement in Just-in-Time Mobile Health Interventions," from *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies, Volume 7, Issue 2*, with permission. https://dl.acm.org/doi/10.1145/3596240 @ACM 2023

Promoting behavior change by delivering timely prompts based on real-time contextual recognition is the aim of AI-based just-in-time (JIT) mobile health interventions. Despite their growing adoption in mobile and wearable technologies, user disengagement remains a key challenge. To better understand this issue, we built a mobile JIT app that prompts physical activities and conducted an eight-week field study with 54 college students. Our findings highlight the impact of personal traits such as boredom proneness and self-control, and identify key disengagement factors. We offer design insights to support sustained engagement in mobile JIT systems.

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Mobile digital behavior change interventions (DBCI), especially those based on just-in-time delivery, leverage AI-driven analysis of mobile sensor data to monitor users' behaviors and contexts in real time and deliver personalized health prompts at optimal moments [1]. These systems, often powered by mobile and wearable technologies, have been applied across various domains, including physical activity promotion, stress reduction, smoking cessation, and disordered eating.

A core factor influencing the effectiveness of DBCI is user engagement, which comprises two dimensions: app engagement and behavioral engagement [2]. App engagement refers to how users interact with the app's features, while behavioral engagement concerns whether users perform the intended health behaviors in response to interventions.

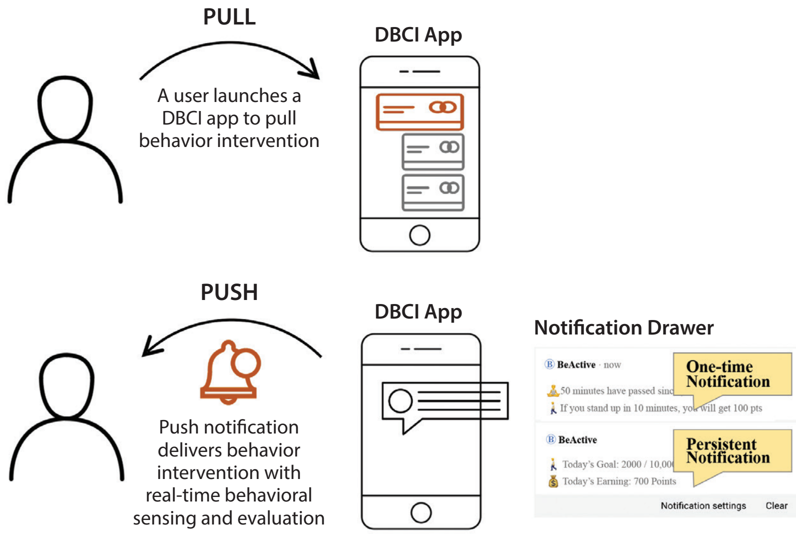


FIGURE 1. Pull-based vs. Push-based DBCI Mechanisms: User-Initiated vs. System-Triggered Just-in-Time Interventions.

However, DBCIs typically experience user disengagement over time, including reduced app usage, attrition, and failure to follow behavioral prompts [3]. Disengagement patterns may be influenced by the way interventions are delivered. As shown in Figure 1, DBCI systems generally adopt either pull-based mechanisms, which require users to manually initiate engagement, or push-based mechanisms, in which the system automatically delivers interventions and evaluates adherence. While pull-based interventions have been widely studied in conventional DBCIs, push-based interventions have become increasingly common, particularly those that use AI-based JIT delivery triggered by real-time behavioral monitoring and evaluation. Despite their growing adoption in real-world contexts using mobile and wearable technologies, there remains a lack of empirical research examining how users engage with these push-based JIT systems over time [4].

This article seeks to understand how user engagement evolves over time in push-based JIT DBCIs with real-time behavioral sensing and evaluation. The investigation focuses on the temporal patterns of disengagement and examines how personal traits and contextual factors influence user responses to repeated, time-sensitive interventions. In particular, the study further analyzes the influence of two key personal characteristics: boredom proneness and self-control [5, 6]. These traits are known to affect attention, decision-making, and behavioral persistence. For example, individuals with high boredom proneness may be more likely to resist or ignore repeated prompts, whereas those with higher self-control are more likely to adhere consistently to the recommended behaviors.

To address these issues, we developed a mobile application that continuously monitors users' sedentary behavior, automatically issues stand-up prompts after 50 minutes of inactivity, and evaluates adherence to the intervention. This application was used to conduct an eight-week field study with 54 college students. We collected behavioral logs and self-reported measures to analyze engagement patterns and factors affecting long-term adherence. Before we detail our user study, let us first review the key concepts of user engagement and its process in JIT DBCI.

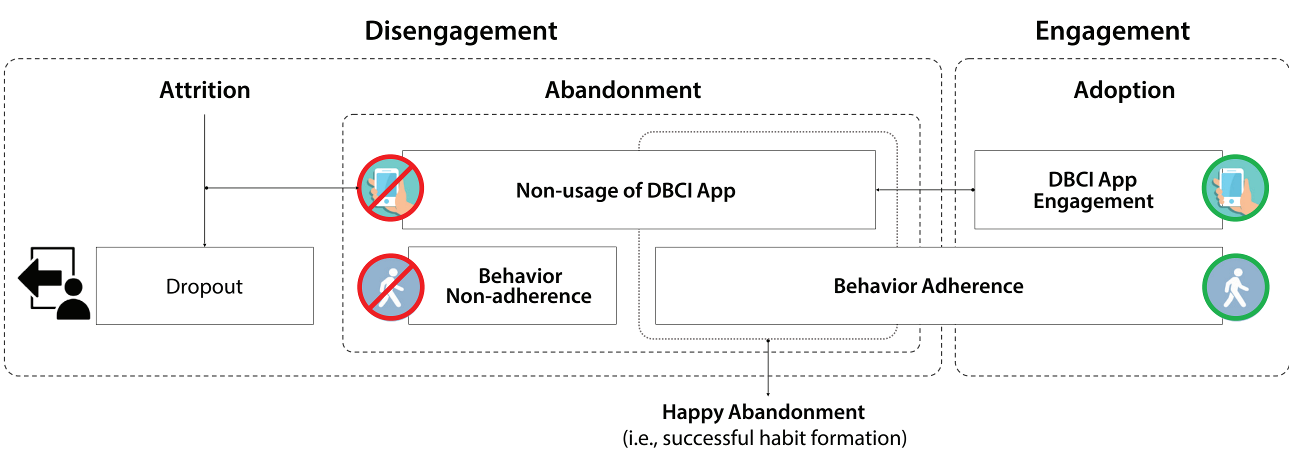


FIGURE 2. Conceptual model of user engagement and disengagement in DBCIs.

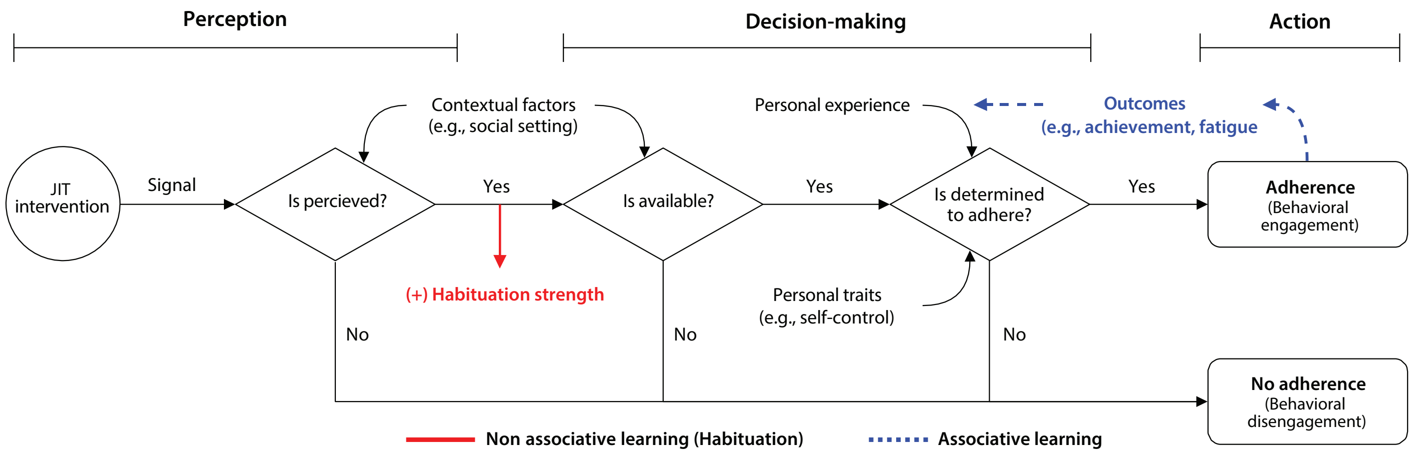


FIGURE 3. Multi-stage model for user engagement in Just-in-Time DBCIs.

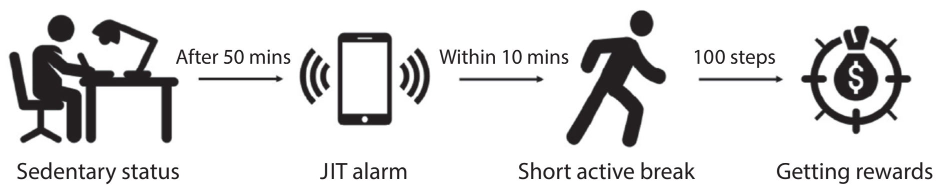


FIGURE 4. Workflow of the AI-based Just-in-Time Intervention System.

User Engagement and Disengagement in DBCI: Key Concepts

User engagement involves both using the DBCI app and performing the target behavior. Yardley et al. emphasize that "effective engagement" includes both app engagement (i.e., using app's features) and behavioral engagement (i.e., following recommended behaviors, such as reducing sitting time) [2].

Disengagement in DBCI appears in several forms [3]. Attrition is the general decline in participation, and dropout refers to leaving the intervention entirely. Non-usage occurs when users stop using the app but remain enrolled. From a Personal Informatics (PI) perspective, abandonment refers to stopping self-tracking. This may include positive disengagement, such as "happy abandonment," when users feel they've achieved their goals.

Overall, disengagement is an umbrella term covering both reduced system use and lack of behavioral adherence. Recognizing these distinctions helps in designing interventions that foster long-term user engagement and reduce dropout.

User Engagement Process in Just-in-Time DBCI

Just-in-time DBCIs differ from traditional app-based interventions in that users can perform target behaviors without launching the app. For instance, sedentary warnings are triggered through real-time context monitoring, and user actions (e.g., standing up) are automatically evaluated. These systems rely on time-sensitive behavioral triggers, making cognitive engagement and behavioral responsiveness critical.

We describe this process using the multi-stage receptivity model [7], which includes three stages: (1) Perception: noticing the intervention cue (e.g., JIT alarm); (2) Decision: choosing to act based on internal and contextual factors; (3) Action: executing the behavior (e.g., walking after standing up).

Over time, users may experience habituation, becoming desensitized to repeated cues. When users ignore prompts at the perception stage, they risk disengagement before any decision or action occurs. Maintaining cue novelty is therefore essential for sustained engagement. Conversely, repeated successful interactions can promote associative learning, where users link intervention cues with positive outcomes. This is similar to Pavlov's classical conditioning experiment, in which dogs learned to associate the sound of a bell with food, eventually salivating at the sound alone. In a similar way, when a health prompt consistently leads to a sense of achievement or reward, users start to anticipate positive outcomes from the cue itself, reinforcing future adherence and strengthening engagement over time.

Personal traits also shape user engagement. Individuals with high boredom proneness may disengage quickly due to the repetitive nature of interventions [5]. In contrast, those with higher self-control are more likely to maintain consistent behavioral responses to time-sensitive prompts [6]. Of course, personality traits, such as conscientiousness, could interact with these factors in more complex ways, but we leave this for future work.

SYSTEM DESIGN

We designed a smartphone-based JIT intervention system to reduce prolonged sedentary behavior and promote light physical activity in daily life. Leveraging smartphone sensors, the system tracks user inactivity and delivers JIT prompts to break sedentary bouts.

JIT Intervention Mechanism: As illustrated in Figure 4, when the system detects that a user has been seated for 50 minutes, it delivers a proactive alarm suggesting a "short active break" mission (e.g., walk at least 100 steps in 10 minutes). This alarm includes a distinct sound/vibration to differentiate it from other notifications. To reduce disturbance, users can select a preferred time window (e.g., 9AM-6PM) during which interventions are delivered.

Feedback and Reinforcement: The system uses positive reinforcement to promote adherence. Users receive 100 points (approx. 0.1 USD) for each completed mission. These micro-incentives are grounded in behavioral psychology and aim to establish healthier habits through repeated reinforcement. Additionally, alarms remain visible in the notification drawer, offering reflection opportunities even if missed initially. A persistent notification also provides real-time summaries of step counts and reward progress.

Intervention Components: The system includes (1) JIT Alarm and Message (push-based), (2) Persistent Notification Display, and (3) Activity Statistics Dashboard (pull-based) (see Figure 5). The dashboard visualizes step data, intervention adherence (stand-up success rates), and accumulated rewards. The persistent notification allows quick access to the dashboard and displays updated activity/reward data in real-time.

METHODOLOGIES

We conducted an 8-week in-the-wild study with 54 college students to investigate how disengagement with JIT interventions emerges over time. All participants used the intervention app in their daily lives and experienced full JIT mechanisms. The study was approved by the institutional review board, and informed consent was obtained.

Participants were recruited based on prior findings that college students are at risk for prolonged sedentary behavior and its long-term health effects. Using the transtheoretical model (TTM), we selected individuals with a stated intent to change their behavior. Out of 75 screened volunteers, 54 students were selected (38 males and 16 females, age: M = 25.83, SD = 4.09).

The study included an orientation and pre-survey (measuring boredom and self-control traits), followed by 8 weeks of app use and bi-weekly surveys. A post-study interview was conducted with 30 participants. Bi-weekly surveys measured hedonic quality (using the user experience questionnaire), adapted boredom scale (e.g., "I'm tired of interventions provided by the system"), and intrinsic motivation inventory (e.g., "I enjoy the active break provided by the system"). During the user study period, we collected activity logs (e.g., steps, alarm reactions), and a total of 12,042 JIT interaction was recorded.

Engagement was analyzed in terms of app usage and adherence to intervention behavior. Daily adherence was defined as the ratio of successful missions to alarms. Repeated measures ANOVA was used to assess engagement changes over time. To explore trait effects, we clustered participants based on boredom and self-control traits, and then analyzed engagement differences using generalized estimating equations (GEE), accounting for temporal correlation. Interview data were analyzed using thematic analysis to identify drivers of disengagement and re-engagement, iteratively reviewed and coded by the research team. The detailed methods can be found in the extended version of this article [4].

RESULTS

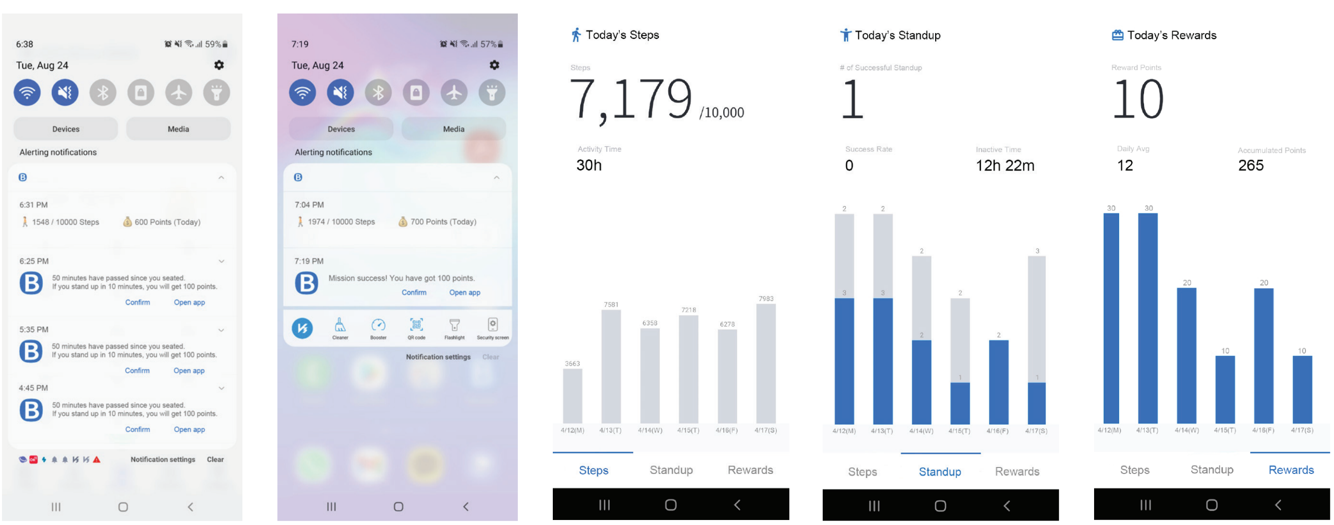
We present findings from an eight-week field study (N = 54) that investigated user engagement patterns in our AI-based JIT intervention system. Our analysis addresses three research topics, concerning disengagement over time, the influence of personal traits, and factors driving disengagement and re-engagement.

Disengagement Over Time

Quantitative results revealed a marked decline in both app usage frequency and behavioral adherence over time. App usage dropped from a daily average of 4.2 times in week 1 to 1.5 times in week 8, and adherence rates declined from 53% to 22% over the same period. Repeated measures ANOVA confirmed statistically significant decreases for both metrics (app usage: $\eta^2 = .81$; adherence: $\eta^2 = .84$). These trends suggest that temporal disengagement is a key challenge in sustaining long-term use of JIT systems.

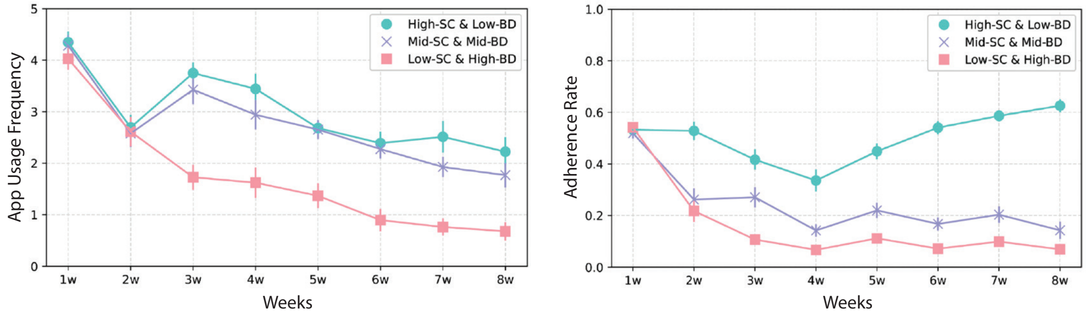
Influence of Personal Traits

Participants were clustered into three groups based on trait self-control and boredom proneness: High-SC & Low-BD, Mid-SC & Mid-BD, and Low-SC & High-BD. As shown



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

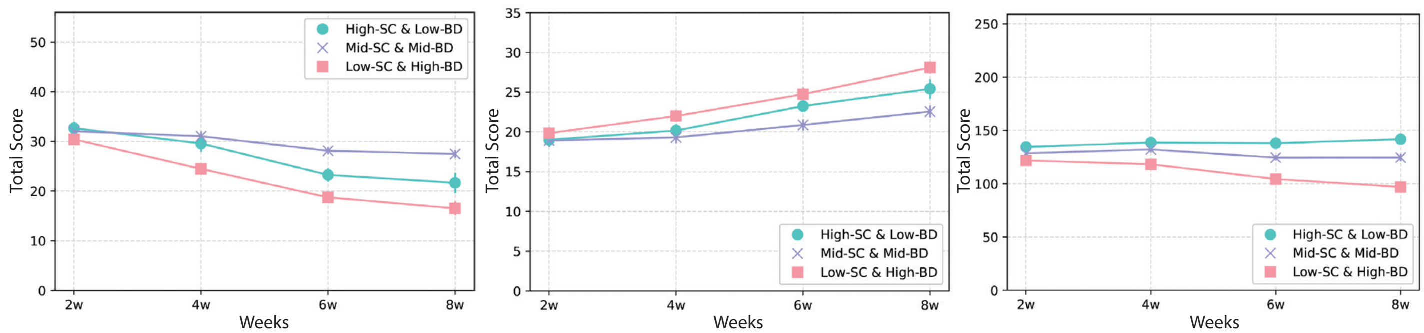
FIGURE 5. Intervention components.



(a) Daily Average App Usage Frequency

(b) Daily Average Adherence Rate

FIGURE 6. Changes in user engagement with JIT Intervention by Trait Groups.



(a) UX: Hedonic Quality Score

(b) UX: Boredom Score

(c) Intrinsic Motivation Score

FIGURE 7. Changes in user experiences on JIT Intervention by Trait Groups.

in Figure 6, the Low-SC & High-BD group showed the most significant declines in both app usage and adherence. In contrast, the High-SC & Low-BD group demonstrated partial recovery in adherence over time. User experience metrics, including hedonic quality, boredom, and intrinsic motivation, also declined more steeply in the Low-SC & High-BD group, indicating that these traits influenced not only behavior but also user experiences of the intervention (see Figure 7).

Factors Influencing Disengagement and Re-engagement

Qualitative analysis identified key factors contributing to disengagement. These included (1) boredom and habituation to repetitive prompts, leading to desensitization, (2) inopportune alarm delivery disrupting concentration, (3) distrust in feedback mechanisms due to perceived inaccuracies in activity tracking, and (4) low motivation linked to minimal or unclear rewards.

Conversely, several mechanisms facilitated re-engagement. First, visible rewards created a tangible sense of achievement that encouraged adherence and strengthened self-efficacy. Second, participants reported that well-timed alarms aligned with natural breaks in daily activities, leading to perceived productivity gains and routine alignment. Finally, persistent notifitions prompted self-reflection, particularly among initially disengaged users, triggering renewed motivation to participate.

Overall, our findings highlight the temporal, personal, and contextual complexity of user engagement with JIT interventions. Designing interventions that adapt to individual traits and support re-engagement pathways, especially through feedback clarity, contextual timing, and self-regulatory cues, may be critical to improving long-term adherence.

DISCUSSION

Our study offers several key insights into user engagement and disengagement in the context of AI-based mobile JIT interventions. First, we identified that *personal traits*, particularly self-control and boredom proneness, significantly shape engagement patterns over time. Participants with high self-control and low boredom (High-SC & Low-BD) were more likely to recover adherence and maintain intrinsic motivation, while those with low self-control and high boredom (Low-SC & High-BD) showed steep declines in both behavioral adherence and user experience.

OUR STUDY OFFERS INSIGHTS INTO USER ENGAGEMENT AND DISENGAGEMENT IN THE CONTEXT OF AI-BASED MOBILE JIT INTERVENTIONS

Second, we found that *micro-financial incentives* serve as both facilitators and inhibitors of engagement. While rewards fostered a sense of accomplishment and reinforced positive behavior via associative learning, some participants experienced motivational crowding out, where external incentives diminished intrinsic motivation, especially when the reward was perceived as insufficient.

Third, we emphasize the need to redefine *disengagement* in JIT contexts. Traditional app usage metrics may underestimate engagement due to the passive and system-initiated nature of JIT interventions. We recommend conceptualizing disengagement by extending existing models, such as the multistage receptivity framework, and suggest alternative evaluation approaches, such as micro-randomized trials, to better identify and contextualize engagement patterns, such as unintended behavior adherence [8].

Lastly, we propose *design strategies* to mitigate disengagement and facilitate re-engagement. These include increasing novelty to reduce boredom, supporting user autonomy for alarm timing, improving transparency to build trust, and adaptively adjusting messaging based on user engagement state. Systems should also promote self-reflection and routine integration to sustain long-term behavior change. Furthermore, it is possible to continuously monitor engagement patterns to detect early signs of disengagement, such as alarm ignoring or delayed action, and adjust strategy accordingly, for example, by varying reinforcement mechanisms or personalizing intervention content. Recent advances in large language models (LLMs) enable systems to support these strategies by automatically generating personalized messages, helping users interpret their behavioral data, and incorporating user feedback to adapt interventions in real time.

CONCLUSION

We built an AI-based mobile app for prompting physical activities and conducted an 8-week study to examine disengagement in JIT interventions. Results showed that usage and adherence declined over time, influenced by trait boredom and self-control. Disengagement negatively impacted user experience, while re-engagement was fostered by positive experiences like self-reflection. Engagement emerged through iterative cycles of disengagement and re-engagement, shaped by individual traits and context. Our findings provide useful insights into how the interplay between personal traits, interaction context, and system design can inform the development of more effective and sustainable AI-based mobile JIT interventions. ■

Acknowledgement

This research was supported by the National Research Foundation of Korea (NRF) funded by the Ministry of Science and ICT (RS-2022-NR068758) and by the Institute of Information & Communications Technology Planning & Evaluation (IITP) grant funded by the Korean government (MSIT) (RS-2025-02305801).

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