Leveraging User Feedback to Inform Just-in-time Adaptive Intervention (JITAI) Delivery in mHealth: An Exploratory Study

by

Rongqi Bei

A thesis submitted in partial fulfillment
of the requirements for the degree of
Master of Science in Information
(School of Information)
in the University of Michigan
2024

Master's Thesis Committee:
Professor Mark W. Newman
Professor Pedja Klasnja
Professor Noelle E. Carlozzi

ACKNOWLEDGEMENT

I am deeply grateful to my advisors, Prof. Mark W. Newman and Prof. Pedja Klasnja, for their unwavering support and guidance throughout this journey. When I first expressed my interest in exploring the research field of human-computer interaction and mHealth, they generously devoted their time and energy to mentoring me. Under their direction, I went deeper into the study of just-in-time adaptive intervention and solidified the research focus for this thesis project. Whether it was framing the research questions, designing the study methods, interpreting the results, or refining various details of the project, they consistently provided insightful, constructive, and sharp ideas that inspired me in every meeting. I am especially thankful for their patience and encouragement during moments when I felt stuck in a dead-end; their warmth and support allowed me the time and space I needed to figure things out. Their contributions to my development as a researcher have been invaluable, and I could not have completed this thesis without their wisdom and belief in my potential.

I would also like to sincerely thank my committee member, Prof. Noelle E. Carlozzi, for her thorough review of my paper draft and for providing invaluable constructive feedback and edits. During my defense, she posed thought-provoking questions that prompted me to reflect deeply on my work and helped me refine my thinking for future research directions. Along with my advisors, her contributions have been essential to the development of this thesis, and I deeply appreciate her support and guidance.

A special thank you goes to my senior graduate colleagues, Dr. Xinghui (Erica) Yan and Soo Ji Choi. Xinghui provided stimulating ideas and feedback during the developmental stage of my research, helping me scope the project and refine the designs. Soo provided significant practical advice and hands-on help during the implementation of my study methods, helping to ensure everything proceeded efficiently. Their mentorship, collaboration, and support truly meant a lot to me.

I would also like to acknowledge the support of the Master Thesis Option Program research grant provided by the University of Michigan School of Information, which provided the financial resources necessary to make this research possible.

I also deeply appreciate the participants in this study. Your engagement and insights were vital, and without your willingness to take part, this work would not have been possible.

Lastly, I want to express my deepest gratitude to my parents, Lin Wang and Chao Bei, and my partner, Zikang Jia, for being a constant source of strength and balance throughout this journey. I am deeply thankful for the encouragement and stability you provided, which helped me stay focused and grounded during the most demanding moments of this process.

ABSTRACT

Just-in-time adaptive interventions (JITAIs) have become increasingly popular in mobile health (mHealth) technologies to promote health behavior changes. Despite their potential, one of the key challenges in applying JITAI in practice is the limited information these systems have about individual users. Personalized messaging depends on accurate and complete data about users' behavior, context, and preferences. Inspired by interactive reinforcement learning and the demonstrated superiority of combining human input with algorithmic processes, our study explores collecting additional user feedback on received interventions to enrich data and improve algorithm training. We conducted a two-week Wizard of Oz study with 18 participants randomly assigned to three groups, each experiencing different feedback interaction designs. We logged their interactions, collected daily survey responses, and conducted exit interviews. Our findings provide insights into (1) user attitudes towards providing feedback and users' feedback-providing behaviors and motivation; (2) users' reasoning processes and logic behind providing feedback; and (3) design implications that support effective feedback-provision experiences. Our study contributes to the human-computer interaction (HCI) community by looking into the innovative idea of leveraging user feedback as a richer data source, offering the potential to enhance the personalization and effectiveness of mHealth interventions.

1 INTRODUCTION

Just-in-time adaptive interventions (JITAIs) are increasingly being incorporated into mobile health (mHealth) technologies to promote health behavior changes across a variety of domains (Nahum-Shani et al., 2018). As suggested by its name, JITAIs "operationalize the individualization of the selection and delivery of intervention options based on ongoing assessments of the individual's internal state and context" (Nahum-Shani et al., 2018, p. 448), presenting personalized health behavior suggestions to each user. Such tailored intervention messages have been shown to be effective across multiple studies (Wang & Miller, 2020), where JITAIs were applied to increase physical activity levels (Klasnja et al., 2019; Park et al., 2023), quit smoking (Hébert et al., 2020), improve mental health status (Carlozzi et al., 2022), etc.

Although the application of JITAI is promising, a key challenge facing its performance is the impoverished information available about individual users. Personalized messaging relies on accurate and complete data about users' behavior, context, and preferences. Without this information feeding into JITAI's pre-established decision rules or reinforcement learning algorithms, the intervention loses necessary data sources to select and deliver intervention messages that are tailored to each user's unique needs (Wang & Miller, 2020). Inspired by the concept of interactive machine learning (Dudley & Kristensson, 2018) and the demonstrated superiority of combining human input with algorithmic processes in the human-in-the-loop approach (Amershi et al., 2014), our study explores the novel idea of collecting additional feedback from users—specifically, their responses to the interventions they receive—as a richer data source for algorithm training to address the issue of data impoverishment. To our knowledge, few studies have investigated this approach within the context of mHealth interventions. Thus, this exploratory study aims to understand the following research questions:

- RQ1: What are user attitudes toward providing feedback, and what behaviors and motivations influence their feedback provision?
- RQ2: What are the users' reasoning processes and logic behind providing feedback?
- RQ3: What design implications can be drawn to support effective learning experiences through feedback provision?

To answer these questions, we conducted a two-week Wizard of Oz study (Bernsen et al., 1994) with 18 participants, allowing them to interact with feedback designs in everyday settings. Participants were randomly assigned to three groups, each experiencing a different type of simulated feedback experience varied in interaction modalities and the type of information collected. To better understand and learn from their feedback experience, we logged their feedback interactions, collected daily survey responses about their experiences, and conducted data-driven exit interviews for debriefing. The qualitative findings obtained in our study contributed to the field of HCI and JITAI by revealing the complex dynamics of user feedback and behavior, highlighting the critical role of context in user feedback and system interactions, and proposing implications for designing engaging and effective feedback mechanisms.

2 LITERATURE REVIEW

2.1 Just-in-time adaptive interventions (JITAIs)

The *just-in-time adaptive intervention (JITAI)* is a promising approach to promoting behavior change in health interventions. As defined by Nahum-Shani et al. (2018), JITAI is an intervention design "aiming to provide just-in-time support, by adapting to the dynamics of an individual's internal state and context." (p. 448). This definition highlights several characteristics that JITAI possesses that contribute to its potential. These advantages, as implied in its name, stress the need for researchers to improve JITAI's performance.

Firstly, the phrase ***"just-in-time"*** speaks of its "attempt to provide the right type (or amount) of support, at the right time" (Nahum-Shani et al., 2018, p. 447). Building on this focus on timing, JITAI is designed to deliver interventions precisely when individuals are most in need of support. This effectively prevents users from disengaging with mHealth interventions due to intervention fatigue caused by offering support when users are not receptive (Sarker et al., 2014). Secondly, the word ***"adaptive"*** describes JITAI's capability to "adapt the provision of support (e.g., the type, timing, intensity) 'over time to an individual's changing status and contexts" (Nahum-Shani et al., 2018, p. 446), including those that "emerge rapidly, unexpectedly, and ecologically" (p. 449).

JITAI systems can operate using either predefined rules or AI-based approaches (Orzikulova et al., 2024). Rule-based JITAI systems trigger interventions based on predetermined rules or conditions decided by domain experts (Carlozzi et al., 2022; Gustafson et al., 2014; Thomas & Bond, 2015). For example, Thomas and Bond (2015) delivered walking break suggestions to someone who had been detected to be sedentary for 120 minutes. Carlozzi et al. (2022) applied statistical analysis to user data, such as sleep, steps, and mood, to deliver tailored intervention messages based on predefined criteria. On the other hand, AI-based JITAI systems continuously analyze user data and use machine learning algorithms to tailor interventions dynamically (Goldstein et al., 2017; Mishra et al., 2021). This includes reinforcement learning algorithms that have been used to adapt JITAI models to individual users for more effective physical activity interventions (Liao et al., 2020; Rabbi et al., 2015). In our paper, we specifically situate the JITAI within the context of reinforcement learning-driven approaches, where the adaptive algorithm learns from user feedback on intervention messages to enhance personalization and effectiveness.

2.2 Challenges related to data sparsity and user burden

Despite the potential of JITAIs, there are also key challenges to optimizing their effectiveness including data sparsity and user burden. A significant issue is the limited information available about users (e.g., their preferences, states, and context), which can diminish the performance of JITAIs, particularly those employing reinforcement learning algorithms. This is because adaptive algorithms require continuous human feedback to refine their performance over time (Arzate Cruz & Igarashi, 2020).

Current methods for collecting user data primarily involve passive sensing and self-reporting. While passive sensing is beneficial for capturing certain constructs with relatively high accuracy (e.g., steps, sleep patterns, heart rate), it may provide missing or partially incomplete data due to factors such as users forgetting to wear/carry the tracking devices or charge them (Kazi & Wiese, 2022; Shih et al., 2015). On the other hand, self-reporting is valuable but can impose a significant burden on users, resulting in poor data quality over extended periods (Intille et al., 2016; Rabbi et al., 2015). This issue of impoverished information necessitates effective strategies to collect richer information from users to inform JITAI's decisions.

Meanwhile, it is equally important to note that the process of soliciting feedback from users can be burdensome, potentially leading to reduced engagement and data accuracy. To mitigate user burden, strategies such as incorporating micro-interactions and progressive disclosure can be undertaken. Micro-interactions, which are small, focused interactions designed to accomplish single tasks, can make feedback collection feel seamless and unobtrusive (Saffer, 2013). For example, Intille et al. (2016) broke down long questions into a series of fast, glanceable interactions; Yan (2020, 2021) developed a series of innovative and swift interaction gestures to support users micro-interact with their smartwatches. Progressive disclosure, which involves progressively revealing information or options as needed, can further reduce cognitive load by presenting users with only the necessary elements at each stage (Tidwell, 2020). These strategies were referenced in our interface design in this study to enhance user experience and engagement.

2.3 Interactive reinforcement learning and users' experience in the loop

While situating adaptive algorithms in mHealth applications for JITAI delivery is relatively new, involving users in the machine learning process to contribute information as the source of algorithm adaptation is not (Dudley & Kristensson, 2018). Given that our study focuses on reinforcement learning-driven JITAI systems and involves users in providing feedback to improve learning outcomes, the following section reviews concepts around interactive reinforcement learning (IRL), which integrates human input into the reinforcement learning (RL) process to enhance the system's performance and tailor its policies to specific tasks.

Specifically, "an interactive RL approach involves a human-in-the-loop that tailors specific elements of the underlying RL algorithm to improve its performance or produce an appropriate policy for a particular task." (Arzate Cruz & Igarashi, 2020, p. 1196) This approach allows the system to benefit from human expertise and adaptability. Additionally, "the user can personalize the output of an RL algorithm based on the user's preferences," (p. 1195) ensuring that the learning process is aligned with individual user needs and contexts. This blend of human insight and algorithmic learning creates a more effective and responsive system.

The effectiveness of combining human insight with algorithmic precision is well-documented, demonstrating the superiority of "people and algorithm" over "algorithm" alone. By involving users in the feedback loop, we can leverage their nuanced understanding and contextual knowledge, which algorithms often miss. This human involvement leads to more tailored and effective outcomes, as highlighted by Amershi et al. (2014). Given this, along with the challenges posed by impoverished data (section 2.2), soliciting more information from users' feedback is both reasonable and essential. The human-in-the-loop feedback input enriches the data, enabling the algorithm to make more informed decisions and adapt more accurately to diverse situations.

To design effective feedback interactions, we reviewed four common types of human feedback found in the literature (Arzate Cruz & Igarashi, 2020). They are:

- ***Binary critique*** evaluates the policy performance with either a positive or negative response. For example, a user might give a thumbs-up or thumbs-down to indicate their approval or disapproval of a suggested workout routine.
- ***Scalar-valued critique*** evaluates the policy performance with scalar values. An example is a user rating the intensity of a recommended exercise session on a scale of 1 to 5 stars.

- ***Action advice***, where users suggest specific actions that they believe the system should take at a given state. For instance, a user might request that the system "Send me more stretching reminders," indicating that they need additional prompts to incorporate stretching exercises into their daily routine.
- ***Guidance***, where users specify goals or desired outcomes that the system should aim to achieve. For example, a user may indicate, "I cannot prioritize physical activity this week due to a busy schedule," guiding the app to adjust its recommendations and expectations to accommodate their current constraints.

Each of these feedback types offers unique advantages for enhancing the interaction between users and the system. Binary and scalar feedback provide quick and straightforward evaluation methods, while action advice and guidance allow for more detailed and context-specific input, enabling the system to better align with user goals and preferences while requiring more effort from users.

Lastly, we reviewed some approaches to improving users' experience of the training process in IRL. Prior work suggested presenting model outputs to users for review. This approach empowers users by giving them control and visibility into the model's learning progress, fostering a more satisfying experience while waiting for the algorithm to learn (Dudley & Kristensson, 2018). Additionally, incorporating mechanisms to indicate uncertainty, such as notifications in JITAI alerting users when the system is unsure about their context change, can notify users when the system is unsure about a decision or situation and prompt further investigation (Gómez-Carmona et al., 2024). Gamification also plays a crucial role by incorporating game-like elements to motivate and engage users during the training process (Lessel et al., 2019). These strategies collectively enhance the user-friendliness of interactive reinforcement learning systems, helping keep users engaged with the teaching process.

3 METHODS

The goal of this study is to explore user attitudes, behaviors, and motivations related to providing feedback on intervention messages in mHealth interventions and to identify design implications that support an effective and user-friendly feedback-provision experience. To achieve this goal, we conducted a two-week in-the-wild Wizard of Oz study (Bernsen et al., 1994) with 18 participants, where we first explained during the onboarding session that a human operator would simulate the system's deliveries. Participants were then asked to interact with the designs as if they were engaging with a fully automated system, allowing us to evaluate feedback interaction designs in real-world settings. These 18 participants were randomly assigned to three groups in this between-subject study, with each group experiencing a different type of simulated feedback design that varied in dimensions, such as interaction modalities and the type of information gathered. During the two-week study, we logged how they interacted with the feedback interactions and inquired about their experiences with the feedback interactions through daily survey responses. We also conducted data-driven exit interviews to debrief their two-week experience.

3.1 Simulated feedback experiences

We designed three distinct sets of feedback interaction designs that are assumed to effectively collect users' reactions. Each set emphasizes different design values, leading to variations in interaction modalities, type of feedback, and type of information collected (Table 1).

	Interaction Modality	Type of Feedback	Type of Information Collected
01 (user-directed flow)	Graphical user interface	Close-ended	Users directly command the system's behaviors
02 (user-system partnered flow)	Graphical user interface	Close-ended	Users share more context and reasoning to explain their attitudes
03 (free-text flow)	Free-text input	Open-ended	Flexible, depends on user input

Table 1. *Design variations between the three sets of feedback interface designs.*

The **close-ended graphical user interface** consists of predefined questions and controls like buttons. Users interact with the controls to answer the questions and provide feedback on the messages they receive. Based on what information the predefined questions can query, we further developed a user-directed feedback flow and a user-system partnered feedback flow.

In **the user-directed** flow (Figure 1), users directly command the system's in-situ or near-future behaviors through specific commands like "mute," "remind me later," or "show another message." This single-click interaction allows users to quickly dictate the system's behavior without providing any background or rationale for their choices. This design aligns with the *action advice* feedback type in IRL (Arzate Cruz & Igarashi, 2020), where users suggest specific actions that the system should take at a given state, thereby directly influencing the system's immediate behavior and learning process.

In the **user-system partnered** flow (Figure 2), users share more context and reasoning to explain their attitudes toward the received messages (e.g., "too exhausted to execute the suggestion now" or "not interested in this message category") instead of directly telling the system what to do next. This design reflects aspects of the *guidance* feedback type in IRL (Arzate Cruz & Igarashi, 2020), where users specify goals or desired outcomes, helping the system to better understand and adapt to their needs and preferences.

The **open-ended free-text** flow (Figure 3) offers users greater flexibility in sharing information, free from the constraints of predefined questions. While we recognize that this approach might place a higher burden on users, its inclusion in our design is deliberate. Our objective with this exploratory study is to investigate the nature and extent of information users are willing to provide when unrestricted. We anticipate gathering feedback that varies in granularity, capturing insights that may extend beyond the scope of our predefined questions.

In this study, all feedback interactions were implemented as low-fidelity simulations using the Qualtrics Heat Map question type[1]. We exported the user interface screens for each design and uploaded them into a Qualtrics survey, where each screen was represented as a Heatmap question. For each interface, we specified distinct regions corresponding to "buttons" or interactive elements. Using Qualtrics' branching logic, we defined pathways such that when a user clicked on a specific region, they were directed to the appropriate subsequent question. This allowed us to simulate an interactive experience while also capturing detailed data on user behavior, including click locations, survey start times, and completion status.

3.2 Participants

We recruited 18 participants (16 females and two males) through university mailing lists and the snowball sampling method. We gave $50 prepaid gift cards to each participant who successfully completed the two-week field study, the onboarding session, and the exit interview session. All participants self-reported meeting the following screening criteria: (1) were 18 years or older, (2) checked and/or sent SMS (text) messages at least with neutral frequency or more, (3) were comfortable navigating mobile phone applications, (4) wanted to receive support to increase their everyday physical activity level, and (5) were at least neutrally motivated to increase their physical activity.

3.3 Study procedure

Pre-study activity. Before the two-week in-the-wild Wizard of Oz study began, we conducted a one-on-one onboarding session with each participant. During these sessions, we clarified the study goals and expected activities and explained the Wizard-of-Oz nature of the study. We also familiarized participants with navigating the Qualtrics-based low-fidelity prototype. Specifically, we sent test survey links to each participant's phone number, guided them through completing the feedback survey and the end-of-the-day survey, and answered any questions they had.

[1] Qualtrics Heat Map question type guide:
https://www.qualtrics.com/support/survey-platform/survey-module/editing-questions/question-types-guide/specialty-questions/heat-map/

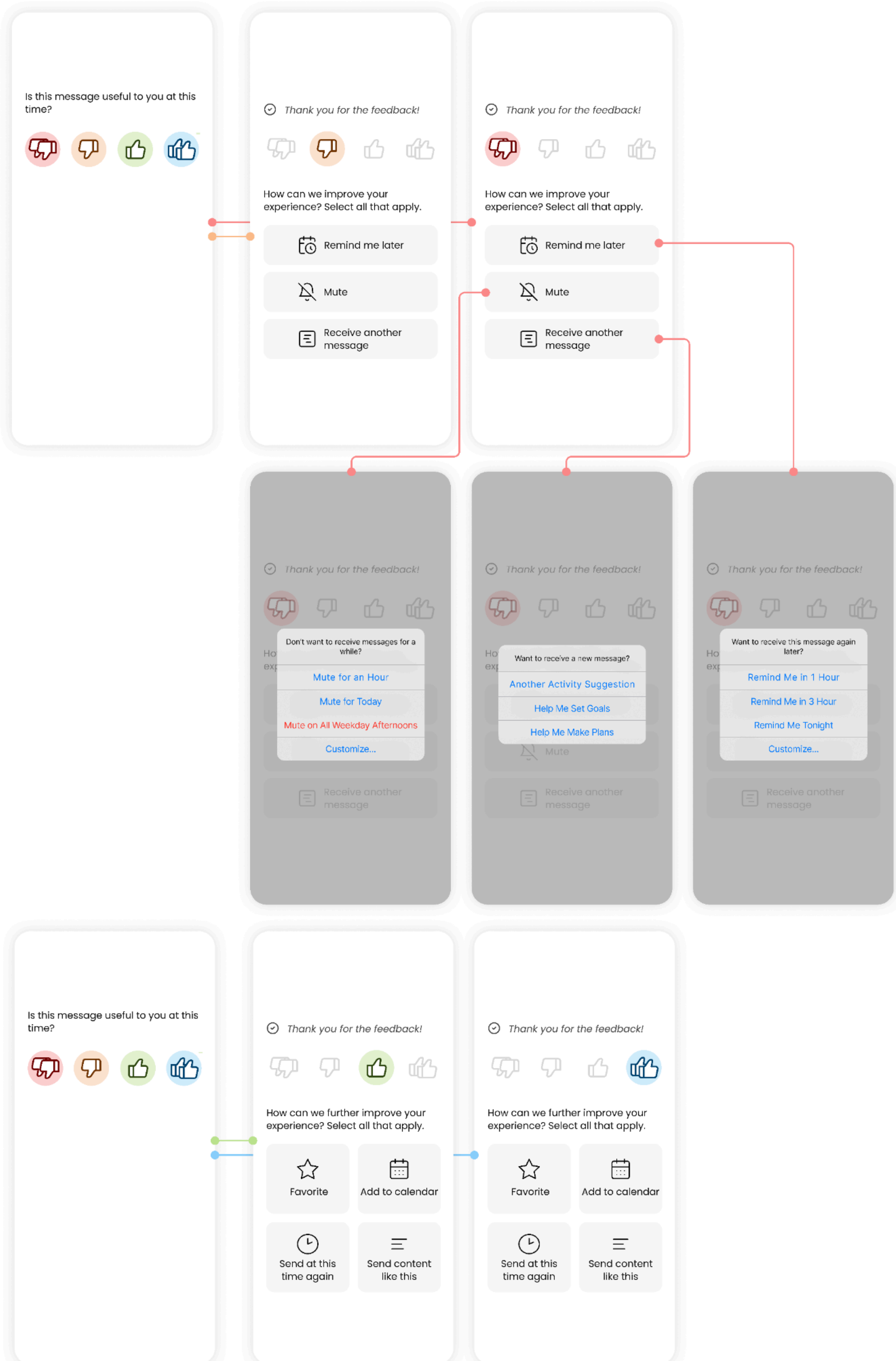

Figure 1. *The user-directed flow (close-ended graphical user interface).*

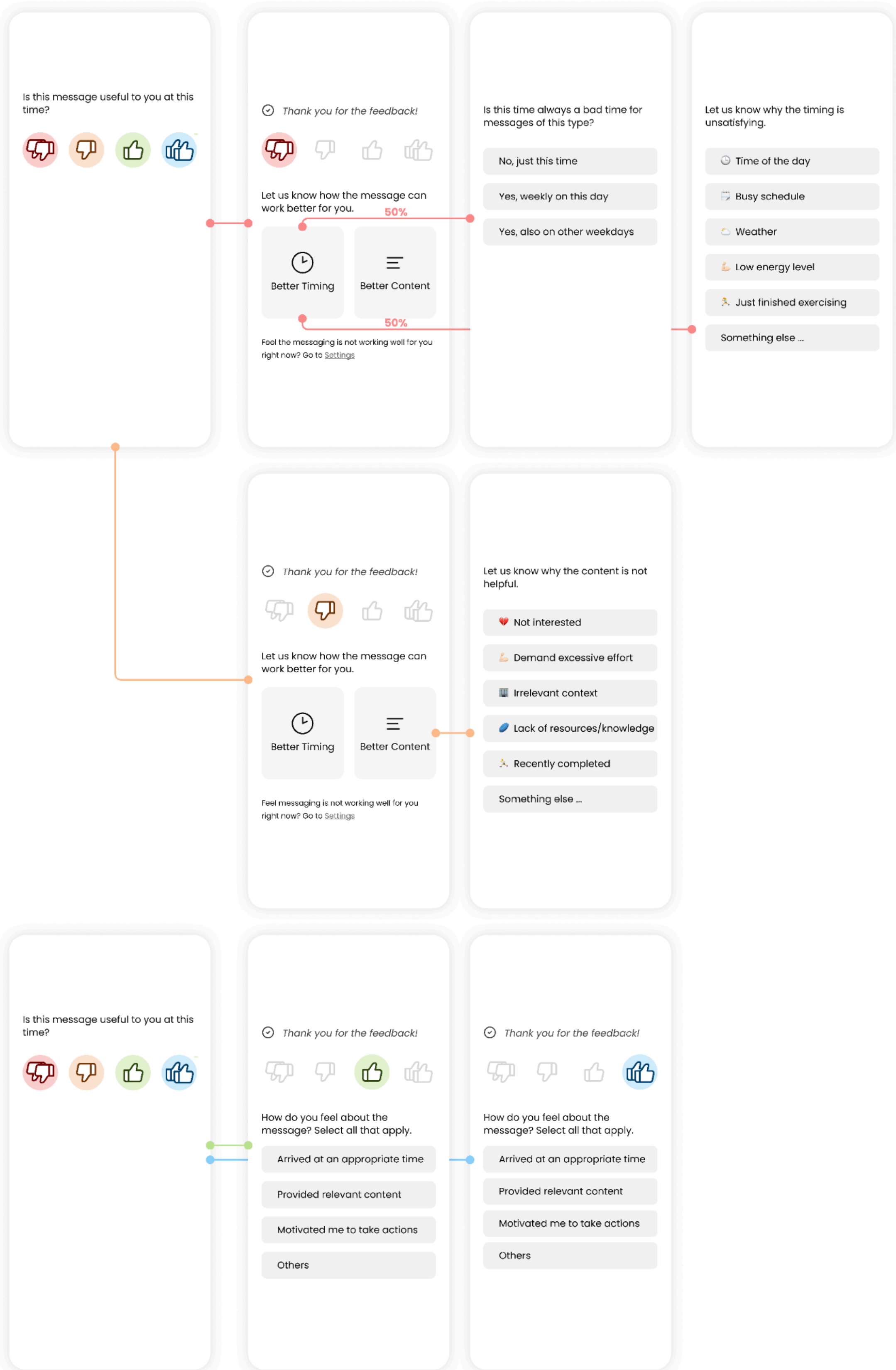

Figure 2. *The user-system partnered flow (close-ended graphical user interface).*

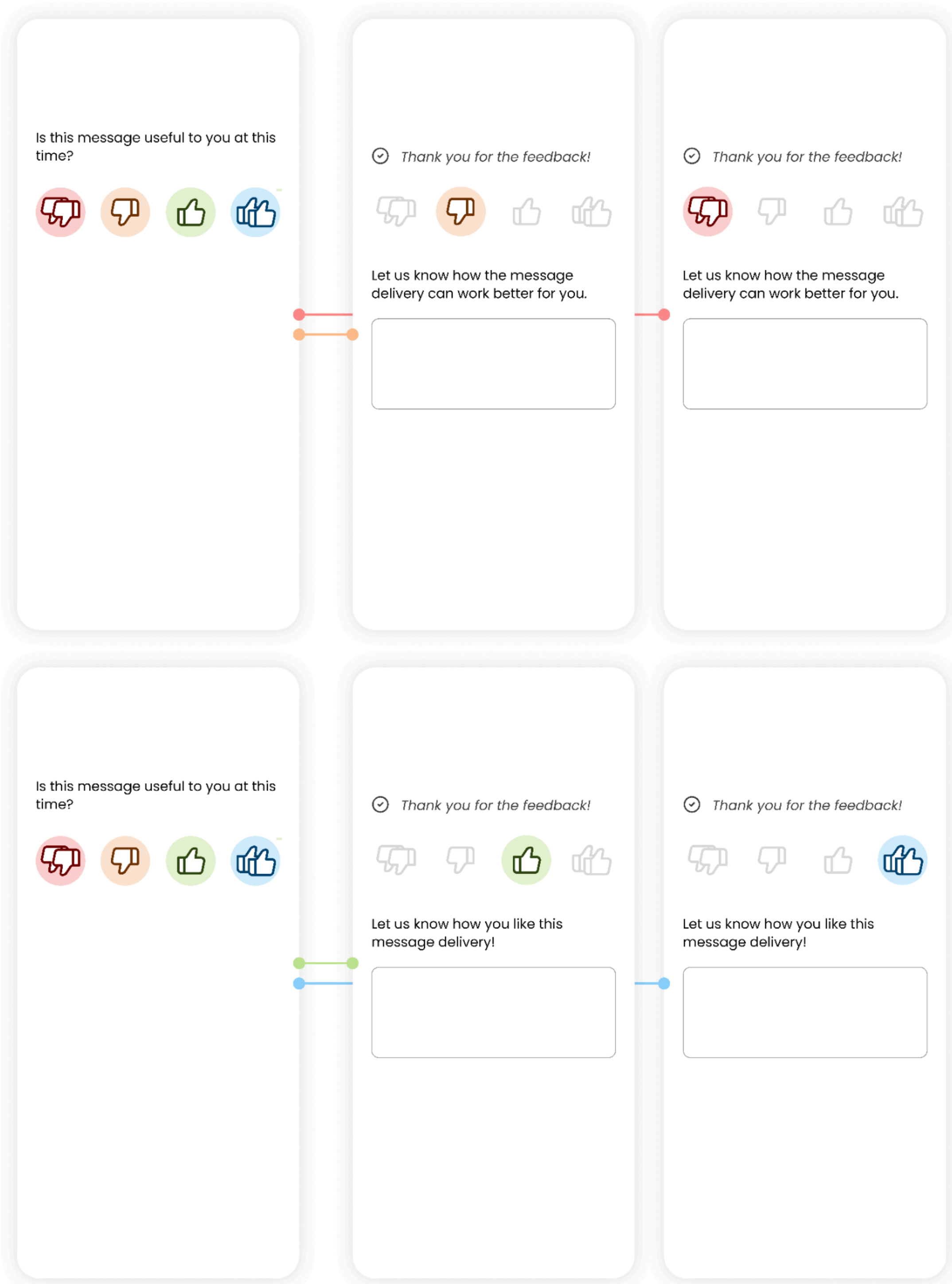

Figure 3. *The open-ended free-text flow.*

Two-week in-the-wild Wizard of Oz study. During the two-week study period, participants received the following three text messages each day (Figure 4). By following this daily routine, the study aimed to gather comprehensive insights into participants' reactions to intervention messages and their feedback behaviors.

- ***The intervention message:*** This daily text message was designed to encourage physical activity. These messages, which serve as the benign intervention component of our research, aim to boost users' activity levels by offering behavioral suggestions, reminding them to set goals, etc. The full list of the text messages can be found in the Appendix for reference.
- ***The link to the simulated feedback experience:*** This link was sent together with each daily intervention message. Participants were asked to interact with the feedback survey as if they were using a real mobile application. They were expected to share their feelings about the intervention message with the adaptive system through this simulated feedback interaction, as introduced in section 3.1.
- ***The end-of-the-day survey:*** Each evening, participants were asked to complete a brief end-of-the-day survey at their designated time (all between 20:00 and 22:00). In this survey, participants were invited to reflect on their earlier feedback-providing experience as if they were discussing it with the research team members.

Exit interview. After the two-week study, we scheduled one-hour semi-structured debriefing interviews with each participant to gain a deeper understanding of their experiences with the messages and the feedback process. These interviews followed a data-driven retrospective approach. Specifically, to help each participant recall and elaborate on their feedback and survey responses, the research team created visualizations that captured the interventions they had received, their response times and contexts, their feedback responses, and their end-of-the-day survey responses (one slide per day, for a total of 14 days). Participants were invited to walk the researcher through their feedback-providing process. When we asked participants to provide additional details about their experiences, we fully respected their privacy, allowing them to decline elaboration if they preferred. Figure 5 shows examples of the slides we used as visual cues. All interviews were conducted virtually on Zoom and were screen-recorded, where participants had the choice to turn off their cameras.

3.4 Data analysis

Prior to each exit interview, the research team thoroughly reviewed all of the participants' survey data to prepare visualizations for the interview. This process enabled the researchers to tailor their questions based on each participant's data, as well as to ask specific questions about each participant's behaviors, motivations, and needs each time they provided feedback. The audio transcripts were transcribed verbatim for analysis, and recordings were deleted immediately after transcription to ensure privacy. All 18 transcripts were imported into NVivo software for coding. We followed thematic analysis (Braun & Clarke, 2012) using an inductive coding approach, deriving initial codes directly from the data while being guided by the research questions. This method ensured that the emergent themes were data-driven and reflective of the actual observations.

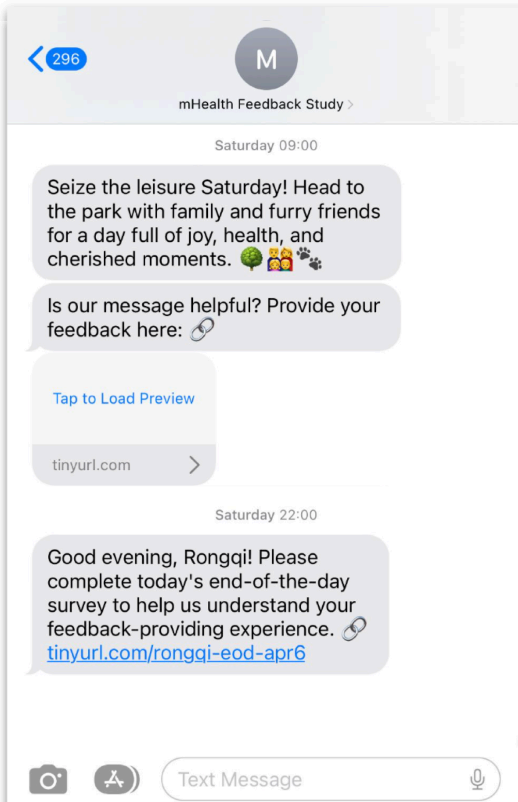

Figure 4. *A sample screenshot of the three messages that each participant received during the two-week study, including the intervention message, the link to the simulated feedback experience, and the link to the end-of-the-day survey.*

4 RESULTS

4.1 Positive feedback on intervention messages does not necessarily guarantee follow-up actions or imply perfect alignment with users' needs.

While a thumbs-up rating on the intervention message indicates a positive reception, it does not necessarily equate to follow-up action or perfect alignment with users' current needs. Our findings highlight the following three key factors contributing to this misalignment.

Unpredictability of the user's future states. Positive feedback on intervention messages does not guarantee follow-up actions. Our interview data showed that even when participants thoughtfully decided to follow the message, which led to their thumbs-up feedback, they might later encounter unforeseen obstacles that hindered their actions. For example, P9 meant to follow the intervention message to do a sunset stroll and responded with a double thumbs-up before noon.

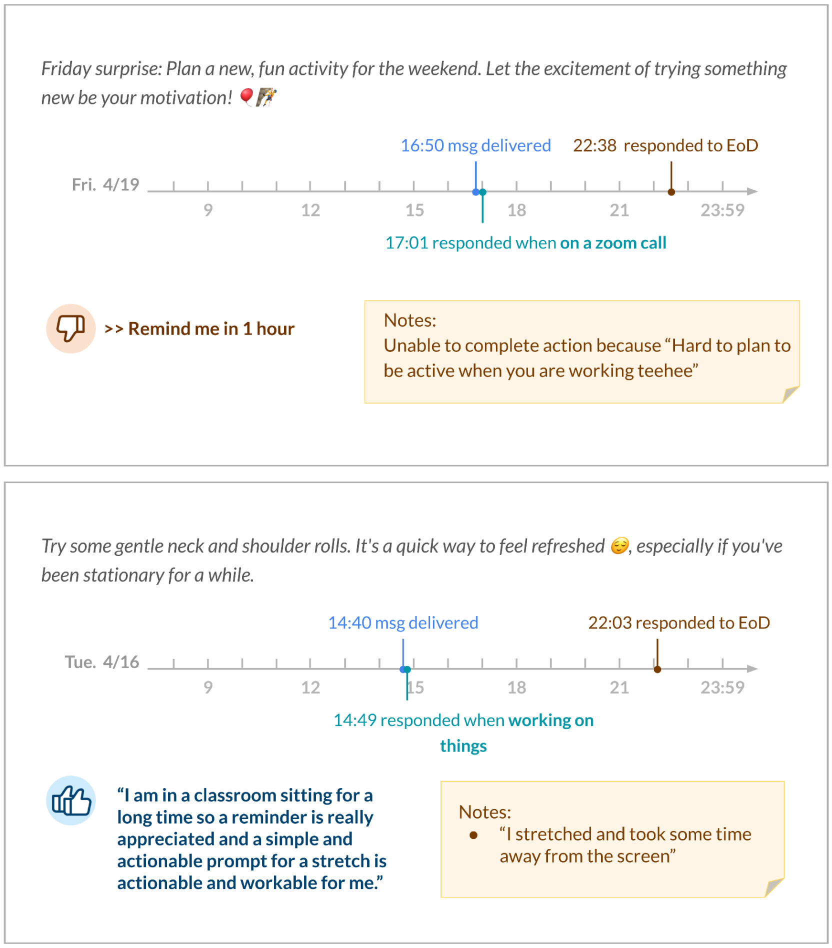

Figure 5. *Examples of data visualization used for the exit interviews with P5 from group B (top) and P11 from group C (bottom).*

However, she wasn't able to follow through due to unforeseen fatigue later in the day: *"...the weather was really nice, so when I received the message, I was motivated to, like, take a walk around the campus… However, I did not. I wasn't able to do that because I was really tired after coming back from Costco."* External circumstances, such as environmental states, can also affect users' ability to act on intentions formed earlier. For instance, P13 rated a message prompting her to increase steps during her evening commute with a thumbs-up and genuinely intended to follow it earlier in the day. However, unexpected rain prevented her from taking steps as planned: *"If it hadn't rained, maybe I could have just, like, walking to the bus stop, taking the bus, and then walking for a while to my home. But that day, you know."*

Perceived future helpfulness. Users provide positive feedback on intervention messages when they foresee potential future usefulness, even if the message is not immediately applicable. For some participants, this perceived future usefulness is more concrete, and they used positive feedback to signal the adaptive system to send similar content again in the future. For instance, P5 could not engage in running activities as suggested by the message on Friday of the final week. Despite this, she rated the message with a thumbs-up and selected "send at this time again" because she enjoyed running and could see herself doing it outside of the final week. She explained, *"I had a final project due that night at midnight, so it was like a bad day for me. But I liked the message a lot. I like to run and walk. I also like that it incorporates friends. But it was just like an individual day. That was unfortunate."* Unlike P5, who saw a specific opportunity to apply the message in a similar context at a different time, P12 appreciated the motivational aspect of the messages more generally. She said, *"I feel like just having that mind, like that thought of, oh, getting to do something to make yourself healthy, makes me feel good. If that makes sense."* This represents a more abstract perceived future usefulness, where the participant values the general positive reinforcement and its contribution to maintaining a healthy mindset without a specific future application in mind.

Intrinsic positivity of the message. Users may rate intervention messages positively based on their belief in the message's inherent positivity rather than its immediate applicability. Our interview findings suggest that participants often provide positive feedback to intervention messages they believe convey a generally "correct" sentiment (P16). For example, although P3 found a message inapplicable to her situation, she still rated it positively, saying, *"I feel like it's not really the system's problem. It's more of, like, my problem if that makes sense..."* Interestingly, she further explained, *"I feel like it would help other people,"* despite being informed that the study's goal was personalization.

In summary, the misalignment between positive feedback and follow-up actions occurs both when users intend to act on the messages and when they do not. Users may thoughtfully plan to take action but face unforeseen obstacles; they may also find the message unhelpful this time but still rate it positively due to its future helpfulness and intrinsic correctness.

4.2 Users' feedback on intervention messages varies according to their context.

Study findings indicate that users' perceptions and responses to intervention messages are moderated by their *in-situ* context. This context consists of different layers that vary across time scales, including more stable, long-term aspects of their lives and more temporary, short-term instances.

For example, a more stable long-term context often involves significant aspects of users' lives, such as daily routines and living environments. This more long-term context can remain consistent for years to decades once established. P1, a senior-year student awaiting graduation, exhibited a unique pattern in responding to intervention messages due to her flexible and volatile schedule. During the study period, P1 often chose the feedback option "receive another message" rather than other options for unsatisfying messages. With minimal school work, she was receptive to getting new suggestions right away because her time was not strictly structured:

"Most of the time, it would have been fine to receive another message." However, P1 anticipated a shift in her feedback behavior once she started her full-time job. She reflected that with a structured 9-to-5 schedule, the timing would become crucial: *"Like next year, when I start my full-time job, I only get a lunch break at, like, from twelve to one, that's when I could get an active message…"* Similarly, P3's feedback was shaped by the context of living in a safe college campus environment. She felt comfortable with outdoor activity prompts in the evening, stating, *"I'm on the college campus. So even if I'm outside at night, it doesn't really, like, matter."* Her feedback might differ if she were in a less safe environment, highlighting how macro context impacts users' interpretation of messages.

How users react to the intervention message is also heavily influenced by more temporary contexts, which can include specific short-term circumstances such as impending deadlines or a weekend trip. For example, feedback during high-stress periods, like during finals, showed a marked difference from feedback given during less stressful times. P5 shared that she wasn't able to adhere to a jogging suggestion, *"I had a big exam the other day, so I was studying on Sunday pretty much all day."* She noted that she would be more receptive to the suggestion if she were not in the middle of finals, *"like the previous week. Or, like this upcoming week, I would definitely be free and enjoy that. But because of my final exam. I was not."* This indicates that immediate situational factors impact user's in-situ perceptions of the messages they receive.

In sum, users' feedback on intervention messages is influenced by both long-term, stable aspects of their lives and short-term, situational factors. This infers that feedback collected in one context may not accurately reflect how users would perceive and respond to messages in a different context.

4.3 Participants provide feedback based on both the expectation of future system improvements and the perception of immediate benefits, with motivations influenced by their perceptions of the system's intelligence and the importance they place on physical activity in their daily lives.

Participants exhibited diverse motivations for providing feedback on intervention messages, which were influenced by anticipated future benefits and immediate values. These motivations were further shaped by their perceptions of the system's intelligence and the importance they placed on physical activity.

4.3.1 Anticipated system improvements (future benefits). Many participants provided feedback with the expectation that it would enhance the system's ability to deliver more personalized and relevant interventions over time. This future-oriented motivation drove participants to provide feedback, especially when the system suggested something that misaligned with their needs. For example, P1 was *"a lot more motivated"* to provide feedback on messages she disliked, *"I just, like, got to the feedback survey faster… I felt like I wanted something different."* Similarly, P5 shared: *"I think particularly, like, when it gave me a suggestion I couldn't do, I was, like, very motivated to reply to it… like I don't need this notification now."* Besides providing feedback to correct misaligned messages, some participants were also motivated to provide feedback on messages they found useful. This feedback serves as a rewarding signal to the system, acknowledging its success in delivering appropriate support and encouraging continued high performance. For example, P13 rated messages suggesting quick stretches positively, hoping the system would deliver more messages with smaller, easy-to-do activities. P12 also shared that she tended to reply more to messages she appreciated, viewing it as a way to reward the system for doing a good job: *"[I] tend to reply to that [helpful messages] more, and I really appreciate it."*

Our study found that the motivation for anticipated system improvement varied in intensity and was influenced by two main factors:

- ***Perception of system intelligence.*** Participants who perceived the system as highly intelligent had higher expectations for its learning outcomes and were more motivated to continue providing feedback outside of the study (e.g., P1, P5, P9, P10, P11, P17). They were willing to give the system a longer training period (three weeks to one month) or didn't mind the training time as long as they saw signs of the system's learning progress. For example, P9 stated: *"If I know that this product is going to benefit me in the long run, that it's going to send me accurate timings and good messages, then I would be willing to spend time to give my inputs."* Conversely, participants who were less aware of the system's learning capabilities (e.g., P4, P14) showed less interest in providing feedback in real-life situations and provided less conscientious feedback during the study. For instance, P14 noted that she neither expected nor considered how her feedback would impact the system's future delivery.
- ***Perceived importance/relevance of physical activity.*** Even when users were aware of the system's intelligence and understood that their feedback would improve it, they were less motivated by future benefits if they did not take physical activity seriously. For example, when asked about the impact of not providing detailed feedback on the system's learning outcome, P16 responded: *"That's not very critical, right? It's not like I'm talking with my lawyer or my accountant or my doctor, where I have to provide exact details to get better results. This is just for leisure."*

These findings highlight how perceptions of system intelligence and the personal importance/relevance of physical activity influence the motivation to provide feedback, affecting the quality and consistency of user input.

4.3.2 Immediate benefits. Feedback provision was also driven by the immediate benefits perceived by participants, offering instant value rather than contributing to the system's learning progress. For example, P10 appreciated the "add to calendar" feature within the feedback process, which allowed her to integrate preferred suggestions into her schedule: *"It [adding to* *calendar] would, like, possibly keep me accountable throughout the week… [I can] plan ahead for, like, the different activities.”* Similarly, P18 valued the ability to stop inapplicable notifications through the feedback process. She compared our study's intervention messages to Apple Watch stand-up reminders: *"When you're sitting for long durations, maybe because you're working or in a meeting, and you cannot get up, it's gonna, you know, vibrate or say, 'Hey, get up!' Sometimes, I want to stop those notifications or give feedback on that, which currently, I'm not sure how to do with the Apple Watch."*

4.4 Users were aware of their preferences and were willing to share them with the system to enhance personalization.

Our interview data reveal that some participants have a relatively clear self-understanding of their personal preferences, such as preferred message content and delivery time, and are willing to share this information with the system to enhance personalization. This implies that not all knowledge related to user preferences needs to be inferred solely from user feedback. Instead, users have the ability to directly share their preference information with the system, allowing for more immediate and accurate personalization.

Preferred message content. During the exit interviews, we found that many participants were aware of the characteristics of the messages they preferred. The level of intensity of the suggested activity is one dimension that participants show clear preference for. As an example, several participants (P6, P7, and P14) reacted negatively to messages suggesting a 5K run because it was too intense for them, given their limited physical energy. In contrast, P9, who considered herself highly self-motivated and had already engaged in sufficient high-intensity activities, showed her preferences in messages that suggested stretching or posture-related reminders. Besides, preferences were also influenced by the type of activity suggested. For instance, P11 reacted negatively to a message asking her to "Set your fitness goals and enjoy the weather!" because she felt overwhelmed by goal-setting in her life: *"I just don't have the bandwidth to set goals because I already have to meet a lot of goals in my life. So I just don't… I'm not interested in doing that."* Similarly, P12 mentioned that she didn't know how to ride a bike and, therefore, would never expect or appreciate biking-related messages. Lastly, some participants also show preferences towards the format and tone of the messages. For example, P3 appreciated the use of a friendly tone and emojis in messages: *"The emojis didn't make it feel like someone was telling me I have to do this… It felt more like my peers were suggesting something to me, rather than instructing me."* She added, *"So then it's like, Oh, okay, that's very cute. Let me actually do this."*

Preferred message delivery time. In addition to preferred message content, some participants demonstrated a clear understanding of their schedules and personal routines, enabling them to specify time slots when they preferred to receive or avoid receiving messages. A commonly mentioned variable was wake-up time, which typically varied between weekdays and weekends (e.g., P1, P13, P18). Additionally, participants had specific exercise schedules that they wanted the system to recognize. For instance, P1 did not want to receive intervention messages on Saturdays because it was her “skip day.” Similarly, P5 preferred not to receive messages on Sundays, explaining, *“Every Sunday, I run 10K or a couple of miles, so I wouldn’t find it particularly useful to do another activity because I’m very tired afterward.”*

5 DISCUSSION

5.1 Implications for implementing RL-driven adaptive algorithms

5.1.1 Go beyond simplistic user feedback interpretation in reward construction. The misalignment between positive feedback and follow-up actions revealed in section 4.1 underscores the complexity for adaptive algorithms to evaluate their message delivery. As described in section 4.1, a thumbs-up does not necessarily indicate that the message aligns with users’ immediate needs, as they may appreciate the message for its perceived future usefulness or intrinsic positivity. Similarly, the lack of follow-up action does not imply the message failed to align with users’ needs, as users may intend to act but encounter unforeseen obstacles. This indicates that the ratings do not always accurately reflect users’ intentions, and thus, the history records of thumbs-up and thumbs-down ratings to earlier messages alone are insufficient indicators for constructing effective reward functions in the context of reinforcement learning. It is worth noting that we would expect not to observe thumbs-up and down ratings for every message that has been sent. To construct more effective reward functions, it is essential for researchers to go beyond simplistic interpretations of user feedback and integrate additional factors. Possible factors from our findings include perceived future helpfulness (i.e., how users anticipate the future applicability of messages), contextual factors (i.e., users’ habitual contexts and potential obstacles they might face), and psychological mechanisms (i.e., elements that influence users’ decision-making processes). We encourage future research to take a more nuanced approach and focus on identifying other influential factors and understanding how to develop reward functions that more accurately reflect and encourage desired user behaviors.

5.1.2 Ensure continuous learning and contextual adaptation. As shown in our findings, feedback collected in one context may not accurately reflect users’ perceptions and responses in a different context (section 4.2). This indicates that adaptive systems need to reassess feedback information when users’ contexts change. It is essential for these systems to continuously learn and adapt to changing circumstances by updating their policies and maintaining some level of exploration to remain responsive to evolving user needs. Besides, users are often willing to provide high-quality feedback for short periods to set up systems that work well for them (section 4.3). This positive attitude toward the training period implies that the system should collect detailed feedback initially and then transition to lighter monitoring or periodic check-ins as the algorithm converges to ensure continued effectiveness. However, to accommodate new contexts, the system is expected to carefully determine when to request more intense feedback from users again.

To effectively identify changes in users' contexts and decide when more intense feedback is needed, we suggest adaptive systems employ the following two strategies. Firstly, periodic check-ins with users. The system can set up periodic, low-effort questions asking users about changes in their context to ensure it remains attuned to any updates. Secondly, backend processing that tracks the confidence in the algorithm's predictions and decisions. When the confidence degrades, the system can ask for more feedback from users. As an example, one approach to realize this is implementing a model predictive controller (MPC) (Qin & Badgwell, 2003), which is an advanced control method that predicts future system behavior and optimizes control actions to achieve desired outcomes within constraints. Implementing an MPC can enhance system performance by tracking its effectiveness and confidence, allowing for real-time adjustments based on predictive modeling. When MPC identifies deviations from expected behavior patterns, it signals that the system's current model is less effective and indicates the need for more intense user feedback to recalibrate its policies. By integrating these practices, adaptive systems can better align intervention messages with users' dynamic contexts, ultimately enhancing their effectiveness and user satisfaction.

5.2 Implications for feedback experience design

Based on findings from sections 4.3 and 4.4, our study derived several design implications for enhancing users' experience of providing feedback to the adaptive system.

5.2.1 Enforce visible and transparent learning progress. As section 4.3.1 reveals, participants are more motivated to provide feedback to the system when they trust its learning ability and believe their feedback will help the system become more personalized to their needs. Therefore, integrating features that highlight the system's learning capabilities and progress can be highly beneficial. Transparency in system learning can enhance perceived usefulness, a critical dimension in the Technology Acceptance Model (Davis & Granić, 1989), by showing users how their input leads to system improvements and reinforcing the value of their contributions. To implement this, adaptive systems are expected to provide clear and accessible information about how user feedback is utilized and how the system evolves over time. This can be achieved through various means, such as visual progress indicators, updates summarizing recent changes based on user input, and real-time feedback responses, including explanations of how the feedback will be used or even simple acknowledgments. By making the system's learning process visible and transparent, users are more likely to trust the system and remain engaged in providing valuable feedback.

5.2.2 Incorporate more immediate benefits. Feedback provision was also driven by the instant utility perceived by participants, such as stopping inapplicable messages and conveniently adding favorite events to the calendar (section 4.3.2). The concept of immediate benefits aligns with the Instant Gratification Theory (Mischel, 2001), which suggests that people are motivated by immediate rewards. These immediate rewards are particularly significant in the context of teaching JITAIs, considering that it may take a long time for the algorithms to converge and for the adaptive systems to learn each individual user's needs and preferences. Features that provide users with quick, tangible outcomes can reinforce the value of providing feedback and enhance their motivation to engage. Future work researchers are encouraged to investigate a variety of immediate reward mechanisms and take more nuanced approaches to explore and experiment with other feedback elements and/or modalities that could help users perceive immediate benefits during the interaction process.

5.2.3 Enable self-reporting mechanisms and global controls. Our findings indicate that there are certain preferences that the system does not need to learn from users' feedback alone. As illustrated in section 4.4, users have a clear understanding of their preferences regarding some dimensions of the intervention delivery (e.g., message content and delivery times) and are willing to share this information directly with the system to enhance personalization. Therefore, by allowing users to participate in the customization process and explicitly state their preferences, the system can immediately tailor the interventions without needing a prolonged learning period. This approach not only speeds up the personalization process but also helps the system give suggestions that are more relevant and respectful of users' routines from the start.

In the meantime, it is noteworthy that users' relatively clear preferences are often tied to constraints in their lives, such as physical strengths (e.g., capable of lower intensity messages), knowledge (e.g., knowing how to ride bikes), and work schedules (e.g., differentiating between weekdays and weekends). However, there may be situations where such strong intuitions for individual preferences do not hold, and users themselves need to explore before understanding their own needs. Therefore, it would be valuable for future work to explore these situations further, summarizing dimensions that rely more on self-reports after experiences or the system's learning outcomes.

The process of self-reporting preferences should not be limited to the initial onboarding phase but should instead be an ongoing, low-burden dialogue between the user and the system. This is because users' preferences may change as their contexts and circumstances evolve (section 4.2, (Yan et al., 2024)). For instance, a user's preferred wake-up times or exercise schedules might vary due to changes in routine, job, or personal commitments. When there is evidence that the model's current knowledge of users' preferences is not working well, it is crucial for the system to suggest that users review the current settings and/or re-collect self-reported data to maintain accurate personalization. The key concern for such a self-reporting process is minimizing user burden. Possible strategies to reduce this burden include carefully choosing the frequency with which the system prompts users for self-reporting, incorporating self-reporting steps into existing activities (e.g., adding one more question in users' weekly review), etc.

There also remains an open question about how to balance users' autonomy (i.e., users' self-report preferences) and the effectiveness of the intervention (i.e., therapeutic outcome). While it is essential to respect and integrate user preferences to enhance engagement and satisfaction, it is equally important to ensure that the interventions are effective in achieving desired outcomes. For instance, when users prefer low-intensity activities, the system needs to carefully consider whether to gently encourage a progression towards higher-intensity activities to meet health goals.

5.3 Limitations

We point out a few limitations of this study. First, this study has a relatively small sample size as a between-subject study, with only six participants per condition and a total of 18 participants. Additionally, the participant pool consisted primarily of individuals from a higher education setting, and only two of the 18 participants were male, which may limit the generalizability of the results to other populations and reduce the comprehensiveness of gender representation in the responses. In addition, although we assigned participants to three different groups with distinct feedback interactions, the current findings did not reveal significant group differences in how participants reacted. Future work will need to revisit the survey data and interview transcripts to investigate any potential differences among the groups further. The study was also conducted using a low-fidelity prototype, requiring users to make an additional click to navigate from the text messages to the feedback survey. This extra step may have unconsciously added to the participants' perceived burden, potentially influencing their willingness to provide feedback and their overall user experience. Finally, we were transparent with our participants that this was a wizard-of-oz study at the beginning of this study. Although the researcher conducted one-on-one onboarding sessions and instructed participants to interact with the prototype as if they were engaging with a real intelligent system, this knowledge may have caused some nuanced differences in how users perceived and expected the system's ability to learn. These perceptions could affect their interactions and feedback, differing from those in a real-world deployment of a fully autonomous system.

6 CONCLUSION

Our exploratory study explored the potential of leveraging user feedback to enhance JITAI in the mHealth context. Through a two-week Wizard of Oz study with 18 participants, we investigated user attitudes, behaviors, and motivations regarding feedback provision, alongside design implications for effective feedback interactions. Our study emphasizes the need for adaptive systems to integrate nuanced interpretations of user feedback, ensure continuous learning and contextual adaptation, and design feedback experiences that balance user autonomy with the effectiveness of interventions. Future research should further explore these dimensions to develop more effective and user-friendly JITAI systems. By addressing these critical aspects, we dive deeper into the idea of leveraging user feedback as a richer data source and are moving closer to realizing the full potential of JITAIs in promoting sustained health behavior changes.

Appendix

The table below summarizes the 14 intervention messages received by participants during the two-week Wizard of Oz study.

No.	Message Content
1	Wrap up your current task and treat yourself to a walk outside. Perfect weather awaits! Why not enjoy a refreshing coffee along the way? ☀️🚶☕
2	Try some gentle neck and shoulder rolls. It's a quick way to feel refreshed 😌, especially if you've been stationary for a while.
3	🌧️👟 The rain's stopped and the breeze is perfect! Why not take a refreshing walk after dinner? Enjoy the cool air!
4	Use your Thursday commute for fitness! Walk part of the way home or park farther. Kickstart your evening with extra steps! 🚶 👟
5	Friday surprise: Plan a new, fun activity for the weekend. Let the excitement of trying something new be your motivation! 🎈🧗
6	Cool, cloudy Saturday—perfect for a refreshing walk or a light jog. Set a fitness goal for today? 🎯 Plan a route, lace up your sneakers, and enjoy the energy!
7	Happy Sunday morning! 🌅 Start your day with some yoga 🧘 or stretching at home. A calm mind and body will set a positive tone for the week ahead!
8	Midday boost! 💪 Take a 20-minute power walk around the block or try some quick stretches at your desk. Recharge your afternoon with some sunshine and movement!
9	Tuesday afternoon slump? 🆙 Beat it with 15 minutes of cardio—jump rope, a HIIT session on YouTube, or jogging in place. Keep your energy up! 💥
10	Think about boosting your routine tomorrow. 🌅 Why not try a standing desk or take the stairs instead of the elevator? Make it a healthy, active day! 🎉
11	Sun's out and flowers bloom! 🌞🌸 Join our Spring Photo Scavenger Hunt in cool weather. Capture the vibrant blooms on your meal break and enjoy the crisp air!
12	The semester's end is near and it's sunny! ☀️📚 Celebrate with a 5K run or walk around campus! 🏃 🏃‍♀️ Gather friends and stride into the weekend with joy!
13	Capture the weekend magic! 🚴 Plan a bike ride through the city's landmarks or along the waterfront. Enjoy the views as you pedal at leisure this weekend!
14	Happy Sunday! ☀️ Warm week ahead in Ann Arbor. Plan for daily jogs 🏃 or sunset strolls. Set your fitness goals and enjoy the weather!

Table 1. *The 14 intervention messages sent to participants during the two-week study*

References

Amershi, S., Cakmak, M., Knox, W. B., & Kulesza, T. (2014). Power to the People: The Role of Humans in Interactive Machine Learning. *AI Magazine*, *35*(4), 105–120.

Arzate Cruz, C., & Igarashi, T. (2020). A Survey on Interactive Reinforcement Learning: Design Principles and Open Challenges. *Proceedings of the 2020 ACM Designing Interactive Systems Conference*, 1195–1209.

Bernsen, N. O., Dybkjær, H., & Dybkjær, L. (1994). Wizard of Oz prototyping: How and when. *Proc. CCI Working Papers Cognit. Sci. /HCI, Roskilde, Denmark*. https://citeseerx.ist.psu.edu/document?repid=rep1&type=pdf&doi=45522a09bebc352de3e27ae1c61bb3bf66f7b681

Braun, V., & Clarke, V. (2012). Thematic analysis. In H. Cooper, P. M. Camic, D. L. Long, A. T. Panter, D. Rindskopf, & K. J. Sher (Ed.), *APA handbook of research methods in psychology, Vol. 2. Research designs: Quantitative, qualitative, neuropsychological, and biological* (pp. 57–71). American Psychological Association.

Carlozzi, N. E., Choi, S. W., Wu, Z., Troost, J. P., Lyden, A. K., Miner, J. A., Graves, C. M., Wang, J., Yan, X., & Sen, S. (2022). An app-based just-in-time-adaptive self-management intervention for care partners: The CareQOL feasibility pilot study. *Rehabilitation Psychology*, *67*(4), 497–512.

Davis, F. D., & Granić, A. (1989). *The Technology Acceptance Model*. Springer International Publishing.

Dudley, J. J., & Kristensson, P. O. (2018). A Review of User Interface Design for Interactive Machine Learning. *ACM Trans. Interact. Intell. Syst.*, *8*(2), 1–37.

Goldstein, S. P., Evans, B. C., Flack, D., Juarascio, A., Manasse, S., Zhang, F., & Forman, E. M.

(2017). Return of the JITAI: Applying a Just-in-Time Adaptive Intervention Framework to the Development of m-Health Solutions for Addictive Behaviors. *International Journal of Behavioral Medicine*, *24*(5), 673–682.

Gómez-Carmona, O., Casado-Mansilla, D., López-de-Ipiña, D., & García-Zubia, J. (2024). Human-in-the-loop machine learning: Reconceptualizing the role of the user in interactive approaches. *Internet of Things*, *25*, 101048.

Gustafson, D. H., McTavish, F. M., Chih, M.-Y., Atwood, A. K., Johnson, R. A., Boyle, M. G., Levy, M. S., Driscoll, H., Chisholm, S. M., Dillenburg, L., Isham, A., & Shah, D. (2014). A smartphone application to support recovery from alcoholism: a randomized clinical trial. *JAMA Psychiatry* , *71*(5), 566–572.

Hébert, E. T., Ra, C. K., Alexander, A. C., Helt, A., Moisiuc, R., Kendzor, D. E., Vidrine, D. J., Funk-Lawler, R. K., & Businelle, M. S. (2020). A Mobile Just-in-Time Adaptive Intervention for Smoking Cessation: Pilot Randomized Controlled Trial. *Journal of Medical Internet Research*, *22*(3), e16907.

Intille, S., Haynes, C., Maniar, D., Ponnada, A., & Manjourides, J. (2016). μEMA: Microinteraction-based ecological momentary assessment (EMA) using a smartwatch. *Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing*, 1124–1128.

Kazi, S., & Wiese, J. (2022). *The challenge for just-in-time adaptive interventions: Incomplete or missing data*. pedel.cs.utah.edu. https://pedel.cs.utah.edu/publications/10938.pdf

Klasnja, P., Smith, S., Seewald, N. J., Lee, A., Hall, K., Luers, B., Hekler, E. B., & Murphy, S. A. (2019). Efficacy of Contextually Tailored Suggestions for Physical Activity: A Micro-randomized Optimization Trial of HeartSteps. *Annals of Behavioral Medicine: A*

Publication of the Society of Behavioral Medicine, *53*(6), 573–582.

Lessel, P., Altmeyer, M., Schmeer, L. V., & Krüger, A. (2019). “Enable or Disable Gamification?”: Analyzing the Impact of Choice in a Gamified Image Tagging Task. *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, Article Paper 150.

Liao, P., Greenewald, K., Klasnja, P., & Murphy, S. (2020). Personalized HeartSteps: A Reinforcement Learning Algorithm for Optimizing Physical Activity. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, *4*(1). https://doi.org/10.1145/3381007

Mischel, W. (2001). The marshmallow test: Mastering self-control. *Https://awspntest.apa.org › Record › 2014-43233-000https://awspntest.apa.org › Record › 2014-43233-000*. https://doi.org/10.1038/scientificamerican0914-92c

Mishra, V., Künzler, F., Kramer, J.-N., Fleisch, E., Kowatsch, T., & Kotz, D. (2021). Detecting receptivity for mHealth interventions in the natural environment. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, *5*(2), 1–24.

Nahum-Shani, I., Smith, S. N., Spring, B. J., Collins, L. M., Witkiewitz, K., Tewari, A., & Murphy, S. A. (2018). Just-in-Time Adaptive Interventions (JITAIs) in Mobile Health: Key Components and Design Principles for Ongoing Health Behavior Support. *Annals of Behavioral Medicine: A Publication of the Society of Behavioral Medicine*, *52*(6), 446–462.

Orzikulova, A., Xiao, H., Li, Z., Yan, Y., Wang, Y., Shi, Y., Ghassemi, M., Lee, S.-J., Dey, A. K., & Xu, X. (2024). Time2Stop: Adaptive and Explainable Human-AI Loop for Smartphone Overuse Intervention. *Proceedings of the CHI Conference on Human Factors in Computing Systems*, Article Article 250.

Park, J., Kim, M., El Mistiri, M., Kha, R., Banerjee, S., Gotzian, L., Chevance, G., Rivera, D. E., Klasnja, P., & Hekler, E. (2023). Advancing Understanding of Just-in-Time States for Supporting Physical Activity (Project JustWalk JITAI): Protocol for a System ID Study of Just-in-Time Adaptive Interventions. *JMIR Research Protocols*, *12*, e52161.

Qin, S. J., & Badgwell, T. A. (2003). A survey of industrial model predictive control technology. *Control Engineering Practice*, *11*(7), 733–764.

Rabbi, M., Pfammatter, A., Zhang, M., Spring, B., & Choudhury, T. (2015). Automated personalized feedback for physical activity and dietary behavior change with mobile phones: a randomized controlled trial on adults. *JMIR mHealth and uHealth*, *3*(2), e42.

Saffer, D. (2013). *Microinteractions: Designing with Details*. "O'Reilly Media, Inc."

Sarker, H., Sharmin, M., Ali, A. A., Rahman, M. M., Bari, R., Hossain, S. M., & Kumar, S. (2014). Assessing the Availability of Users to Engage in Just-in-Time Intervention in the Natural Environment. *Proceedings of the ACM International Conference on Ubiquitous Computing. UbiComp (Conference)*, *2014*, 909–920.

Shih, P. C., Han, K., Poole, E. S., Rosson, M. B., & Carroll, J. M. (2015). Use and adoption challenges of wearable activity trackers. *iConference 2015 Proceedings*. https://www.ideals.illinois.edu/handle/2142/73649

Thomas, J. G., & Bond, D. S. (2015). Behavioral response to a just-in-time adaptive intervention (JITAI) to reduce sedentary behavior in obese adults: Implications for JITAI optimization. *Health Psychology: Official Journal of the Division of Health Psychology, American Psychological Association*, *34S*(0), 1261–1267.

Tidwell, J. (2020). Getting Input from Users: Forms and Controls. In *Designing interfaces: patterns for effective interaction design*. O'Reilly Media, Inc.

Wang, L., & Miller, L. C. (2020). Just-in-the-Moment Adaptive Interventions (JITAI): A Meta-Analytical Review. *Health Communication*, *35*(12), 1531–1544.

Yan, X. (Erica), Baroudi, L., Bei, R., Boudalia, L., Cain, S. M., Barton, K., Shorter, K. A., & Newman, M. W. (2024). Proposing a Context-informed Layer-based Framework: Incorporating Context into Designing mHealth Technology for Fatigue Management. *Proceedings of the 2024 ACM Designing Interactive Systems Conference*, 571–583.

Yan, X., Li, Y., Huang, B., Park, S. Y., & Newman, M. W. (2021). User Burden of Microinteractions: An In-lab Experiment Examining User Performance and Perceived Burden Related to In-situ Self-reporting. *Proceedings of the 23rd International Conference on Mobile Human-Computer Interaction*, Article Article 47.

Yan, X., Raj, S., Huang, B., & Park, S. Y. (2020). Toward lightweight In-situ self-reporting: An exploratory study of alternative smartwatch interface designs in context. *Proceedings of the ACM*. https://dl.acm.org/doi/abs/10.1145/3432212