The Challenge for Just-in-Time Adaptive Interventions: Incomplete or Missing Data

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Just-in-Time Adaptive Interventions (JITAIs) are AI-based personal informatics systems that provide the users with personalized feedback based on their self-tracked data. The performance of these systems is influenced by how users engage with these systems. Therefore, this position paper aims to facilitate discussion about addressing user interactions that may lead to missing or incomplete data and, subsequently, impact the personalization aspect of JITAIs. We posit open questions about two such interactions: episodic abandonment and retrospective tracking. As one approach to answering these questions, we suggest that the algorithms in these systems require active human engagement for more accurate information about the users' current state and their desired personalization.

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JUST-IN-TIME ADAPTIVE INTERVENTIONS (JITAIS)

Just-In-Time Adaptive Interventions (JITAIs) provide the users with personalized recommendations based on Personal Informatics (PI) data. A wealth of research has explored JITAIs for supporting health behavior changes (e.g., [8, 11, 14]). Nahum-Shani et al. identify the critical JITAI components as *distal outcomes, proximal outcomes, tailoring variables, decision points, decision rules, and intervention options* [13]. They define these components as the following:

- The *distal outcome* is the ultimate goal that the intervention aims to achieve.
- *Proximal outcomes* are the short-term goals through which the JITAI aims to achieve the distal outcome.
- *Tailoring variables* are information that helps decide the right time and right type of intervention to deliver.
- *Decision points* are the time(s) at which an intervention decision is made.
- *Decision rules* are the rules that specify which intervention option to offer, for whom, and under which contexts.
- *Intervention options* are the possible interventions that might be delivered at any given decision point.

Among these components, *tailoring variables* are typically informed by PI data and the *decision rules* can leverage artificial intelligence (AI) based algorithms. In this position paper, we discuss how users' diverse interactions with PI systems may impact the algorithms' performance in AI-based PI systems like JITAIs.

EPISODIC ABANDONMENT

Prior research has revealed diverse perceptions of the users about the PI systems: from perceiving these systems as burdensome [2, 3] to abandoning them [6]. In this broad spectrum of interactions, we are particularly interested in

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those that can potentially lead to missing and partial or incomplete data. For instance, prior literature mentioned the concept of intermittent or episodic tracking where users have consistent but sparse use of self-tracking methods (e.g., a wearable device or a smartphone app) [7, 9, 12]. Gorm et al., [9] suggested that episodic tracking can be a strategy to help manage the temporal contextual factors (e.g., changes in personal circumstances). Again, participants may adhere to a recommended set of health behaviors without tracking them.

Even without episodic use or abandonment, the JITAIs could encounter incomplete data due to different technical issues, they might forget to carry the device or charge the device, or they might forget to respond to the self-report questionnaires [15]. In such situations, when users track episodically or do not track at all, the system will have missing data (e.g., during the lapse stages). Traditional JITAI implementations interpret these situations as 'user forgot to track' or 'user had a lapse in adherence' and sends reminders to track (e.g., [4, 10]). However, such reminders are irrelevant for users who adopt an episodic abandonment by choice. As Epstein et al. suggested, when users do not feel tools help them act to change their situation, tracking may add to their frustration [6]. Subsequently, irrelevant reminders can potentially lead to complete abandonment of the technology. To send relevant personalized feedback accurately, AI-based PI systems need to be able to identify episodic abandonment or tracking scenarios. However, identifying and integrating episodic abandonment within an AI-based PI system is not a straightforward task at the implementation level. We identify the following challenges for integrating episodic abandonment within an AI-based PI system:

- Which application contexts can allow episodic abandonment without causing harm for the users? For instance, if a JITAI for reducing smoking or drug abuse integrates episodic abandonment and stops sending interventions during lapse stages, that personalization would cause more harm for the users.
- Users may start the lapse stages at different times, and the length of the lapse stages can also be different for each of them. Moreover, the same person can have different lengths for the lapse stages at different points of their system engagement. How should systems identify the lapse stages and their expected duration?
- How should the system estimate the temporal resolution that would be appropriate for the JITAI and the right unit of analysis for estimating the long-term adherence of the users and presenting it to them?
- How can the system differentiate between a one-time 'forgot to track' event and the beginning of an 'episodic abandonment' event?
- What should the JITAI do during a lapse stage? Should it stop sending interventions, or should it send a different intervention to support the users in maintaining adherence during the lapse stages?

RETROSPECTIVE TRACKING

Another critical issue is that some participants might want to track in retrospect (i.e., at a later time) when they fail to track due to different personal circumstances [5]. For instance, devices like *Fitbit* allow users to track a physical activity event at a later time [1]. In such cases, the data from the self-tracking devices or applications may arrive after an intervention decision has been made. Current implementations of JITAIs do not account for a retrospective tracking scenario. For instance, JITAIs for supporting medication adherence (e.g., [4], and [10]) assume that if a signal was not received from the medicine containers, then the user did not take medicine and they remind the users to take their medicine. These implementations did not include tracking in retrospect for scenarios where users might have taken their medicine; however, no signal was sent from the medicine container due to technical issues. In such cases, the PI system will have incorrect data about the user's long-term adherence. While it is expected that some users may track data in retrospect, we identify the following challenges for integrating this behavior in a JITAI:

- How should the JITAI incorporate the retrospective data? For example, would the JITAI use that data for future intervention decisions (e.g., long-term adherence) or allow users to monitor their progress but not use the data for intervention decisions?

- How accurate the retrospective data can be? Furthermore, how may the accuracy of the data impact the quality of the personalized intervention? For instance, an EMA (ecological momentary assessment) response about perceived mental health in retrospect might be inaccurate since the perception of stress, anxiety, etc., are highly momentary.

DISCUSSION

Previous PI literature has identified user interactions like episodic abandonment and retrospective tracking. On the one hand, HCI research acknowledges that these interactions represent real-life user behaviors, and they are expected for AI-based PI systems while deployed for a diverse set of users. On the other hand, these interactions are highly challenging to integrate into an AI-based PI system due to the uncertainty of their occurrence. Here, a researcher has to balance between designing a personalized system that does not account for these interactions, marginalizing the users who adopt these interactions, and asking the users for more information on the uncertain events that may increase their burden of using these systems.

While the PI system can sense some contextual information through different sources (e.g., the location from GPS, meeting and travel information from calendar and email), there are scenarios that the user can better inform (e.g., temporary abandonment, unforeseen events). We suggest AI-based PI systems like JITAIs leverage the combination of personal data, reminders, and explicit input from the users to inform the algorithms (e.g., decision rules in a JITAI) contained in these systems. For instance, a JITAI incorporating retrospective tracking could remind the users to track at a later time if the data is missing. A 'no response scenario' to such reminders could trigger the algorithm to seek further information on temporary abandonment from the users and integrate episodic abandonment. Figure 1 shows a snippet of a potential algorithm that may address episodic abandonment and retrospective tracking. Direct input from the users can provide more accurate information in such cases, which may, in turn, improve the performance of the algorithms contained in the AI-based systems.

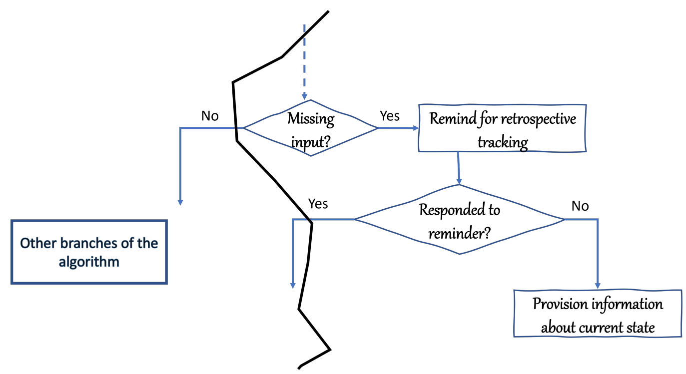

Fig. 1. A branch of an algorithm that may address user interactions like episodic abandonment and retrospective tracking

CONCLUSION

This position paper aims to facilitate discussion about addressing user interactions that may impact the personalization aspect of AI-based PI systems like JITAIs. While the designers have open questions about whether their specific application would integrate these interactions and how they will integrate them, we suggest that the algorithms in these systems require active human engagement for more accurate information about the users' current state and their desired personalization.

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