Beyond Reading a Message: Envisioning the Use of Microinteractions to Augment AI-powered Behavioral Support

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Artificial Intelligence (AI) has taken behavior change-based interventions to the next level owing to its capability of optimizing intervention signals to tailor for individuals' needs and situations. However, system-generated behavioral support is not always perceived helpful and may even be obtrusive to one's concurrent activities, which negatively impacts user adherence and engagement with the intervention over time. This position paper draws on previous research that investigated informal caregivers' experience with a message-based mHealth intervention. We suggest the use of microinteractions to facilitate positive actions on behavioral suggestions (e.g., activity planning, snoozing and getting reminded later) and enrich user feedback for machine teaching. We envision that with microinteractions, minimal additional burden is placed on users, while systems are able to incorporate rich information (e.g., user intention) to optimize modeling and deliver effective behavioral support.

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1 INTRODUCTION AND BACKGROUND

Advances in mobile technologies and artificial intelligence (AI) methods have drawn new perspectives for behavioral change-based interventions [12]. With sensing techniques, today's smartphones have the capabilities to capture individuals' physiological states and sense environmental and contextual information (e.g., location). With rich data streams as inputs, AI-powered intervention systems model user behavior and deliver personalized support at right, appropriate, and receptive moments [5, 8]. AI-powered mHealth interventions have been growing to cover a wide range of healthy behaviors, such as healthy eating, stress management, and physical activity promotion [2, 9]. However, current AI-powered mHealth systems still have large room for improvement due to technological limitations (e.g., mobile sensing capabilities), sparse individual data records, and the complexity of context and human perceptions [6]. A disturbing notification sent at inappropriate moments, or a suggestion that could not drive actions, can lead to users' negative feelings toward the intervention and disengagement over time [10].

In this regard, we see a strong need to design to facilitate positive actions in exposure to intervention signals (e.g., behavioral suggestions). To that end, we conducted interviews with informal caregivers to investigate their perceptions and actions in response to different behavioral suggestions targeting at physical and mental wellbeing. This position paper builds upon this ongoing work and discusses possible design strategies to bridge the behavioral gap between

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user and system-generated suggestions. In our interviews, we got an impression that although participants showed appreciation toward having behavioral suggestions, they seldom acted on these suggestions either instantly or later in time. Echoing with the literature [4], interview data showed multiple factors that result in action barriers, such as the lack of capabilities or resources, and lower priority for the suggested behavior. Choi et al. have proposed a multi-stage receptivity model to describe people's decision-making process in response to each intervention signal and factors that impede expected behavioral outcomes [1]. For example, a person might be available and capable of engaging in a target behavior (assessment of availability) but decides to ignore the intervention signal as it is perceived less significant than ongoing tasks (determination of adherence) [1]. This suggests the need to design to nudge people to overcome possible barriers and smoothly move through the decision making process. In this position paper, we provide several examples of participants' actions in response to *general and specific* behavioral suggestions and discuss the implications for leveraging interaction features to facilitate the transformation from perception of suggestions to target behavior. Specifically, we propose to create a set of semantic UI components (e.g., tags, buttons) to assist the user in (1) specifyig actions for target behavior; (2) communicating with the AI system to gain more user autonomy (e.g., providing feedback). We focus on the microinteraction level (i.e., interactions that are completed within 4 seconds [11]) to minimize additional burden introduced by user inputs in context [7]. We envision that introducing an assortment of microinteractions to AI-powered intervention systems could not only enhance the actionaiblity of behavioral suggestions but also enrich the understanding of the end user (e.g., preference and attitudes to a suggested behavior) from the AI perspective.

2 BRINGING MICROINTERACTIONS TO FACILITATE USERS' POSITIVE DECISION MAKING AND MACHINE TEACHING

We share several examples drawn from our interviews with informal caregivers about their experience with a message-based mHealth intervention for general wellbeing. Some of these messages offer general suggestions to encourage reflection on self-care, while others suggest a specific activity (e.g., listen to music). Differing in the concreteness of behavioral support, these message-based intervention signals are perceived differently by users. Briefly, general suggestions were helpful in enhancing self-care awareness, but were challenging for participants to specify actionable items within the moment of perceiving an intervention signal. On the other hand, specific behavioral suggestions seemed more likely to elicit negative feelings. For example, some participants felt frustrated because of *"not being able to take care of oneself"* as external responsibilities suppressed the motivation to adopt a healthy behavior (e.g., set up an exercise routine). Overtime, such negative experiences with mHealth interventions would gradually disengage participants, largely limiting AI to personalize behavioral support. In this regard, we see a critical challenge for current AI-powered behavioral interventions: with little access to the end user's momentary internal states (e.g., feelings, thoughts, and intention), it is difficult for AI to interpret why an intervention signal fails and further update its model.

We reflect on the aforementioned challenge and are driven to explore possible design strategies to (1) facilitate the transformation from perception to actions and (2) collect more information to empower machine teaching. To that end, we propose to leverage microinteractions to enhance the interactivity with intervention signals (e.g., push notifications) to benefit both end users and systems. Microinteractions are defined as interactions that are completed within 4 seconds [3], which only induce a minimal level of user burden. In Figure 1, we preliminarily create a semantic mapping of possible user reactions to an intervention signal and microinteractions that support machine teaching. These microinteractions can be used to (1) provide feedback to AI (e.g., want to see more specific suggestions) and (2) nudge the user to try to reduce behavioral barriers for engaging in target behavior (e.g., activity planning to make oneself accountable). For example, the user may find a general suggestion thought-provoking but needs some concrete ideas to try out. He/she

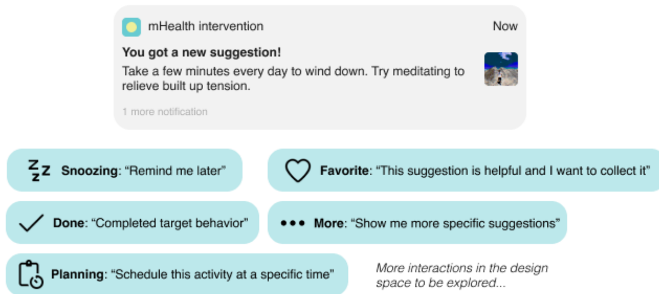

Fig. 1. Exploring the semantic mapping between possible user reactions to an intervention signal and microinteractions

may select the "More" option to receive a few more specific suggestions. The user's willingness in exploring more options represents a high level of receptivity to the intervention signal in the moment. In another example, participants may be incapable of following a suggestion owing to ongoing tasks but recognizes the importance of doing so. In this regard, snoozing a suggestion to a later moment may increase the likelihood of carrying out target behavior (e.g., being reminded to take a walk after work). There has been ongoing discussion regarding how user feedback informs machine teaching, however, the design for getting direct feedback through user input is still understudied. We also lack knowledge about how microinteractions can be connected with positive behavior change. Therefore, we propose to study microinteractions that better bridge the gap between end user and AI. Especially for AI-powered behavior change-based interventions, we would like to learn about how using microinteractions impacts people's perception and actions in response to intervention signals (e.g., collecting a message and thus being reinforced and motivated to adopt behavior). Furthermore, considering that there might be limited interaction space on the screen (e.g., limited numbers of buttons supported by a push notification), we also need to investigate what microinteractions should be prioritized for what types of behavioral suggestions (e.g., general vs specific), given that user reactions would vary with suggestions.

3 LEVERAGING INTERFACE DESIGN TO IMPROVE HUMAN-AI COMMUNICATION FOR BEHAVIOR CHANGE

A key component of interface designs is to anticipate what the user might think and need to do and then design elements to facilitate those actions. Currently, the emerging trend of introducing AI into mHealth interventions suggests researchers and designers to think about how user interfaces can better connect end users and AI systems for behavior change goals. The complicated cognitive process in behavior change underpins the importance for an AI-powered system to understand and unpack what users think and what they need in order to adopt a healthy behavior (e.g., availability, motivation, and capability). Currently, manual data input is still a primary approach to collecting information about people's internal states and thus it is critical for researchers to study how to design interfaces to collect user perceptions and direct feedback for optimizing interventions. Our preliminary ideation of possible microinteractions suggests that users' reactions to intervention signals might be more complicated than general feedback for machine teaching (e.g., "Is this suggestion helpful? Yes/No"). This suggests future work to investigate users' possible reactions to and actions on different intervention signals and design microinteractions to facilitate human-AI communication for behavior change.

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