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Utilization of EMA and the Transtheoretical Model of Behavior Change to Prevent Relapse during Long-Term Socially Assistive Robot Based Interventions

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***Abstract*—Longitudinal research is fundamentally important for understanding *sustainable* behavior change related to human health. This is particularly true for chronic illnesses, such as dementia and mental illness, where treatment is often measured in months and years over the long-term. For research on human-robot interaction (HRI) geared towards addressing such health-related issues, this presents a challenge in that many HRI studies (particularly in lab settings) are performed in a matter of minutes or at most hours. Given that reality, this suggests a need for innovative approaches to longitudinal research in HRI for such health-focused scenarios. Here, we argue that such methodological approaches to longitudinal HRI research should be grounded in existing models of behavior change (e.g. transtheoretical model) and leveraged via novel technology-enabled real-time sampling strategies for user activities outside of lab settings (e.g. ecological momentary assessment, EMA), all geared toward supporting *data-driven* methods for connecting robot behavior and human behavior over the long-term in in-the-wild settings.**

Keywords—human robot interaction, transtheoretical model, ecological momentary assessment, machine learning, healthcare, relapse

I. Introduction

A fundamental question for use of robotics in long-term deployments in real world scenarios is whether the robot's behavior should change over time, and, if so, to what degree. Moreover, changes in the robot behavior should ostensibly be connected to changes in human behavior, if we intend for robots to inhabit human work and living spaces. However, answering this question in a *data-driven* manner remains a methodological challenge within the human-robot interaction (HRI) field, particularly for specific applications such as health-related activities in user homes. Approaches that can more clearly connect long-term human behavior change to robot behavior change in-the-wild are needed to address such challenges.

Ecological momentary assessment (EMA) is a relatively novel research method that has gained much attention in the past several years as an approach for studying deployed health-related technologies in the field [1-5]. EMA is based on the notion of randomly sampling each user's behavior multiple times throughout the day over a period of time (days, weeks, months) to capture realistic human behavior when no one is directly observing them. This is typically done by using an EMA mobile app or other software to "ping" users with EMA prompts anywhere from a few times to more than 20 times a day [6]. Although the majority of research utilizing EMA methods has been conducted cross-sectionally [4,7,8], there has also been a sufficiently large body of knowledge accumulated that utilizes a longitudinal design within the construct of an EMA approach [9-11]. On the other hand, while there is also an extensive body of knowledge focusing on socially assistive robotics (SAR) employing both cross-sectional [12-14] and longitudinal designs [15-17], **there yet remains a gap in the literature emphasizing the *combination* of SARs with EMA as a longitudinal research approach**.

For instance, novelty effects, where the impact of technology or interventions erodes (i.e. "wears off") over time, is a commonly reported issue in technology-focused research in general [18-20], as well as in SAR research in particular [21-23]. However, the precise timing and sequence for the erosion of such novelty effects that typically occurs for a given participant during long-term user studies are unclear, with the factors affecting the process still difficult to study. This phenomenon is something an EMA longitudinal approach could better elucidate. Since performed behavior while using SARs varies among participants as well as within participants over time [4],

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establishing long term behaviors that vary in terms of novelty and identifying the exact moment when behavior change takes place can contribute to understanding how the SAR will be used in a long run. Furthermore, given that SARs hold great potential to revolutionize chronic illness management outside clinical settings [24-26], EMA longitudinal design could help better understand how users might interact with SARs beyond the constraints of a given research study [27,28] as well as identify possible health-related benefits of the SARs.

II. Transtheoretical Model for SAR Interventions

If an EMA longitudinal approach in SAR research does indeed identify the precise timing of behavioral changes within participants, such changes could be further associated with the *transtheoretical model* of behavioral change [29,30]. Such a model then could serve as a platform to create long-term individualized treatment plans, promoting beneficial behaviors for people experiencing various chronic health conditions that have a significant behavioral component, such as mental health issues (e.g. depression) and lifestyle-related diseases (e.g. Type II diabetes). The intersection of EMA, technology-based interventions, and the transtheoretical model of behavior change has been successfully utilized in recent research [31-33], which suggests its potential for SAR-focused longitudinal research around patient interventions while simultaneously enhancing our understanding of long-term human-robot interactions in the field. There are 6 stages of behavioral change according to the transtheoretical model: precontemplation, contemplation, preparation, action, maintenance, and termination (see Figure 1). This 6-stage continuum is useful when assessing patients with chronic illness by linking lifestyle choices (e.g. activities of daily living, or ADL). By pinpointing patients' specific position in the process of behavioral change can help health providers to establish a course of treatment that would elicit behavior change compatible with the suggestions for managing chronic illnesses.

Here, we propose an **method for the utilization of the EMA longitudinal approach with SARs conceptualized through the transtheoretical model in in-home community health settings**, which seeks to motivate behavioral changes in the human patient (i.e. participant) rather than simply monitor them. By means of a mobile-based EMA app paired with an interactive social robot, researchers, doctors, and therapists alike could establish the patient's baseline behavioral patterns and discover the patient's location on the 6-stage continuum through appropriate modeling methods, e.g. machine learning, of data collected in real-time (see Section 4 below). If it is identified that the patient is in the initial precontemplation stage (i.e. not intending to take action in the foreseeable future) then more frequent reminders in the form of suggestions can be sent to the patient to encourage them to take action (in general, non-specific reminders) and thus move to the next stage. As observed in previous research, the emergence of the Hawthorne effect may take place if an action is constantly suggested to the individual, thus eliciting a behavior change [4,34]. This approach is a delicate balance because while at this early stage more *general* reinforcement can provoke actual change in behavior and motivate future growth, on the flip side overly *specific* suggestions can undermine the principle of self-motivated change (leading to higher relapse rates later). When the contemplation stage sets in (the inflection point at which the person first develops the intention to change behaviors) the reminders would become more concrete towards specific behaviors and the advice thus more precisely goal-oriented. The preparation stage occurs when people are intending to take action in the immediate future, which means that the person in the past two stages has already created some mental plan of action on how to change their lifestyle. In this stage, it would be more beneficial to engage in an open-ended question-response mode of EMA interaction between the patient and the health care provider, so the patient could maintain the focus on what they have already planned to do, in keeping with the principles of cognitive-behavioral therapy [35]. An example of such a process flow can be seen in Section 3. Such open-ended questions and responses can be viewed as a form of "journaling" (written or voice recorded), which can help the patients navigate all the ideas that they have come up with during the contemplation stage. Thus the patient would be more prepared to enter the action stage of the transtheoretical model of behavior change with a lower risk of relapse, having cognitively processed the potential effects and internal conflicts that typically come with changed behaviors.

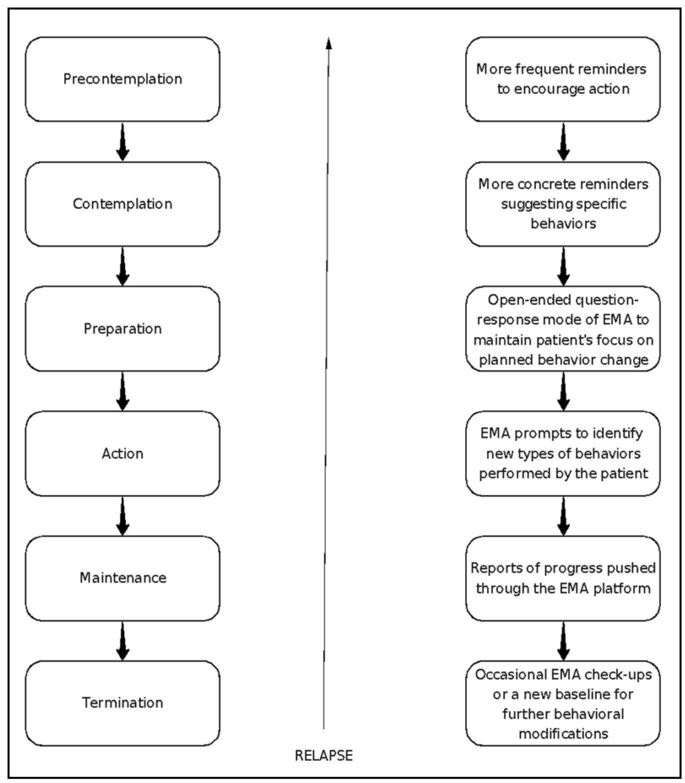

Fig. 1. Transtheoretical Model in EMA Research

The subsequent action stage represents a period where the client has made specific overt modifications in their lifestyle and concurrent daily behaviors [29,30]. During this time, EMA prompts could focus on identifying which new types of behaviors are actually being performed by the patient (also their frequency), as well as gather psycho-behavioral and emotional responses through the same EMA prompt mechanisms. To maintain the action stage and prevent relapse (i.e. maintenance state), reports of progress can be pushed through the EMA

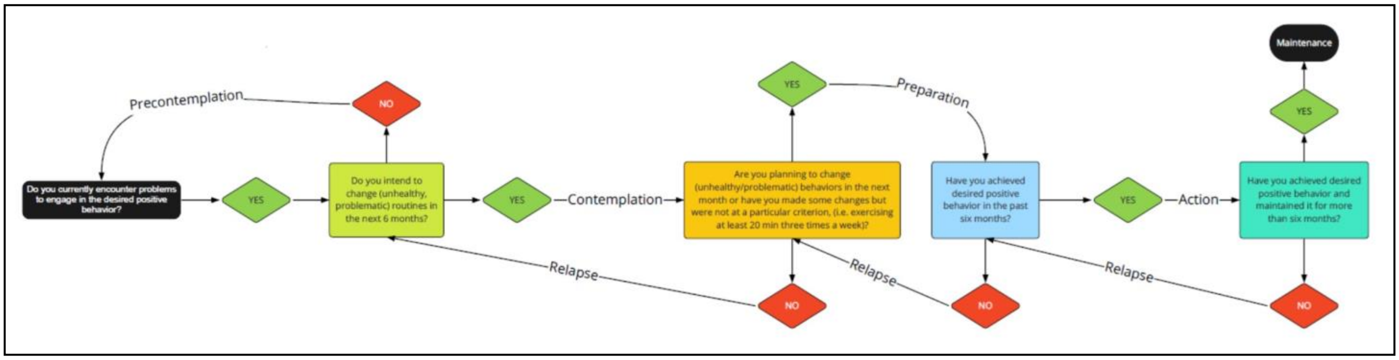

Fig. 2. Example Question Flow for Pinpointing Relapse Risk

platform. In this way health care providers and/or researchers can track changes in the psycho-behavioral responses of the patient regarding their progress. If the patient endures in their new and healthier behaviors within the maintenance stage, then the termination stage occurs where the client experiences 100% self-efficacy within the modified behavioral patterns and is not in immediate danger of relapse [29,30]. Only occasional EMA check-ups would be necessary at this point, or a new baseline for further behavioral modification could be established, depending on the long-term goals of the patient, health care provider, and/or researcher.

For some conditions, such as chronic illnesses with a significant behavioral component (see above), this may be a long-term process stretching over a multi-year span if the patient relapses often. For this reason, the process requires extensive tracking of a patient's progress on the continuum of the transtheoretical model while encouraging them to be better aware of their own intentions to change behaviors.

III. Understanding Behavioral Relapse Risk via SARs

Prochaska et al. (1994) originally proposed a set of general questions to determine patient's position on the transtheoretical model continuum and the exact points of relapse risk [36]. An example of those general questions for 12 "problem behaviors" can be seen in Figure 2. Here, we propose an extension to that original framework to adapt to the needs of SARs in in-home health-related settings, so that every general question would be accompanied by set of questions that are specific to an individual patient's health condition. This is critical, in that **different health conditions are often associated with different behaviors, and thus robot behavior in long-term situations must be adaptive in the same manner**.

We take as a starting point that the utilization of the transtheoretical model with EMA is a means of successful positive behavior change for a range of health conditions, but recommending a set of specific questions for every possible condition is beyond scope of this paper. Rather, we emphasize the need for designing condition-specific surveys (or using already validated assessment tools) that would be used in research or treatment (e.g. individual with bipolar disorder might receive the Young Mania Scale [37]). This is where EMA becomes so fundamentally important, by enabling the delivery of such surveys in real time. Incorporating condition-specific questions via EMA allows researchers and healthcare providers to have a better understanding of the patient's intentions, needs, and barriers to sustainable behavior change, which can then potentially be linked to the robot's behavior and human-robot interactions over time with the aim of mitigating relapse risk. We discuss this linkage more in the next section.

IV. Predictive Modeling to Support Longitudinal SAR Research

For the transtheoretical approach to SARs-induced behavioral changes to be effective requires that we have tools available to make sense of the collected data. At a high level, this entails that we have:

1) Appropriate modeling techniques available to model the collected EMA data, alongside any sensor data obtained from the robot itself
2) Identified behaviors that are both detectable in the robotic sensor data, while also being meaningful health-related behaviors for the condition of concern (e.g. depression, Type II diabetes, etc.)
3) Psycho-behavioral indicators of current transtheoretical stage (see Section 2) as part of the SAR-specific EMA prompts

For bullet #1 (in above list), an existing challenge is to identify appropriate modeling techniques, ranging from traditional statistical methods (e.g. linear regression) to machine learning methods (e.g. Gradient Boosting) to deep learning methods to temporal Markov models, and beyond. In simple terms, this may involve direct comparisons of different modeling methods on EMA data collected during longitudinal studies. Though at a deeper level, we may also need to consider that the choice of modeling method might depend on the goals of the deployed SAR intervention [4,38,39]. For instance, there may be times where accurately identifying a small number of individual behaviors is more useful, while in other situations we may care more about the *sequence* of multiple behaviors rather than individual ones. The latter case might require that we trade some accuracy in exchange for broader coverage of more behaviors and choose methods that explicitly model time (e.g. Markov models or recurrent deep learning networks).

Beyond the choice of appropriate modeling method, we also need to ensure that the health behaviors are detectable by the available robotic sensors (bullet #2), so that they can then be linked to the EMA data collected during longitudinal studies.

Conversely, another option may be to detect interaction behavior *modalities* with the SAR that can serve as a "proxy" for health-related behavior and associated health status. For instance, one could hypothesize that the frequency of talking to or petting a robotic pet is indicative of behavioral symptoms of mood disorders (fatigue, loss of interest, social isolation). Whether this is possible is still an active area of research, and likely dependent on the interaction modalities of interest within specific clinical domains [4,14,24,25].

Adapting the transtheoretical model of behavior change into EMA research on SARs also necessitates that we incorporate psycho-behavioral indicators of the transtheoretical state as part of the EMA prompt questions (bullet #3), in order to establish "ground truth" for later predictive modeling. Ostensibly, it may even be possible to estimate the current stage based on behavioral data (e.g. interactions with the SAR, see previous paragraph about bullet #2), but that remains a question for future research. Part of that may entail developing new psycho-behavioral indicators specifically designed for SARs research, rather than using general ones [29,30].

V. Discussion

EMA is a powerful approach for rigorous assessment of a person's behaviors over an extended period of time (e.g. a patient), and thus represents a very suitable method for use in a longitudinal data collection process. EMA is known to reduce recall bias and can offer potentially valuable information in real-time to health care providers beyond what is reported by the patient after-the-fact. Furthermore, deploying SARs in patients' homes complemented with mobile-based EMA platforms during extended periods of time not only provides patient-generated information from outside the traditional "clinic walls" but also sensor data about human-robot interactions generated via the SAR. By then utilizing predictive modeling (e.g. machine learning algorithms) on such data, such an approach can allow researchers and clinicians to discern what types of behaviors were performed by the patient and establish a connection to their underlying health status. Both of these aims are situated within the EMA philosophy and can **contribute to an understanding of how patient behaviors change over time in response to technological interventions** (such as in-home robotic platforms), particularly when rooted in established models of behavior change such as the transtheoretical model. Depending on the patient's location on the transtheoretical model continuum, researchers or healthcare providers can utilize different strategies to promote positive behavior change in patients, while minimizing the risk of later relapse.

This paper proposes a number of such appropriate strategies, depending on the patient's current stage in the transtheoretical model. For instance, in the early stages it is important that patients are motivated toward reconsidering their behaviors, without overly specific suggestions for change, in order to foster *self-motivated* behavior change. Only once the patient has moved to the later stages of the continuum should we begin making more specific suggestions. This construct is important for reducing the risk of relapse, based on known cognitive factors that lead people to fail when attempting behavior change [34]. Anecdotally, that is something all of us have experienced at times when we attempt to start a new diet or struggle to succeed with some New Year's resolution. In a healthcare sense, relapsing occurs when a patient loses sight of their goal and their behaviors then regress toward their previous lifestyle. In reality, most health behavior relapses typically occur during the action stage of the transtheoretical model, due to the patient's insufficient mental inclination to successfully follow through with changing their behaviors [29,30]. After the relapse occurs, the patient usually returns to the contemplation or preparation stage. More broadly, this is an issue related to the disconnect between the *intention* to perform a behavior and the actual performance of the behavior (*actual use*), which is a long-known issue within the field of technology adoption and use [40,41], as well as Azjen's Theory of Planned Behavior [42].

These concepts have important implications for longitudinal research in HRI, particularly health-focused research involving the long-term deployment of robots in user homes (e.g. SARs). Most such research thus far has focused on two primary concerns: 1) monitoring the user's health status and behavior outside the clinic walls, and 2) using the robotic platform as an "intervention" to encourage users to change their behaviors and/or make better health choices [43,44]. Framing these long-term deployments through a combination of rigorous real-time data collection methodology (such as EMA) and established models of behavior change (such as the transtheoretical model) is critical for providing a grounded approach for advancing research on these types of HRI applications. Moreover, if we want to establish *data-driven* models of how the robot's behavior over the long-term should change in response to changes in the human's behavior over time in-the-wild, it will be necessary to adopt approaches such as the one described in this paper to enable that in a sustainable way.

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