Designing a Motivational Agent for Behavior Change in Physical Activity

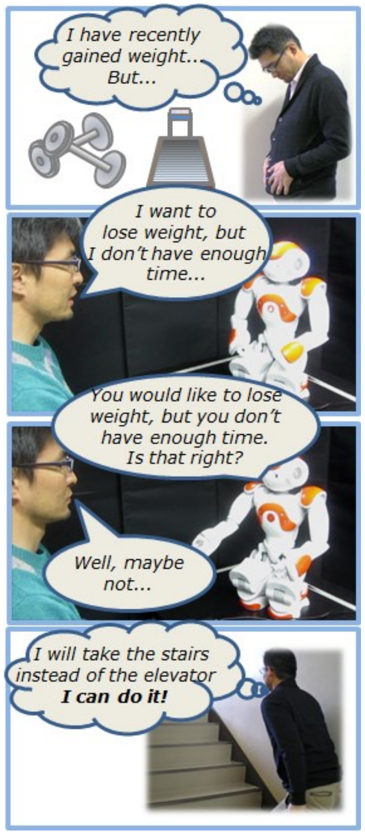

Figure 1. The concept of our automated counseling system.

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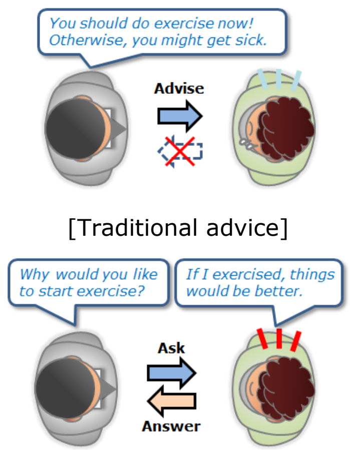
Abstract

People find behavior change—particularly long-lasting change in habits regarding physical activity—to be difficulty. While new technologies such as mobile applications that help individuals measure, log, and reflect on their activities hold great promise, they rely on individuals already having the motivation to change their behaviors. How can technology motivate people in increasing their level of physical activity? We explore this question through the design, development, and evaluation of an automated assistance system that draws on a counseling method called *motivational interviewing (MI)* and utilizes a humanlike robot as a motivational agent. Through dialogue and nonverbal engagement, the agent enables individuals to talk about and reflect on underlying reasons for their lack of motivation regarding physical activity in order to increase intrinsic motivation for behavior change. In this work-in-progress, we describe our system design and discuss findings from a preliminary study that evaluated the impact of the robot's use of MI on user motivation and behavior.

Author Keywords

Human-robot interaction; User-centered design; Motivational interviewing; Dialogue system; Social behavior; Physical activity promotion



[Motivational Interviewing]

Figure 2. A Comparison of traditional advice and Motivational Interviewing (MI). Traditional advice involves one-way communication and targets *extrinsic* motivation, i.e., driven by punishments or rewards. MI involves two-way communication between the counselor and the individual and targets intrinsic motivation, achieved by uncovering interests and goals through reflection.

ACM Classification Keywords

H.5.2. Information interfaces and presentation: User Interfaces—*input devices and strategies, evaluation/methodology, user-centered design*; **H.1.2 Models and Principles**: User/Machine Systems—*human factors, software psychology*

Introduction

Physical Activity Guidelines (PAG) for Americans [7] recommend that all adults avoid physical inactivity, yet less than half (48%) of adults in the U.S. meet the criteria for physical activity. The Guidelines suggest that some physical activity is better than none and that any amount of physical activity offers health benefits. For many individuals, increasing activity to the recommended levels requires changes in attitudes toward and eventually behavior regarding physical activity. Research in pervasive health has demonstrated the promise of mobile computing applications in helping individuals measure, track, and reflect on their levels of physical activity [4], although the success of these technologies rely on these individuals already having the motivation to engage in such activities. Existing technologies are also designed to elicit *extrinsic* motivation and do not seek to improve users' *intrinsic* motivation to pursue physical activity, which may result in longer-lasting behavior change. How could technology intrinsically motivate individuals to become more active in order to pursue a healthier lifestyle?

In this Work-in-Progress, we explore this research question by designing a coaching system that draws on a counseling approach called motivational interviewing (MI) that is widely used for the treatment of addictions [11]. MI is a powerful client-centered, goal-directed counseling method, particularly when the goal is to improve intrinsic motivation. The method involves helping individuals explore and resolve ambivalence about and improve intrinsic motivation toward behavior change, as illustrated in Figure 2. Drawing on the principles of MI, we designed an automated counseling system that includes a humanlike robot performing counseling sessions with users and seeking to increase their intrinsic motivation toward physical activity. We outline the design of our system, describe the findings of a preliminary study of the effectiveness of our counseling system, and discuss our findings and future directions regarding the development of our system.

Related work

Prior work on computer-based counseling for behavior change includes the development of dialogue-based counseling systems and investigations of the role of social engagement in user perceptions of such systems.

Bickmore et al. [2,3] developed numerous dialogue-based behavioral interventions that were delivered by an embodied conversational agent (ECA). Users interacted with the agent by selecting from among a set of responses presented on a touchscreen display. A key innovation in this work is the use of computational ontologies that enable the flexible re-use of behavioral interventions [2]. An evaluation of this system in the context of behavior-change interventions for physical activity and healthy eating showed that the participants in the intervention groups increased their walking and healthy eating compared to the no-intervention group [3]. Lisetti et al. [8] extended the ECA-based system to integrate an intervention based in MI and evaluated it in the context of alcohol consumption behavior change, finding a significant increase in users' intention to use the system over a text-based system.

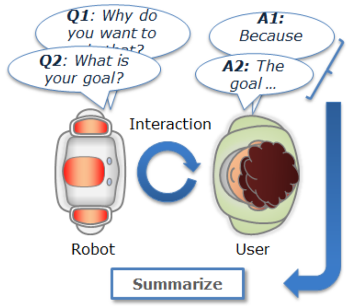


Figure 3. The conceptual design of our MI-based automated counseling system that asks the user a predefined set of open-ended questions in a predefined order and summarizes the answers to illustrate ambivalence and elicit reflection. Below is an example summarization based on recognized responses (underlined).

"You want to start exercise because *you want to lose weight (A1)*, and also, if you achieve your goal, *you would be a much healthier person (A2)*. On the other hand, *you don't have enough time to start exercise (A3)*."

A key to the success of conversational interventions such as MI in achieving behavior change is the social interaction between the individual and the counselor in order to establish rapport and trust. In these interactions, the counselor must engage in emphatic listening, seek to elicit self-motivating statements, and respond to resistance—the three core skills counselors employ in MI [11]. An automated counseling system must be designed to employ similar skills for social engagement with its users. In a Wizard-of-Oz study, Looije et al. [9] investigated the impact of social behaviors, such as gaze, posture, facial expressions, and turn-taking, in older adults' perceptions of a "robotic health assistant," finding that these behaviors improved perceptions of the robot in measures of empathy, social personality, and acceptance.

Prior work highlights the great promise that automated counseling systems that offer social engagement hold for behavior change. The novel contribution of our work is an exploration of whether a *physically* embodied agent can autonomously offer situated, face-to-face MI-based counseling sessions, employing spoken dialogue and social behavior, including gaze cues and gestures, how the users of such a system may perceive it, and whether such an agent can achieve behavior change.

System design

Performing MI sessions requires counselors to build and put into use four core interviewing skills that form the acronym OARS: asking Open questions, Affirming, Reflecting, and Summarizing [11]. In order to realize a motivational agent that employed such skills to perform MI sessions with its users, we designed and developed three components:

MI-based Interview — For the counseling system to follow the MI principles in its interaction with its user, we developed a model that directed the system to ask open-ended questions developed to encourage the user to discover and reflect on their ambivalence toward physical activity, dialogue acts that summarize user answers back to them, and prompts that encourage the user to verbalize, confirm, and pursue concrete steps they can take to resolve their ambivalence (Figure 3).

Spoken Dialogue — User interaction with our system was enabled by a spoken dialogue component that integrated speech recognition, speech synthesis, and dialogue management. The dialogue manager maintained a memory of user responses as key phrases or whole sentences as detected by the speech recognition system and formed responses, questions, and prompts based on the dialogue acts defined in the MI-based interview model for the speech synthesis system to produce (Figure 4).

Social Engagement — Our counseling system included a NAO humanlike robot developed by Aldebaran Robotics as the physically embodied motivational agent. To support social engagement with users, we designed a wide range of social behaviors, including gaze, nonverbal backchannels, and hand/arm gestures, into the robot based on prior work [1,6,12]. These behaviors aimed to facilitate turn-taking and establish nonverbal engagement during listening.

These components were implemented as an autonomous system that worked in real time with no operator control or intervention.

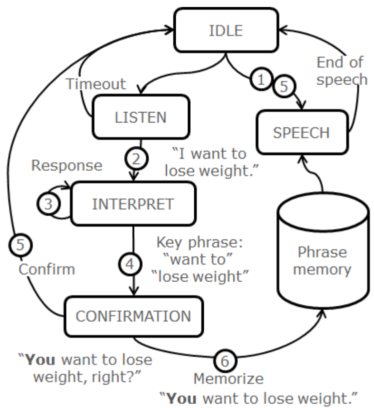


Figure 4. Dialogue flow in our system implementation. Below is an example dialogue resulting from this flow.

Robot (R): (1) "*Why do you want to start exercise?*"
User (U): (2) "*I want to lose weight.*"
R: (3) "*Good*."
System (S): (4) [Find key phrase "*lose weight*"]
S: (5) [Do confirmation]
R: (5) "*You want to lose weight, right?*"
U: (2) "*Right*"
S: (6) [Memorize the phrase]
S: (1) [Ask next question]
R: (1) "*Good. Why do you want to lose weight?*"
U: (2) "*Because …*"

Formative Study

To build a better understanding of the interactions that take place in MI sessions and implement the necessary dialogue acts into the dialogue system, we conducted a formative study that involved human counselors trained in MI carry out counseling sessions with participants. Eight participants (four males and four females) took part in this study. The participants were recruited from an online job posting site and flyers put on the University of Wisconsin–Madison campus. Their ages were between 18 and 25 (M=20.88, SD=2.23). They were compensated $5.00 USD for their time.

We collected video data from eight interviewer-interviewee dyads as they performed MI sessions. In each of these interviews, an experimenter trained in MI played the role of the interviewer and asked the participants questions designed to facilitate reflection on their physical activity. The analysis of the videos involved transcribing and coding the dialogue recorded during the interview tasks. Participants gave a variety of answers and tended to respond in great detail. Consequently, we found it necessary to implement a user response model including not only specific phrases directly related to the question (e.g., "*lose weight*" or "*to be healthier*") but also phrases that describe participant desires and attitudes (e.g., "*want to,*" "*feel,*" or "*think*"). Additionally, we administered a questionnaire before and after the interviews that measured participant motivation.

Evaluation Study

To assess user perceptions and effectiveness of our system, we designed a user study consisting of three conditions: our proposed MI condition (MI), a traditional robot advice condition (TA), and a reading-based intervention condition (CTRL). The goal of each condition was to increase the participants' physical activity. The TA and CTRL conditions had identical content that was delivered by the robot in a monologue in the TA condition and via a document on a computer display in the CTRL condition.

Hypotheses — We developed two hypotheses:
H1: Participants in the TA condition will experience greater increases in physical activity compared to participants in the CTRL condition.
H2: Participants in the MI condition will experience greater increases in physical activity compared to participants in the TA condition.

Procedure and measures — Each participant was involved with the experiment for two weeks, with the intervention being delivered at the conclusion of the first week. At the beginning and end of the experiment (one week prior to and after the intervention) we collected two measures of the participants' physical activity: walking steps (obtained from a pedometer) and responses from the International Physical Activity Questionnaire (IPAQ) [13]. At both of these times, we also collected data from one subjective measure: participants' motivation about physical activity [5]. Furthermore, we gathered information about participants' impressions about each task after the intervention (Figure 5, 6).

Participants — A total of 24 participants (11 females and 13 males) were recruited from an online job posting site and flyers put on the University of Wisconsin-Madison campus. They were aged between 18 and 48 (M=22.78, SD=6.24). To be eligible for participation, participants were required to be aged

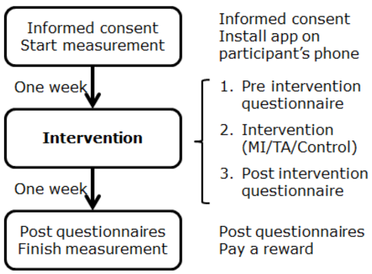


Figure 5. Study procedure.

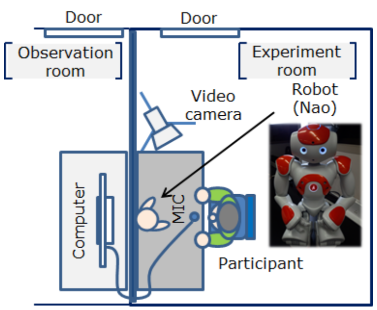


Figure 6. Physical layout of the experimental space.

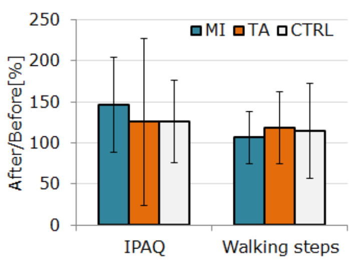


Figure 7. IPAQ and walking steps one week before and after the intervention.

between 18 and 64, native English speakers, free of physical or cognitive disabilities, smartphone users (for the pedometer application), without health concerns from their doctor, in the Pre-contemplation, Contemplation, or Prepare stages of change (assessed via the current DHHS/ACSM guidelines for Physical Activity [7])[10], and involved in low or moderately-intensive physical activity (assessed using IPAQ [13]). Participants received $30.00 USD for compensation.

Results — We present the results from our objective measures in Figure 7, which shows the percent change in the IPAQ measure and walking steps between the week before and after the intervention. We found no significant differences among the conditions across these measures, revealing no objective support for either hypothesis. As illustrated in Figure 8, we found that intrinsic motivation in the TA condition was significantly higher one week after the intervention compared to the week before. Figure 9 shows the results from the willingness for advice scale (two items: "liking" and "willing;" *Cronbach's* α=0.89). We conducted a one-way analysis of variance (ANOVA) to test whether there were differences in the level of willingness between advice conditions and found a significant effect of condition on willingness, $F(2, 21)=4.92$, $p=.02$. We found that the TA condition had a significantly higher level of willingness than the other conditions. Figure 10 illustrates the results from the friendliness of robot scale (four items: "cute," "understanding user," "liking user," and "easy to communicate with;" *Cronbach's* α=0.85). We found the robot in the TA condition was perceived as significantly friendlier than in the MI condition.

Discussion — The results from our objective measures provided no support for our hypotheses. We observed a large amount of interpersonal variance in our physical activity measurements. While we sought to eliminate individuals who are already highly active during recruitment, a significant number of our participants still had a high baseline level of activity, potentially due to occupational demands. A larger participant population and a longer period for measurement may be necessary to identify effects of our manipulation.

Our analysis showed that participants who interacted with the robot providing traditional advice reported higher willingness to receive advice on physical activity than those who interacted with the robot performing MI and received traditional advice on paper. Additionally, we found a significant increase in intrinsic motivation among participants in the TA condition before and after the intervention but not among participants in other conditions. These findings were unexpected, as we predicted the MI approach to more effectively elicit behavior change and positive perceptions from users.

One explanation for the lack of a more positive effect of MI on participant perceptions and behavior is a lack of fluency in the dialogue between the robot and the participant due to errors in speech recognition and incongruous nonverbal behaviors. We observed participants to lean over toward the microphone placed in front of the robot following speech-recognition errors rather than looking toward the robot during their responses. We also noticed that the robot's backchannels interrupted participant speech. We argue that this lack of fluency "broke" the illusion of what they expected in a social interaction based on their experience with human-human interactions. On the

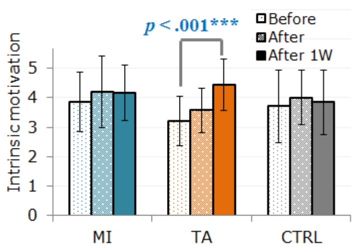


Figure 8. Intrinsic motivation.

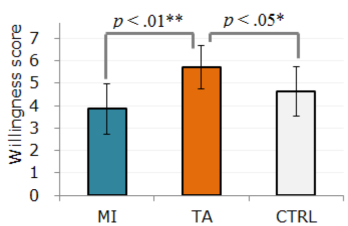


Figure 9. Willingness to receive advice.

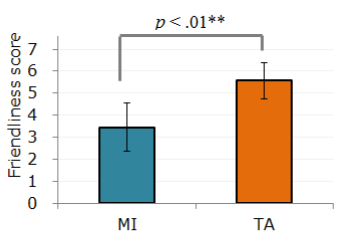


Figure 10. Friendliness of the robot.

other hand, participants responded positively to the monologues performed by the robot in the TA condition, as these scripted behaviors did not suffer from such breakdowns. We expect more robust speech recognition and refined models for behavior generation to help alleviate such breakdowns.

Conclusion

In this Work-in-Progress, we presented the design of an automated counseling system that drew on the MI counseling approach and situated social interaction with a humanlike robot to improve participant motivation and promote behavior change. Our evaluation of the system demonstrated the promise of the embodied social interaction while highlighting potential avenues for future improvement, particularly in improving the robustness and fluency of our dialogue system.

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