Tailorable Autonomous Motivational Interviewing Conversational Agent

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Abstract

In this work, we present our development effort on the Tailorable Autonomous Motivational Interviewing Conversational Agent (TAMICA). TAMICA incorporates Motivational Interviewing (MI) techniques to help parents come up with healthier eating goals for their families. TAMICA builds on an open-source language model GPT-2 and all data are managed within the university network. The system is accompanied by a tailoring interface designed for parents and clinical psychologists to be able to tailor the MI script generated by TAMICA as well as the agent's communicative behaviors. We describe the participatory design (PD) sessions to be held with parents and clinicians to investigate the design requirements of the tailoring interface. These sessions will help tailor the TAMICA system to better suit the health needs and lifestyle constraints of the end users.

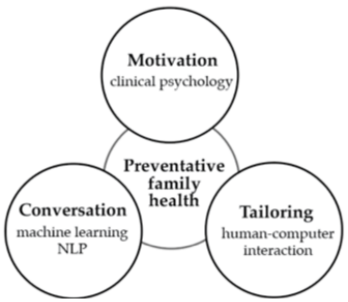
Author Keywords

Family Healthy Eating; Motivational Interviewing; Human-Computer Interaction; VUI; Conversational Agents; Voice Agents.

CSS Concepts

• **Human-centered computing~Human computer interaction (HCI)~HCI design and evaluation methods**; *User studies*;

Conceptual Framework of the TAMICA system



The critical pillars include motivation, conversation, and tailoring for preventative family health. In this work, we focus on discussing the Tailoring pillar of the TAMICA system. Tailoring of the conversational agent will be achieved through an interface for parents and clinicians allowing them to personalize the TAMICA system.

Introduction

Reedy et al. reported high fat foods or sugary drinks account for "empty calories" in the daily caloric intake of approximately 40% of U.S. children [30]. Concerns about obesity [38], and other linked chronic illnesses, including diabetes and cardiovascular diseases are fueling the need to adopt healthy eating behaviors among American children today. Among many factors, parents' feeding styles [25] and preferences towards food carries a significant role in child's eating patterns [34]. Accordingly, involving parents as core participants to the interventions improve children's healthy eating [38].

Motivational Interviewing (MI) Technique is a known effective counseling method that helps individuals interact with the clinician to discover motivations and strategies for personalized behavior change [33]. This interactive approach has been successful in various clinical trials in the contexts of mental health, healthy eating, or addiction as it empowers the individuals by allowing them to tailor the goals as per their needs [11].

Technology-Adapted MI (TAMI) approaches, which deliver adaptations of MI using technology and various types of media [36], have shown to reduce therapist burden [16], foster ways to extend the intervention beyond what a therapist could offer face to face, and expand the range of clients who are underserved (e.g., rural populations) [22]. The current TAMIs, however, would require considering all possible user response scenarios and a priori preparing TAMI's responses accordingly, thus lacking the ability for broader scalability to other behavioral-induced illnesses [36]. Furthermore, these systems will not be effective for the conversations that require in-the-moment reassessment of clients' contextualized, historical barriers and emotional contexts that alter how and when appropriate responses should be delivered.[36]

The solution involves designing, developing, and evaluating a privacy-sensitive and tailorable autonomous conversational agent (CA) called TAMICA (Tailorable Autonomous Motivational Interviewing Conversational Agent). TAMICA will incorporate automated MI to help individuals adopt healthy eating practices, building on the Theory of Planned Behavior [1] and Cognitive Dissonance [2]. Freely available as a web app or as a chatbot through mobile texting, TAMICA will help to facilitate scalable MI interventions in a cost-effective method that is also in an intuitive, accessible, and usable form. TAMICA will build its engine based on open-source software and manage all data locally protected within the Drexel University network.

TAMICA will (1) help parents **increase and maintain motivation** to overcome barriers to eating healthy as a family, (2) help parents **converse** with the agent using MI technique to generate self-formed goals and strategies that work for their specific lifestyle constraints, barriers, and facilitators, and (3) empower parents (as well as clinicians) to **give feedback and tailor the agents' interaction** for themselves as well as others.

To allow for the parents and clinicians to be able to give feedback and personalize the agent's interaction, we designed initial prototypes for the tailoring interface. The tailoring interface will provide for a means of communication between the agent, parents, and clinicians.

in this work, we discuss the preliminary prototypes designed so far and propose using Participatory Design (PD) [37] to inform the tailoring interface design for parents as well as clinicians.

Related Work

Below, we discuss the gaps and opportunities in MI-based Conversational Agents in the context of family's healthy eating.

Healthy Eating, MI Agents, and Interpersonal Interaction Principles

Parents and family food preparers bring a critical role to how children establish their eating habits [5], which will pose a long-term health effect as adults. However, due to multiple barriers related to parenting stress—work-life stress [26], lack of time [4], maternal stress [3], even with parents' high intent to eat healthy as a family, confidence and willingness to eat healthy can continue to be discouraged and hindered [6]. The MI technique has emerged as an effective counseling model for diet modification [32, 40, 41]. MI helps to use nonconfrontational and person-centered approach to help clients resolve ambivalence, reduce resistance, and foster commitment to lifestyle changes in modifying healthy behavior [41]; especially when the change requires resolving environmental, economical, and cultural complexities [31].

Many technology-adapted MI (TAMI) were tested as efficacious in delivering low-cost solutions to behavior modification [36]. These agents, however, were developed using extensive branching logic, which requires manual coding for each agent's context. A systematic review showed very few TAMIs operate on all four core pillars of the "spirit of MI": collaboration, support of autonomy, evocation, and empathy [21]. Making meaningful therapeutic change requires these elements of MI, and the agent flexibly adjusting to interpersonal cues on-the-fly [12]. Interpersonal Interaction Principles (IIP) represents the underlying complexity that drives the quality of the therapeutic alliance during therapist-client interaction [12, 15, 27]. Thus, IIP can play a pivotal role in psychological interventions and clinical outcomes, and concentrated efforts were made to manipulate various facets of the therapist-client dyad to elucidate the impact that these variables have on rapport, dropout, and treatment outcomes [23]. The natural next step in building scalable, sophisticated MI agents would be to enable IIP, requiring dynamic, in-the-moment responses in reaction to users' input, rather than following a static, pre-determined transcript that supports a finite range of clients' emotions and responses.

User Tailoring of Agent Design

Tailoring the intervention to each client plays a critical role in maximizing therapeutic change. While the terms vary across literature, tailoring involves making something suitable for individuals' needs through implicit (e.g., automated modeling based on observed user interaction with system) and explicit processes (e.g., users' stated preferences of functionality, content, interface) [17, 29]. Kocaballi [18] found that, out of 1,958 studies on the use of CAs in health care, only 13 papers discussed personalization features. These features, however, were implemented without theoretical frameworks or prior evidence [8, 28, 39]. Only two studies have reported allowing conversational

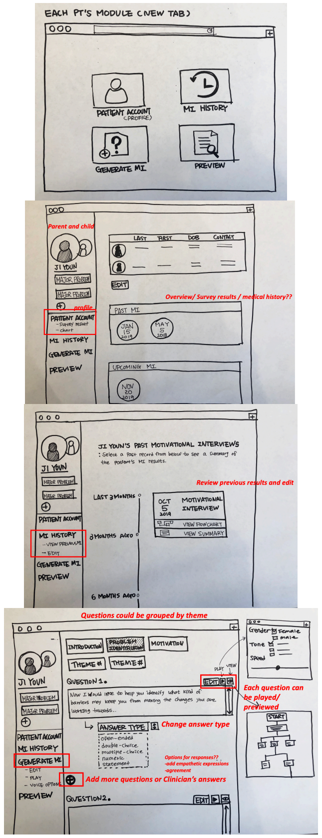


Figure 1: TAMICA's tailoring interface for Clinicians. Clinicians can view patient's profile, view patient's MI history, generate automated MI script for each patient, and tailor the MI script generated by TAMICA which better suits the needs and goals of the patient.

styles to be tailored, such as affect-adaptive feedback [19, 20]. This lack of conversational adaptation can impede user experience, especially when certain cultural or interest groups show more effect when the therapeutic partner shares similar communication styles [10]. Adaptive conversational strategies improve system performance, usability, and efficiency [7, 9]. For instance, shorter questions should be used for follow-up sessions [42] or didactic, relational, or motivational conversational styles can address unique user needs and goals of the intervention [35]. Tailoring has been underexplored, despite its critical role and effectiveness in increasing motivation and user experiences in using an automated therapeutic system due to the technical limitations in sophisticating communication stylistic tailoring in an automated system.

Participatory Design Research Method

Holzinger argued placing a 'human-in-the-loop' in machine learning problems greatly reduced the complexity of problems which would otherwise take much effort and time to solve [13, 14]. Tailoring an AI agent's interactions according to the needs and goals of each individual is one such complex problem which would benefit such an approach of involving users in modifying the machine learning processes and giving feedback to retrain the agent. Participatory design research method [37] allows for early validation of ideas and fleshing out the design requirements by directly involving the end users. Participatory design research method also allows for stronger acceptance of the technology designed among the targeted users as they are involved in the decisions early on which result in the final designs [24]. We propose to apply this method of research to inform our design decisions around the tailoring interface for the TAMICA system.

Method

To provide parents and clinicians to easily tailor TAMICA according to the needs and goals of the parents, we designed the initial prototypes of the tailoring interface. Here, we discuss the prototypes and the process which we adopted to arrive at the design decisions. We then describe plans to conduct participatory design sessions to develop the design requirements for the tailoring interface.

User Tailoring Interface Prototypes for Clinicians

The tailoring interface ensures the presence of users' feedback in training and designing the automated MI component of TAMICA. Two of our collaborators—one nurse MI expert and a clinical psychologist trainee—spent weekly 1.5 hour meetings with the team consisting of HCI, natural language processing, and machine learning experts for 3 months formulating the overall TAMICA structure, its design, and the tailoring interface. This continued interdisciplinary collaboration led to the preliminary formulation of design requirements for the tailoring interface for clinicians as presented below.

Although the TAMICA system we build currently will be tested as research prototype purposes, the eventual scenario of TAMICA will be a supportive addendum to existing clinical sessions with clinicians. The target clinician users of this interface would be clinical psychologists, nutritionists, or MI experts. The goal of the tailoring interface for clinicians includes direct manipulation of MI scripts, including choices of probing questions and the pace at which parents arrive at their

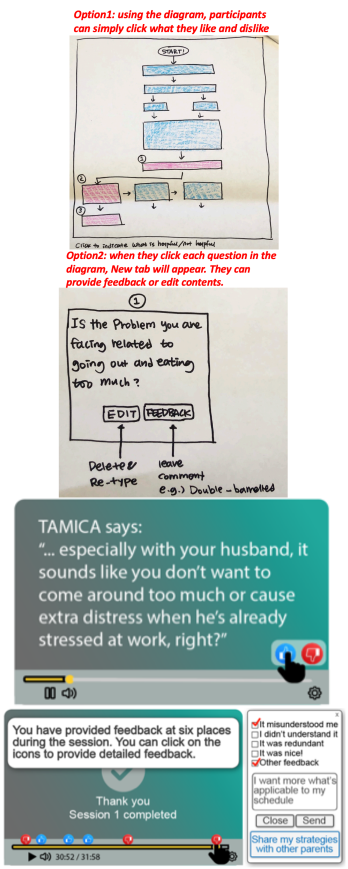


Figure 2: Prototypes of TAMICA's feedback system for Parents. Parents can give quick and detailed feedback on the MI script. This feedback will be used to improve the TAMICA's automated machine learning component.

goals and strategies. The interface also allows tailoring of communication styles (authoritative vs. informal). Clinicians can also choose dosage--frequency and intervals of the TAMICA sessions.

When clinicians log into the tailoring interface, they will be shown a list of their patients. They can visit a particular patient's profile (usually a parent-child dyad) to see the parent and child's needs, goals, and barriers for healthy eating. Based on the pieces of information available about the parent and child, the clinician can automatically generate a template MI script. After the script is generated by TAMICA, the clinician can then choose to modify the script by clicking at various places on the script. The clinician will also be able to hear how TAMICA's MI script will sound to the patient, and be able to change the verbosity, the tone, gender, and communication styles (empathetic, didactic, motivational). This will aid in clinicians tailoring the MI script to better suit the needs and goals of the patient. The screens for the same have been prototyped in Figure 1.

User Tailoring Interface Prototypes for Parents

The team regularly visited community advisory board meetings of community health centers in the neighboring areas to gain insights on parents' needs around healthy eating at home. Together with the clinical collaborators' insights gained from their experiences working with parents, we developed initial starting points for patients' needs and goals for the tailoring interface. The interface would allow parents to tailor and give feedback on the MI scripts generated by TAMICA, its appropriateness, and any shortcomings that TAMICA showed during the MI sessions. The feedback system for parents has two main aspects to it. The first is making the feedback system real-time while parents are in a MI session with TAMICA, and the second is giving feedback after the session. In the initial feedback interface prototype, quick real-time feedback can be given by those parents who are either new to the MI sessions or will not have time to give detailed feedback. Figure 2 shows this initial design of the parents' feedback interface. Here, the parents can provide quick, real-time feedback on the script during the session, and later reflect on their feedback and provide more detailed feedback as needed.

The interface should also help parents to personalize before and after the MI sessions given their parenting needs and health profiles. Similar to the clinician tailoring interface, the parents can look at their profile, their past MI sessions with TAMICA, and schedule their upcoming MI sessions. Parents can also fill any self-reports sent by the clinicians (See Figure 3). The parents can also directly interact with the clinician through the message center.

Participatory Design Sessions

Based on these screens, we will conduct participatory design sessions with 5-6 clinicians (clinical psychologists, nutritionists, MI experts). We will also conduct participatory design sessions with 20 parents to help us validate and expand the initial design decisions. We will develop the following design requirements from the participatory design sessions:

- The acceptability of the tailoring interface by the parents and clinicians.
- Probing the participants' existing experiences working with conversational agents to understand whether they felt they wanted to

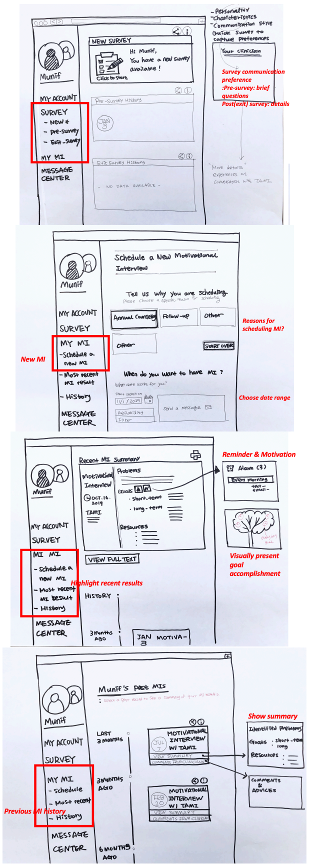


Figure 3: TAMICA's tailoring interface for Parents. Parents can view their profile, their past and upcoming MI sessions, complete surveys pre- and post-sessions, and can also message the clinicians directly in case of questions.

change any aspect of the communication style of the agent.

  - Understanding how the current feedback system can better allow parents to achieve this.
  - Understanding how the current MI tailoring system can better allow clinicians to do this.
- The perceived usefulness of the feedback system design in helping parents provide feedback to TAMICA.
- The perceived usefulness of the tailoring interface in helping clinicians modify the automated MI script generated by TAMICA to better suit the needs and goals of their patients.

Conclusion

Tailoring the interactions of an AI agent in accordance with the needs and goals of the targeted users has been underexplored in automated therapeutic systems. The tailoring interface we propose to design and develop is a novel feature of the TAMICA system that will help tailor the conversational agent from the perspective of two different users, i.e., the clinicians and the parents. Examining the design requirements and perceived acceptability of the tailoring interface for clinicians and parents will help us further expand the field's understanding around human-in-the-loop component for AI systems [13, 14]. This work will further inform how conversational agents and AI systems can be tailored by the multiple stakeholders of the system.

Acknowledgements

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