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A Robotic Coach Architecture for Elder Care (ROCARE) Based on Multi-user Engagement Models

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***Abstract*—The aging population with its concomitant medical conditions, physical and cognitive impairments, at a time of strained resources, establishes the urgent need to explore advanced technologies that may enhance function and quality of life. Recently, robotic technology, especially socially assistive robotics has been investigated to address the physical, cognitive, and social needs of older adults. Most system to date have predominantly focused on one-on-one human robot interaction (HRI). In this paper, we present a multi-user engagement-based robotic coach system architecture (ROCARE). ROCARE is capable of administering both one-on-one and multi-user HRI, providing implicit and explicit channels of communication, and individualized activity management for long-term engagement. Two preliminary feasibility studies, a one-on-one interaction and a triadic interaction with two humans and a robot, were conducted and the results indicated potential usefulness and acceptance by older adults, with and without cognitive impairment.**

***Index Terms*—human-robot interaction, socially assistive robotics, system architecture, elder care, affective computing**

I. Introduction

In 2010, 13% of the US population was 65 years or older and this number is projected to double by 2030 with the oldest-old, those 85 years and older, growing at the fastest pace; this is the group most likely to have problems with physical functioning, functional decline, cognitive impairment, dementia, falls, and injury [1][2][3][4]. Up to 70% of older adults will develop significant disabilities and 35% will eventually reside in assisted living or enter a nursing home [5]. Health care costs for the behavioral consequences of these disorders are staggering [3][6]. Thus, maintaining or improving physical and cognitive function, promoting communication and social interaction, and enhancing engagement are pivotal in geriatric care.

Nonpharmacologic interventions for these disorders such as physical activity, exercise, social interaction and engagement, cognitive stimulation, music, art therapy, reminiscence therapy, and caregiver intervention have had inconsistent results [7][8] and can be resource intensive. Additionally, considering nursing shortage and high staff turnover in long term care settings, there is an urgent need for efficacious strategies that are tailored to the individuals within resource strained environments. Recently, socially assistive robotic (SAR) systems appear promising in addressing the physical, cognitive and/or social needs of older adults. A SAR system, unlike robotic wheelchair and exoskeleton, provides assistance and/or achieves measurable user progress through social interaction [9]. As compared to other interactive technologies, SAR has the advantage of embedding novel quantitative metrics, sensor-based non-invasive methodologies, incorporating physical movement into realistically embodied interactions, and meaningfully responding to pivotal aspects of human engagement and behavior, and thus has substantial promise for impacting function and engagement of older adults.

Earlier work of SAR systems with older adults [10][11] primarily fall into two categories: companion robots, generally animal shaped, for social engagement [12], and service type robots supporting independent living, such as intelligent reminder etc. [13]. There is a growing interest in SAR systems that act as a coach or a guide to engage and encourage users through a series of therapeutic tasks for enhancing their physical or cognitive functions, as well as their health conditions. *We refer to such systems as robotic coach systems.* Several investigators have used the Wizard of Oz (WoZ) experimental paradigm [14] or open-loop robotic systems [15]. These systems are limited in their capacity for HRI, requiring remote human control for change of robot behaviors, and often times requiring sophisticated users.

More recently, closed-loop robotic systems have been developed. Commercial robots NAO [16][17], RoboPhilo [18], and Manoi-PF01 [19] were used to build robotic coach systems

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to assist older adults in performing physical exercises. Fasola and Matarić [20] designed and implemented a robotic coach system, Bandit, that monitored and encouraged older adults to perform chair exercises. Bandit personalized its interaction via task performance, progress, and session history. Tapus et al. [21] tested the effectiveness of robot-mediated cognitive intervention with dementia patients once per week over eight months and observed an improvement in task performance. These works relied on explicit task performance as feedback to adapt robot's behaviors. McColl et al. included implicit channel of communication in their robotic system Brian 2.1 [22]. Brian 2.1 was developed to engage older adults in eating activity and a cognitive stimulation activity, and had the capability of adapting its behavior based on the state of the activities as well as user's body language (attentive or distracted). These researchers also developed a robotic system Tangy [23][24] for use in long-term care facilities to provide telepresence and group-based cognitive intervention. Robotic coach systems were also developed for stroke rehabilitation, autism intervention, and weight loss [21][25][26].

Most systems to date have predominantly focused on one-on-one interaction. Multi-user interaction is pivotal for fostering social interaction. Only two studies to our knowledge have investigated group-based closed-loop robot-mediated interaction for older adults. Kanoh and associates devised a robot-assisted activity program comprised of one robot with five to six human participants, but required one human assistant to mediate communication between the robot and the participants [27]. Louie and associates were able to provide autonomous interaction by the robot with an individual, but not between individuals [24]. The objective of this work was to develop a robotic coach system architecture that allows effective interaction with one or multiple older adults and achieve long-term engagement for the purpose of maintaining functional abilities as well as socialization. In this paper, we present the mathematical models of the system architecture which a) is capable of one-on-one interaction and multi-user interaction; b) contains both explicit and implicit channels of communication; and c) allows dynamic adaptive robotic behavior and activity management based on real-time human interaction. Further, we performed two feasibility studies on older adults to assess our design paradigm and test on older adults' acceptance of the robotic coach system.

The paper is organized as follows. Section II presents the mathematical models of the RObotic Coach ARchitecture for Elder care (ROCARE) and places it in context with existing SAR architectures. Section III describes the preliminary feasibility studies and system implementation. Section IV and V presents the results and discusses their implications, respectively. Finally, we summarize the contributions of the paper and highlight future directions in section VI.

II. Design of a Robotic Coach System Architecture

The primary goals of the ROCARE are: a) it should be able to adapt its behavior to each individual user as the HRI progresses; b) it needs to perform quantitative measurements of the user's task performance on activities, as well as the user's affective states and gaze position; c) the robotic coach system must be designed so that it can be operated by a non-technical caregiver; and d) the system can target activities designed to be beneficial in addressing mobility and functioning simultaneously satisfying user's preferences and ability. To achieve these goals, ROCARE needs to have the following features: a) multimodal HRI; b) individualized robot behavior adaption; c) rigorous measurements and well-structured task design; and d) administrator friendly control panel.

ROCARE (Fig. 1), which possesses the aforementioned characteristics, is comprised of five modules: *Sensing*, *Actuation*, *Database*, *Supervisory Controller* and *Graphical User Interface* (GUI). A human administrator is responsible for initializing the session and monitoring task progression via the GUI. *Database* maintains a knowledge base of each user to facilitate the decision-making process of the *Supervisory Controller*. *Supervisory Controller* is the core element of ROCARE. It estimates the states of HRI and human-human interaction (HHI) based on engagement models, and generates control policies for dynamic system adaptation. Users interact with ROCARE through *Sensing* and *Actuation*. *Sensing* collects both implicit and explicit interaction cues from users, whereas *Actuation* performs the actions the system needs to take as determined by the *Supervisory Controller*. The five primary modules are composed of submodules that are responsible for specific functionalities.

A. Comparison with Existing SAR Architectures

There are several existing SAR architectures designed for behavior intervention for children with autism spectrum disorder [28], functional intervention or companion purpose for older adults [13][20][24][29][30][31][32], as well as other applications [33][34]. All these architectures including ours have component(s) or module(s) dedicated to sensing and actuation, which provide the interface between SAR systems and targeted users; and decision making, for system behavior adaptation. SAR Architectures in [28] and [20] incorporated a database to store HRI history. In ROCARE, the submodule

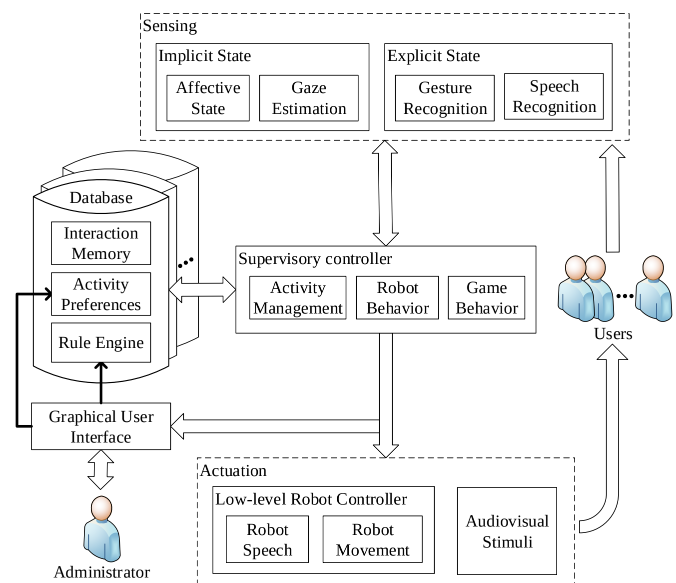

Fig. 1. Robotic coach system architecture (ROCARE).

interaction memory in *Database* serves a similar purpose.

Our approach is tightly coupled with the primary goals described earlier and results in some differences and rearrangements of the modules. First, in *Sensing* we modified and extended the Sensory Input Recognition and Analysis Modules proposed by Chan and Nejat [29] [30] and the User State and Activity State Modules presented by Louie et al. [24]. The *implicit state* submodule in ROCARE is dedicated to implicit channel of communication between the SAR system and users, whereas the *explicit state* submodule is dedicated to explicit channel of communication. Second, two submodules, *activity preferences* in *Database* and *activity management* in *Supervisory Controller*, were added to keep track of user's preferences and select appropriate activities for the purpose of promoting engagement while maximizing the efficiency of the interaction. Third, we integrated a GUI to allow intuitive control, operation, and monitoring of the robotic coach system by an administrator.

Several characteristics distinguish ROCARE: a) mathematical models for each module and relationships among modules instead of simple interconnection; b) engagement models to capture the dynamics of HHI and HRI; c) capacity for both one-on-one interaction and multi-user interaction; and d) generalizability of the architecture for different HRI scenarios. In what follows, we describe each module along with its submodules in detail.

B. Engagement Models

In HRI, engagement is a critical component, defined as the act of being occupied or involved in an external stimulus [35]. We capture the dynamics of HHI and HRI using engagement models. Our models leverages the models for multiparty engagement proposed by Bohus and Horvitz [36]. We adopted their idea of representing user engagement using three engagement variables but modified the model for each engagement variable. The three engagement variables for each agent $a \in \{user(s), robot\}$ and interaction $i \in \{HRI, HHI\}$ are: the engagement state $ES_a^i(t)$, the engagement action $EA_a^i(t)$, and the engagement intention $EI_a^i(t)$.

The engagement state $ES_a^i(t)$ represents whether agent a is involved in interaction i and is modeled by a timed automaton with two states: *engaged* or *not-engaged* (Fig. 2). We presume that all agents are in the state *engaged* at the beginning of the interaction. Since engagement is a collaborative process, agent a is *engaged* either with an engagement action $EA_a^i(t)$ initiated by agent a, such as gestures or direct responses, or with engagement intention $EI_a^i(t)$, which indicates agent a is

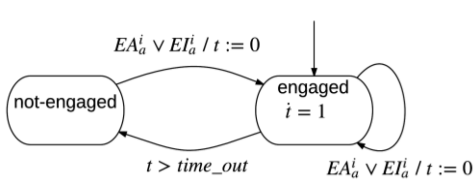

Fig.2. Timed automaton model of $ES_a^i(t)$

paying attention to other agents. Agent a becomes disengaged, in state *not-engaged*, if he/she is not actively involved in the interaction for *time_out* amount of time. The engagement action $EA_a^i(t)$ is estimated by a conditional statistical model of the form:

$$P(EA_a^i(t) \,|\, \Psi_a(t), \{ES_a^i(t-1)\}_{a\in\Omega,i}, \{ES_a^i(t)\}_{a\in\Omega,i}, \Lambda(t)) \quad (1)$$

Occurrence of engagement action of agent a in the interaction i depends on gestures, speech or direct inputs detected by the system, i.e., *explicit state* of agent a $(\Psi_a(t))$; previous engagement states of all the agents in the interaction i $(\{ES_a^i(t-1)\}_{a\in\Omega,i})$; current engagement states of all the agents in the interaction $(\{ES_a^i(t)\}_{a\in\Omega,i})$; and the current game behavior $(\Lambda(t))$. Similarly, the engagement intention $EI_a^i(t)$ is estimated by:

$$P(EI_a^i(t) \,|\, \Gamma_a(t), \{ES_a^i(t-1)\}_{a\in\Omega,i}, \{ES_a^i(t)\}_{a\in\Omega,i}) \quad (2)$$

where $\Gamma_a(t)$ denotes the agent's *implicit state* detected by the system, including affective states (engaged, bored, frustrated, etc.) as well as direction of attention measured by gaze position. We describe $\Psi_a(t)$ and $\Gamma_a(t)$ in more detail in the next section. For agent $a = robot$, $\forall t \in \mathbb{R}, i \in \{HRI, HHI\}$, $ES_a^i(t) = engaged, EI_a^i(t) = true$.

C. Sensing and Actuation

The multimodal HRI feature is reflected in *Sensing* and *Actuation*. *Sensing* is responsible for logging and interpreting data collected by sensors and cameras. It is composed of *implicit state* $(\Gamma_a(t))$ and *explicit state* $(\Psi_a(t))$. *Implicit state* facilitates the inference of the engagement intention of agent a through affective states recognition and gaze estimation. For example, in a multi-user interaction scenario, when the robot is interacting with one user, another user may be engaged by having eye contact with the robot even though he/she is not directly involved in the interaction. *Explicit state* aids the inference of the engagement actions. According to the context of the interaction, i.e., game behavior $(\Lambda(t))$, detected gesture or speech inputs are engagement actions if they are directly related to task performance. Otherwise, based on the previous and current engagement states of all the agents, detected $\Psi_a(t)$ may be social cues during interaction (an engagement action) or random noise (not an engagement action).

Both $\Gamma_a(t)$ and $\Psi_a(t)$ are detected by *Sensing* and are sent to the *Supervisory Controller* to estimate $EA_a^i(t)$ and $EI_a^i(t)$. *Sensing* communicates with *Supervisory Controller* in two modes: a) sending current *implicit state* and *explicit state* upon request. For instance, the *Supervisory Controller* queries *gesture recognition* about the user's performance on the exercise motions during the physical exercise task. b)

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Whenever a significant event is detected. Example of a significant event is the user's gaze shifts away when the robot is dancing, which indicates the user is not interested or distracted; in this event, actions need to be taken to reengage the user. Behaviors of the robotic system are generated via *Actuation*, which consists of the *low-level robot controller* and *audiovisual stimuli*. *Low-level robot controller* manages and controls the robot hardware to realize *robot behavior*, a.k.a. $\left\{EA_a^i\left(t\right)\right\}_{a=robot,i}$, while the *audiovisual stimuli* operates all the other hardware involved in the interaction, e.g. monitors, and updates the *game behavior* $\Lambda\left(t\right)$.

D. Database and Graphical User Interface

Database contains three main submodules: *interaction memory*, *activity preferences*, and *rule engine*. It is individualized; in other words, each user $a\in\left(\Omega-\left\{robot\right\}\right)$ has his/her own database which is independent from other databases. *Interaction memory* stores the history of HHI and HRI, represented by the following tuple:

$$\left\langle ES_a^i\left(t\right),EA_a^i\left(t\right),EI_a^i\left(t\right),\Psi_a\left(t\right),\Gamma_a\left(t\right),\Lambda\left(t\right)\right\rangle_{a,i\in\Omega,t\in\mathbb{R}} \quad (3)$$

Activity preferences and *rule engine* submodules provide key information for activity management. They maintain three sets of parameters, including each user's degree of likes and dislikes regarding different types of activities AT (AP_a^{AT}), the importance of each activity type for each user (AI_a^{AT}), and the appropriate difficulty level of each activity type for each user (D_a^{AT}). These parameters are updated during the interaction based on the following model:

$$AP_a^{AT} = f_1\left(\left\{ES_a^i\left(t\right)\right\}_{a,i\in AT,t\in\mathbb{R}}, f_{GUI}\left(AP_{GUI}\right)\right) \quad (4)$$

$$AI_a^{AT} = f_2\left(\left\{\Lambda\left(t\right)\right\}_{t\in\mathbb{R}}, f_{GUI}\left(AI_{GUI}\right)\right) \quad (5)$$

$$D_a^{AT} = f_3\left(\left\{\Psi_a\left(t\right),\Gamma_a\left(t\right),\Lambda\left(t\right)\right\}_{a,t\in\mathbb{R}}, f_{GUI}\left(D_{GUI}\right)\right) \quad (6)$$

AP_a^{AT} is a function of user's engagement state corresponding to activity AT, as well as direct input by an administrator through the GUI. AI_a^{AT} is a function of the history of the game behavior, i.e., past activities, and changes made via the GUI. And the difficulty level parameters D_a^{AT} is determined by the user's task performance and implicit state, as well as GUI inputs. f_{GUI} is a monotonically increasing function which weighs the direct inputs from the GUI. The sole purpose of the GUI is to allow non-experts to operate ROCARE and monitor the progress.

For illustrative purposes, we give an example of updating AP_a^{AT}. We assume that there are m types of activities and $\sum_{AT=1}^{m}AP_a^{AT}=1$; the user likes the activity if he/she is engaged for more than half of the activity duration and the weights for engagement and GUI inputs are w_{ES} and w_{GUI} respectively. Initially, $\forall AT$, $AP_a^{AT}=1/m$. The robotic system starts with the activity "dance to music". At the end of this activity, the new set of AP_a^{AT} is calculated as:

if $AT=music$,

$$\Delta AP_a^{AT} = w_{ES}\cdot\left(\sum_{t=ATstart}^{ATend}ES_a^i(t)\Big/\sum_{t=ATstart}^{ATend}t-0.5\right) + w_{GUI}\cdot\Delta AP_{GUI} \quad (7)$$

$$AP_a^{AT} = \frac{1}{m}+\Delta AP_a^{AT} \quad (8)$$

$\forall AT\neq music$,

$$AP_a^{AT} = \frac{1}{m}-\frac{\Delta AP_a^{music}}{m-1} \quad (9)$$

E. Supervisory Controller

Supervisory Controller is responsible for making autonomous decisions related to the robot's behavior ($\left\{EA_a^i\left(t\right)\right\}_{a=robot,i}$) and task adjustment ($\Lambda\left(t\right)$) (e.g., repeat the exercise, establish mutual gaze, etc.) regarding the ongoing activity chosen by *activity management*. *Activity management* is dedicated to activity selection and scheduling by analyzing AP_a^{AT}, AI_a^{AT}, and the goal of the system (G). In a one-on-one interaction scenario, it can be realized by simply selecting the activity that has the highest $AP_a^{AT}+AI_a^{AT}$ value. System goal can be represented by the engagement variables. For example, in one-on-one interaction scenarios, the system goal could be to maximize user engagement during HRI, i.e., $G=\max_{HRI}(ES)$, whereas for the multi-user case, the goal could be to maximize user engagement with another user, i.e., $G=\max_{HHI}(ES)$. *Robot behavior* and *game behavior* are either controlled by a reactive model or through learning algorithms. The control policies for *robot behavior* and *game behavior* are conditioned on task difficulty level D_a^{AT}, the engagement variables of all the users $\boldsymbol{EV}$, previous robot behavior and game behavior $\boldsymbol{H}$, and the goal of the system G.

$$\boldsymbol{EV}=\left\langle ES_a^i\left(t\right),EA_a^i\left(t\right),EI_a^i\left(t\right)\right\rangle_{a\in\left(\Omega-\left\{robot\right\}\right),i\in AT,t\in\mathbb{R}} \quad (10)$$

$$\boldsymbol{H}=\left\langle\left\{EA_a^i\left(t'\right)\right\}_{a=robot,i\in AT,t'<t},\left\{\Lambda\left(t'\right)\right\}_{t'<t}\right\rangle \quad (11)$$

$$\pi_{robot,game}\left(\left\{D_a^{AT}\right\}_{a\in\left(\Omega-\left\{robot\right\}\right),AT},\boldsymbol{EV},\boldsymbol{H},G\right) \quad (12)$$

III. Feasibility Studies

We conducted two preliminary feasibility studies to determine whether ROCARE a) can be used for both one-on-one and multi-user interaction; and b) could engage older adults' interest and participation. While the architecture does not assume any particular robot, our system was built around the NAO robot platform (www.aldebaran.com) because of its availability as well as its open architecture that allows relatively easy pathways for custom software development and integration with other devices.

A. HRI Scenarios

Scenario 1 – individual user performing multiple activities. This scenario was designed to explore older adults' behaviors and responses to ROCARE, and the feasibility of inferring their engagement intention variables ($EI_a^i(t)$) based on implicit communication cues, in this specific case, through electrophysiological signals and gaze position ($\Gamma_a(t)$). Several activities were selected: an orientation activity where the robot points to pictures hanging in the experiment room, simple math, observing the robot dance to music, a form of the "21 questions" game where the robot guesses the person's birth state, and joint chair exercises. Each participant sat in a straight back chair directly in front of and six feet away from the robot. Three pictures were hung on the walls of the experiment room at different locations. Electrophysiological sensors were placed on the head and the body of the participant. A Kinect RGBD sensor was used to augment NAO's vision for gesture recognition and gaze estimation. A researcher initiated and observed the session via the GUI and a one-way mirror in an adjacent room.

Scenario 2 – paired users performing single activity. We extended the interaction to allow simultaneous interaction with two older adults mediated by the robotic coach. The triadic HRI scenario consisted of introduction and "Simon says" game [37], where each individual and the robot took turns as Simon. Physiological sensors were excluded in this scenario.

1) One-on-one Interaction

The implemented *Sensing* module is capable of electrophysiological signal collection, gaze estimation, gesture recognition, and speech recognition. We used a 14-channel Emotiv EPOC neuroheadset (www.emotiv.com) to record electroencephalography (EEG) signals, and a Biopac MP150 physiological data acquisition system (www.biopac.com) to collect physiological data. The bandwidth of the EEG signals is from 0.2 to 45Hz and the sampling rate is 128Hz. Regarding physiological signal, tonic and phasic responses from galvanic skin response (GSR), were logged with a sampling rate of 1000Hz. These signals have been shown to be sensitive to affective states in our previous work as well as others [38][39][40]. The signals were collected for offline analysis.

Gaze estimation was approximated by participant's head pose around yaw axis (horizontal head turn) extracted from the Kinect Face Tracking engine. For *gesture recognition*, we adapted a rule-based finite state machine (FSM) gesture recognition method [26] based on the upper body skeletal data from Kinect to accommodate for motor control declines in older adults. Both skeleton and head pose were updated at a frame rate of 30Hz. *Gesture recognition* was used during the joint chair exercise activity for monitoring participant's performance on an exercise motion demonstrated by the robot. Four gestures were recognized, including raise one arm up, raise both arms up, extend arms to the sides, and wave. The robot provided feedback prompts based on older adult's performance and then demonstrated the next exercise motion. *Speech recognition* was designed to understand three types of user responses: affirmative answer (e.g., yes, sure, ok, correct), negative answer (e.g., no, wrong), and repeat question (e.g., repeat). We are aware of the limitations of NAO's speech recognition software. It requires participants to speak loudly and is sensitive to different accents. Even though we informed the participants to speak loudly and clearly, and provided a word list that robot could understand, there were times when they forgot robot was not as intelligent as a human and would engage in conversation! For these experiments, we increased the robustness of *speech recognition* by asking the administrator to select the correct user response using the GUI. Both *gesture recognition* and *speech recognition* were in idle states unless invoked by the *Supervisory Controller*.

Fig. 3(a) illustrates the *Supervisory Controller* for one-on-one interaction. *Activity management* scheduled the five activities in a predefined order as shown in the figure. The control policy for *robot behavior* and *game behavior* was modeled using hierarchical FSMs. We expanded the hierarchical FSM and participant's engagement model during the math activity, shown in Fig. 3(a). The set of states in the hierarchical FSM model of control policy represents *robot behavior* and *game behavior*. The machine starts in state *s0*, which has a refinement that is another FSM with states and transitions designed to realize the math activity. When the engagement state of the participant is *not-engaged*, the machine transitions to state *s1*. In this state, robot gently prompts the participant to come back to the activity. The transition from *s1* to *s0* is guarded by *engaged* and is a history transition. When this transition is taken, the destination refinement *s0* resumes in whatever state it was last in. This ensures that the robot does not restart the activity from the beginning. The refinement FSM initially enters the state *Start activity* and sends the start marker to the electrophysiological data acquisition systems. For each math question, the robot either repeats the question or gives feedback based on the participant's response. The activity ends after finishing all the math questions or if the participant indicates his/her unwillingness to proceed. In this activity, the engagement action variable of the participant $\left\{EA_a^i(t)\right\}_{a=user,i}$ was conditioned on *speech recognition* and *game behavior*, and the engagement intention variable $\left\{EI_a^i(t)\right\}_{a=user,i}$ was conditioned on *gaze estimation*. Since *speech recognition* was enabled only when robot expected a response from the participant, $\left\{EA_a^i(t)\right\}_{a=user,i}$ is true when *speech recognition* return values and is false otherwise. The participant's gaze, on the other hand, was monitored continuously. The Kinect Face Tracking engine tracked the head pose yaw angle from -45 degrees (turn towards the right) to 45 degrees (turn towards the left). $\left\{EI_a^i(t)\right\}_{a=user,i}$ is true when the participant's gaze focuses on the robot, defined by $|yawAngle| \le 28$. The engagement state transitions in Fig. 3(a) indicates that when the participant looks away from the robot over a consecutive

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three-second time window, his/her engagement state $\left\{ES_a^i\left(t\right)\right\}_{a=user,i}$ changes to *not-engaged*. The engagement state model omitted $\left\{EA_a^i\left(t\right)\right\}_{a=user,i}$ because responding to the robot is usually accompanied by mutual gaze.

The robot's movement and speech were controlled through the NAOqi programming framework. A library of primitive robot motions, such as cheers, pointing, etc., were established. The primitive robot motions together with robot speech were building blocks for robot behaviors.

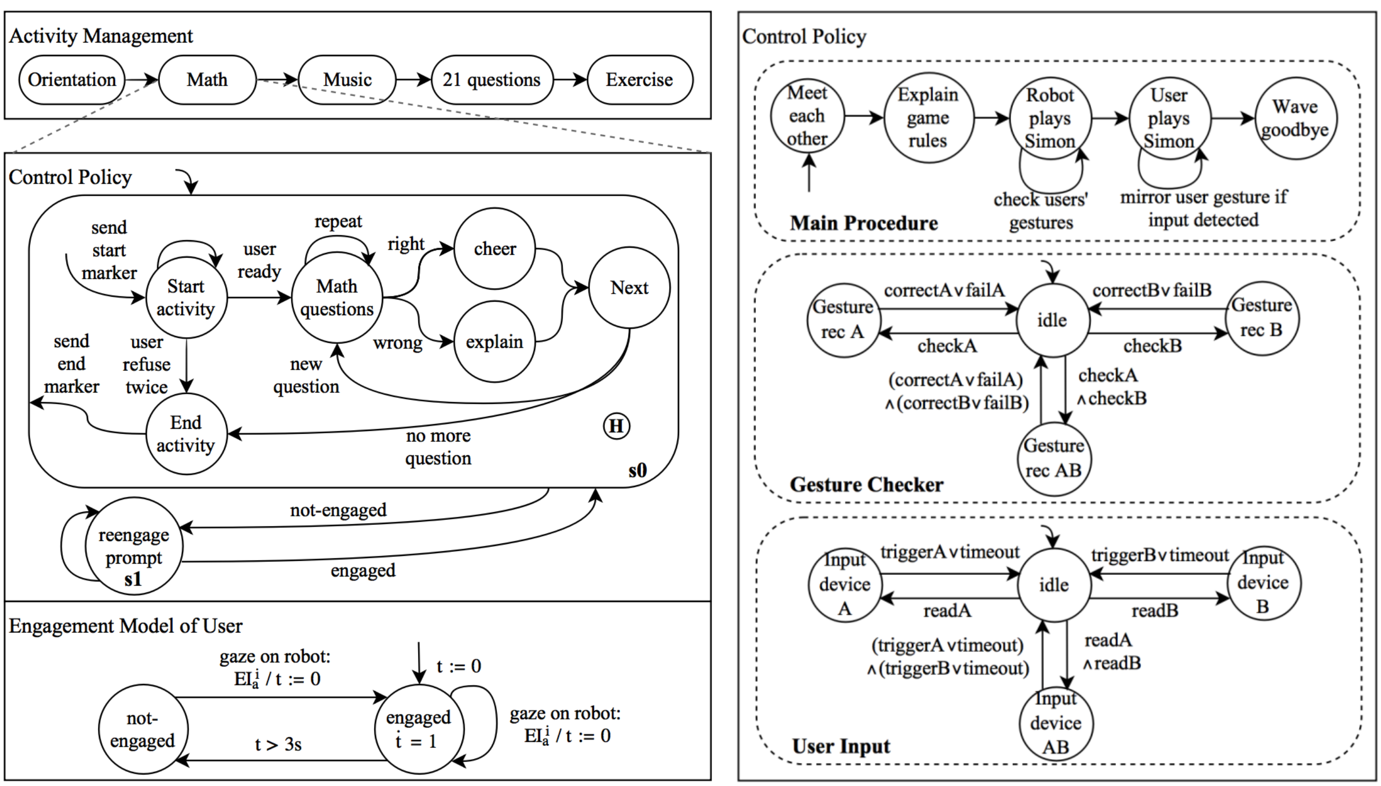
2) Triadic Interaction

The chair exercise activity was expanded into a form of "Simon says" game in this HRI scenario. One player takes the role of Simon and instructs other players to perform physical movement. The other players should only follow the instructions prefaced with the phrase "Simon says". Due to the technical challenge of recognizing speech inputs from two individuals at the same time, we used a Razer Hydra (sixense.com), which has two separate controllers, to record trigger buttons click inputs instead. The control policy modeled by a hierarchical FSM is shown in Fig. 3(b). There are three AND states, *Main Procedure*, *Gesture Checker*, and *User Input*, implemented using threads and processes with socket communication. The refinements of *Gesture Checker* and *User Input* control the communication between *Supervisory Controller* and *Sensing*. *Robot behavior* and *game behavior* were defined in the refinement of *Main Procedure*. The initial state is *Meet each other*, when the robot and the participants introduce themselves and say "hi" to each other. In the next state the robot explains the rules to the participants. The transition from *Explain game rules* to *Robot plays Simon* takes place if both participants indicate understanding of the rules. The robot leads the chair exercise first. It checks the performance of each participant and provides feedback prompts. When the robot finishes three or four commands, each participant takes turns to play Simon. If the participant who plays Simon signals "Simon says" to the robot by pressing the trigger button, the robot mirrors his/her movement.

B. Participants and Protocol

Informed consents were obtained before the experiments, according to the protocol approved by Vanderbilt University Institutional Review Board.

Scenario 1 – One-on-one interaction. We recruited 11 community-residing older adults (6 females, 5 males, age: 66-94 years, mean: 82.5) of which 4 had a preexisting diagnosis of MCI or dementia. The entire session, approximately 60 minutes in duration, was video-recorded. Electrophysiological signals were collected for a three-minute resting baseline and during HRI. A survey (Robot User Acceptance Scale-RUAS) was conducted pre- and post-experiment to determine the participants' acceptance and anticipated use of the robot on a 7-point scale (1 most positive to 7 most negative response). This survey was adapted from the Unified Theory of Acceptance and Use of Technology (UTAUT) and reflects the user's acceptance and intention to use new technology based on performance expectancy, effort expectancy, attitude toward using technology, and self-efficacy. The UTAUT framework posits that the person's pre-use attitudes influence the person's acceptance and use of the technology [41]. For this study, items were modified to reflect adults' interactions specific to robots.



(a) One-on-one Interaction (b) Triadic Interaction

Fig. 3. (a) Supervisory controller module for one-on-one interaction (b) Control policy for triadic interaction

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The final RUAS consisted of 29 items (9 performance expectancy, 5 effort expectancy, and 15 attitude). Participants also completed a post-experiment questionnaire that provided opinions about the activities (from "extremely interesting (1)" to "extremely boring (7)").

Scenario 2 – Triadic interaction. We recruited 14 older adult participants (9 females, 5 males, age: 70-90 years, mean: 82.7) who were paired for simultaneous interaction with the robot. One pair of the participants had a formal diagnosis of MCI or dementia. Paired participants came to the lab once for approximately 30 minutes. EEG signals and the RUAS were collected following the same procedure as in scenario 1. Participants also completed a pre- and post-experiment questionnaire on the degree to which they enjoyed interacting with and helping others. After the experiment, a questionnaire was provided to gain feedback on the level of enjoyment or interest with the activity.

IV. Results

A. Data Analysis Methods

The Wilcoxon signed-rank test was applied to determine the survey's ability to be sensitive to change. RUAS and its three subscales (performance expectancy, effort expectancy, and attitude) were subject to pre and post-experiment comparison. The Wilcoxon signed-rank test, a non-parametric statistical hypothesis test of median, was used because it does not assume normal distribution of the data, and is suitable for ordinal data.

EEG engagement index (EEI) and GSR-based arousal state (GAS) were extracted as measures of affective states to characterize participant's engagement intention. Filtered EEG signals from baseline and different activities were used to compute both an engagement threshold and engagement traces. EEI was the ratio of beta band spectral power (13-22 Hz) to the sum of alpha band spectral power (8-13 Hz) and theta band spectral power (4-8 Hz) [42][43]. We calculated the EEI at time t from 40-second sliding window preceding time t. Bin powers within beta, alpha, and theta bands were summed together to compute the ratio and the ratios from all 14 electrodes were combined to obtain the EEI at time t. This procedure was repeated every two seconds to generate the engagement traces. The mean value of the baseline engagement trace was set as the engagement threshold. A summarized EEI was calculated by $\sum_{i=1}^{n}\left(EEI(i)-threshold\right)/n$ for each activity, where n is the number of EEI in the related activity.

GAS was computed using preprocessed GSR signal measured from participant's fingers. Tonic and phasic components were decomposed separately from the raw signal. The signal was first filtered by a 0.5 Hz lowpass filter to remove noise. Then tonic component was acquired by using a 0.05 Hz highpass filter. Phasic component was then calculated by deducting tonic component from the denoised signal. GSR rate, which could be used as arousal state, was calculated by averaging the first derivative of phasic component. For baseline and each activity of the robot experiment, a set of GAS values were calculated using a 40-second sliding window with 38-second overlap. A threshold value was computed by averaging baseline GAS values. Similar to EEI, a summarized GAS was calculated for each activity.

B. One-on-one Interaction Results

All the participants finished the interaction and completed the surveys and questionnaires (Table I). Cronbach's alpha coefficients were 0.88 and 0.92, pre- and post-survey respectively. Perceptions became more positive for effort expectancy, attitude, and RUAS post-experiment. Wilcoxon signed-rank test results are shown in the table, including the standard score of the Wilcoxon signed ranks, p value, and effect size. It can be seen that attitude subscale and RUAS were statistically significantly more positive after HRI at the 0.05 level with medium effect sizes.

EEI and GAS were computed for 10 participants, because the start/end marker were not recorded properly for the third participant. For each activity and participant, we calculated the corresponding summarized EEI and summarized GAS. The scatter plots (Fig. 4) illustrates participants' summarized EEI and summarized GAS with respect to self-rated activity preferences. In the case of EEI, the dispersion of the data points along each rating level shows that there are individual differences. For example, one participant rated the exercise activity as "extremely interesting (1)" with the summarized EEI of -0.05 whereas another participant provided the same rating with the summarized EEI of 0.18. We further computed the Pearson's r to assess the relationship between the summarized EEI and participants' self-rating data. There was a strong correlation between the two variables ($r = -0.73$, $N = 27$, $p < 0.001$). This strong negative correlation implies that the EEI is high when participants enjoy the activity whereas the EEI is relatively low when participants show less interest to the activity.

Similarly, individual differences were found for GAS. For

TABLE I. Survey Results for One-on-one Experiment N=11

	Pre [a] M (SD)	Post [a] M (SD)	Z	p	r
Performance Expectancy	25.5 (6.5)	28.6 (7.2)	1.89	0.059	0.40
Effort Expectancy	19.1 (6.6)	15.6 (6.1)	1.73	0.084	0.37
Attitude	50.5 (10.7)	39.7 (13.9)	2.31	0.021	0.49
RUAS	100 (21.8)	84.4 (25.0)	2.19	0.028	0.47

[a]Lower values are more positive.

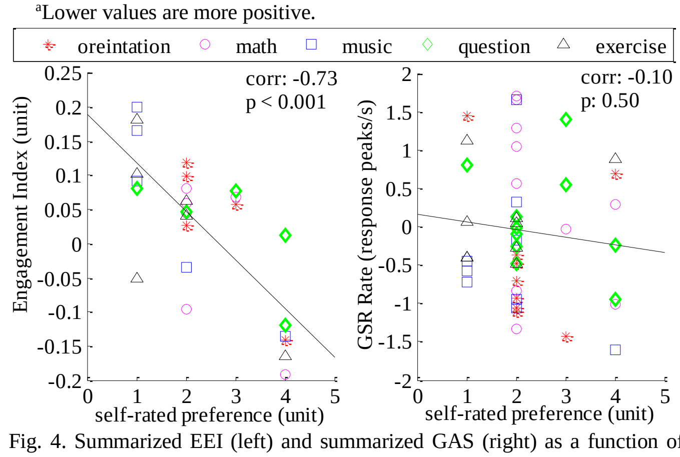

Fig. 4. Summarized EEI (left) and summarized GAS (right) as a function of self-rated activity preferences.

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the music activity and rating level 2, participants' summarized GAS ranged from -1.05 response peaks/s to 1.66 response peaks/s. No correlation was found between the summarized GAS and self-rated activity preference. The summarized GAS is an important indicator of the intensity of participants' emotion state. Since the self-rating data indicated the level of likes or dislikes of the activities and were not necessarily associated with changes in arousal states, it is not surprising that no correlation was found. As shown in Fig. 4, on average participants had a better opinion on the music and exercise activities compared to the other three activities.

C. *Triadic Interaction Results*

Survey data were collected for all 14 participants and the results are shown in Table II. Cronbach's alpha coefficients were 0.93 and 0.92, pre- and post-survey, respectively. All the subscales and RUAS indicated more positive perceptions on ROCARE after the experiment. Effort expectancy subscale was statistically significantly more positive after triadic interaction at 0.01 level with a large effect size. Attitude subscale and RUAS were statistically significantly more positive after triadic interaction at the 0.05 level with medium effect sizes.

Participants' perceptions on interacting with another person were recorded by a four-item questionnaire. Eleven participants completed this pre- and post-experiment questionnaire. The items were a) I would enjoy doing activities with another person (pre mean score 1.64, post mean score 1.55); b) I would feel comfortable talking to another person (pre mean score 1.36, post mean score 1.18); c) I would help another person when needed (pre mean score 1.18, post mean score 1.27); and d) I would accept help from another person (pre mean score 1.09, post mean score 1.27). While no statistically significant conclusion could be drawn from the questionnaire data, the very small post mean scores show that older adults enjoyed interacting with another person in addition to the robot.

We logged EEG data for 6 participants. Their engagement threshold and summarized EEI during the triadic interaction are listed in Table III together with self-rating data. Each participant had different engagement threshold and different opinions on the "Simon says" activity. Similar to the one-on-one experiment results, the summarized EEI is individualized. Participant 009 rated the "Simon says" activity to be "Somewhat interesting (3)" with an EEI equals 0.27 whereas participant 014's EEI equals 0.09.

Head pose data were recorded for participants 009 to 014 to analyze whether the participants communicated with each other. The yaw angle results are presented in Fig. 5. The first row of plots show yaw angles from participants sitting on the right chair (PR), whereas the bottom row plots include data from participants sitting on the left chair (PL). The yaw angle should increase when participants' turn their head to the left and decrease otherwise. Before the triadic interaction, we asked the participants to look at the robot and then look towards the other person. The corresponding head pose yaw angles were horizontal lines in the plots. Pair 007's head pose yaw angles towards each other were not properly recorded. The solid dots in the plots represent instances when the robot provided instructions to elicit HHI. This includes a) acquiring name of PL/PR from PR/PL; b) asking older adults to say hi to each other; c) asking older adults to check each other's gesture if one of them failed; and d) wave goodbye. The number of dots are different for the three pairs because a) and c) might not occur based on real-time human interaction. At the onset of the solid dots, we expect to see that PR's head pose yaw angles increase and PL's head pose yaw angles decrease. From Fig. 5, this is the case for the majority of the time.

TABLE II. SURVEY RESULTS FOR TRIADIC EXPERIMENT N=14

	Pre [a] M (SD)	Post [a] M (SD)	Z	p	r
Performance Expectancy	27.9 (9.7)	24.2 (8.4)	1.82	0.069	0.34
Effort Expectancy	18.6 (6.5)	12.9 (7.2)	2.82	0.005	0.53
Attitude	46.4 (15.6)	36.5 (15.0)	2.28	0.023	0.43
RUAS	94.8 (30.9)	77.2 (26.4)	2.14	0.033	0.40

TABLE III. SUMMARIZED EEG ENGAGEMENT INDEX FOR SIX PARTICIPANTS

	P009	P010	P011	P012	P013	P014
Threshold	0.95	0.39	0.78	0.65	0.41	0.57
"Simon says" Activity	0.27	0.00	-0.13	-0.20	0.01	0.09
Self-rated Preference	3	2	1	1	1	3

V. DISCUSSION

ROCARE is designed to complement and augment care in the existing resource-strained healthcare environment. Several useful interactions between a robot and older adults were developed and tested by small feasibility studies. Overall, one-on-one interaction and triadic interaction systems worked as designed. No participant dropped out of the studies and the sensors were tolerable. Participants' perceptions after the one-on-one and triadic experiments were significantly more positive on the attitude subscale and RUAS. In addition, the survey measurements were sensitive to change from pre- to post-experiment.

EEG and GSR data demonstrated individual differences in baseline features and variation from baseline during HRI. The results also show that the participants had different degree of likes or dislikes of the activities, and therefore it is important for ROCARE to be able to keep track of the preferences of each older adult to maintain engagement. The strong negative correlation between the summarized EEI and participants'

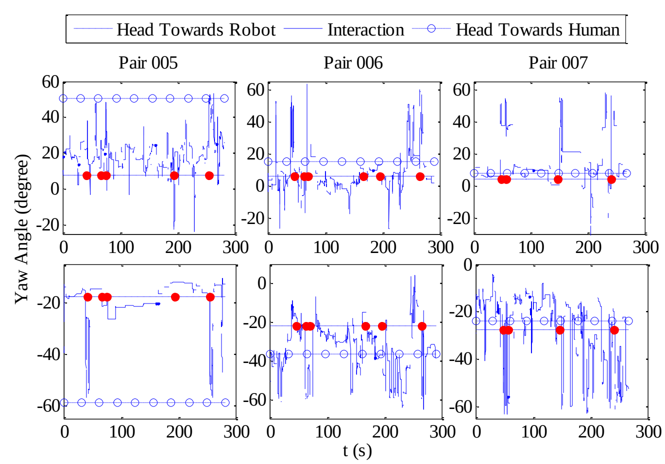

Fig. 5. Participants' head pose yaw angles during triadic experiment.

self-rating data indicates the potential for objectively measuring participants' engagement intention and harnessing it to realize individualized activity management. Because the correlation was computed using data from all the participants, we cannot be certain that this result applies to each individual in the same way. As for GAS, although no correlation was found between the summarized GAS and self-rated activity preference, it is worthwhile to develop an arousal state-related rating scale and explore the reliability of using GAS as arousal index. In the future, we intend to conduct multi-session experiment and implement the *activity management* submodule using activity preferences learned from electrophysiological signals. This study will provide results on how individual difference affect the EEG and physiological features as well as the effect of activity management.

ROCARE allows for adaptation on two levels of abstraction: a) activity level, which automatically schedules engaging activities; and b) low level, which adapts system behavior based on older adults' real-time interaction, such as gaze and gesture. In this paper, the low level adaptation was implemented. There are several adaptive elements in the system, including EEG and GSR sensors, head pose yaw angle estimation of gaze, and performance related measurements. The EEG and GSR results will serve as the basis for activity level adaptation in the future.

While the current work has demonstrated the potential of a novel HRI architecture with small feasibility studies, it is important to understand the long term effect of such systems in the nursing homes with longitudinal study. Ethical issues and the potential of misuse with robots and older adults have been raised, including decreased human contact, loss of control, loss of privacy, and feelings of objectification [44][45]. These are serious issues and safeguards need to be considered before their deployment in nursing homes.

VI. Conclusion

Building upon the works of Bohus and Horvitz on multiparty engagement in open-world dialog [36], Louie and associates on multi-user planning and scheduling architecture [24], and state of the art SAR architectures [20][28][30], we proposed the mathematical models of ROCARE, a robotic coach architecture, for augmenting elder care. This architecture is capable of one-on-one and multi-user interactions between a SAR and older adults. By incorporating a database for each individual user and including both implicit and explicit sensing submodules, ROCARE allows individualized activity management and dynamic adaptive robotic behavior for long-term engagement. We have conducted two preliminary feasibility studies: a one-on-one HRI and a triadic HRI. Both systems functioned as desired. Participants' perceptions on the robotic systems were significantly more positive after HRI for the attitude subscale and RUAS. Social communication between pairs of participants could be elicited by the robot as seen from both video recordings and head pose data. In addition, there were strong correlation between the summarized EEI and participants' self-rating data ($r = -0.73$, $p < 0.001$), which indicated the potential of using EEG signals for online affective states recognition.

The current work is limited in several ways. First, with the small sample size and the short interaction duration, user perception and compliance results are susceptible to the novelty of the technology. Second, electrophysiology-based affective state recognition was limited to offline analysis. Third, since each participant only took part in one session, no activity preference data were learned and therefore the order of the activities were predefined. Nonetheless, the preliminary studies verified that 1) ROCARE was positively accepted by older adults with and without cognitive impairment; 2) ROCARE can be used for one-on-one and multi-user HRI; and 3) our selection of the EEG feature has strong linear correlation with participants' self-rating on each activity, and can be used for online affective state recognition.

ROCARE is the first to our knowledge that defined multi-user engagement-based mathematical models for robot-mediated interaction for elder care. Future works on building individualized database and activity management need to be carried out with longitudinal studies and a larger sample size. The effectiveness of the architecture to maintain long-term engagement, promote functioning and social communication also needs to be studied.

References

[1] N. C. f. H. Statistics, "Older Americans 2012: Key Indicators of Well-being," 2012.

[2] S. M. Friedman and D. A. Mendelson, "Epidemiology of fragility fractures," *Clinics in geriatric medicine,* vol. 30, pp. 175-181, 2014.

[3] A. s. Association, "2014 Alzheimer's disease facts and figures," *Alzheimer's & Dementia,* vol. 10, pp. e47-e92, 2014.

[4] J. N. Vega and P. A. Newhouse, "Mild cognitive impairment: diagnosis, longitudinal course, and emerging treatments," *Current psychiatry reports,* vol. 16, pp. 1-11, 2014.

[5] V. Freedman, "Disability and care needs of older Americans: An analysis of the 2011 National Health and Aging Trends Study," 2014.

[6] K. Tabata, "Population aging, the costs of health care for the elderly and growth," *Journal of Macroeconomics,* vol. 27, pp. 472-493, 2005.

[7] J. Cohen-Mansfield, M. S. Marx, M. Dakheel-Ali, and K. Thein, "The use and utility of specific nonpharmacological interventions for behavioral symptoms in dementia: an exploratory study," *The American Journal of Geriatric Psychiatry,* vol. 23, pp. 160-170, 2015.

[8] S. C. Forbes, J. P. Little, and D. G. Candow, "Exercise and nutritional interventions for improving aging muscle health," *Endocrine,* vol. 42, pp. 29-38, 2012.

[9] D. Feil-Seifer and M. J. Mataric, "Defining socially assistive robotics," in *Rehabilitation Robotics, 2005. ICORR 2005. 9th International Conference on*, 2005, pp. 465-468.

[10] R. Bemelmans, G. J. Gelderblom, P. Jonker, and L. De Witte, "Socially assistive robots in elderly care: A systematic review into effects and effectiveness," *Journal of the American Medical Directors Association,* vol. 13, pp. 114-120. e1, 2012.

[11] E. Mordoch, A. Osterreicher, L. Guse, K. Roger, and G. Thompson, "Use of social commitment robots in the care of elderly people with dementia: A literature review," *Maturitas,* vol. 74, pp. 14-20, 2013.

[12] K. Wada, T. Shibata, T. Saito, K. Sakamoto, and K. Tanie, "Psychological and social effects of one year robot assisted activity on elderly people at a health service facility for the aged," in *Robotics and Automation, 2005. ICRA 2005. Proceedings of the 2005 IEEE International Conference on*, 2005, pp. 2785-2790.

[13] H. Gross, C. Schroeter, S. Mueller, M. Volkhardt, E. Einhorn, A. Bley, C. Martin, T. Langner, and M. Merten, "Progress in developing a socially assistive mobile home robot companion for the elderly with mild cognitive impairment," in *Intelligent Robots and Systems (IROS), 2011 IEEE/RSJ International Conference on*, 2011, pp. 2430-2437.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TNSRE.2016.2608791, IEEE Transactions on Neural Systems and Rehabilitation Engineering

[14] R. Looije, M. A. Neerincx, and F. Cnossen, "Persuasive robotic assistant for health self-management of older adults: Design and evaluation of social behaviors," *International Journal of Human-Computer Studies,* vol. 68, pp. 386-397, 2010.

[15] Y. Matsusaka, H. Fujii, T. Okano, and I. Hara, "Health exercise demonstration robot TAIZO and effects of using voice command in robot-human collaborative demonstration," in *Robot and Human Interactive Communication, 2009. RO-MAN 2009. The 18th IEEE International Symposium on*, 2009, pp. 472-477.

[16] B. Görer, A. Salah, and H. L. Akın, "A Robotic Fitness Coach for the Elderly," in *Ambient Intelligence*, ed: Springer International Publishing, 2013, pp. 124-139.

[17] M. Simonov and G. Delconte, "Humanoid Assessing Rehabilitative Exercises," *Methods Inf Med,* vol. 53, 2014.

[18] P. Gadde, H. Kharrazi, H. Patel, and K. F. MacDorman, "Toward monitoring and increasing exercise adherence in older adults by robotic intervention: a proof of concept study," *Journal of Robotics,* 2011.

[19] K. Yoshino, M. Kouda, and Z. Shanjun, "Correct Motion Advice on Rehabilitation Instruction Robot by Superimposing Instructor CG Model," in *Intelligent Networks and Intelligent Systems (ICINIS), 2012 Fifth International Conference on*, 2012, pp. 333-336.

[20] J. Fasola and M. J. Matarić, "A Socially Assistive Robot Exercise Coach for the Elderly," *Journal of Human-Robot Interaction,* vol. 2, pp. 3-32, 2013.

[21] A. Tapus, C. Tapus, and M. Matarić, "Long Term Learning and Online Robot Behavior Adaptation for Individuals with Physical and Cognitive Impairments," in *Field and Service Robotics*, 2010, pp. 389-398.

[22] D. McColl, W. Y. G. Louie, and G. Nejat, "Brian 2.1: A socially assistive robot for the elderly and cognitively impaired," *Robotics & Automation Magazine, IEEE,* vol. 20, pp. 74-83, 2013.

[23] W. Y. G. Louie, J. Li, T. Vaquero, and G. Nejat, "A focus group study on the design considerations and impressions of a socially assistive robot for long-term care," in *Robot and Human Interactive Communication, 2014 RO-MAN: The 23rd IEEE International Symposium on*, 2014, pp. 237-242.

[24] W. Y. G. Louie, T. Vaquero, G. Nejat, and J. C. Beck, "An autonomous assistive robot for planning, scheduling and facilitating multi-user activities," in *Robotics and Automation (ICRA), 2014 IEEE International Conference on*, 2014, pp. 5292-5298.

[25] C. D. Kidd and C. Breazeal, "Robots at home: Understanding long-term human-robot interaction," in *Intelligent Robots and Systems, 2008. IROS 2008. IEEE/RSJ International Conference on*, 2008, pp. 3230-3235.

[26] Z. Zheng, S. Das, E. M. Young, A. Swanson, Z. Warren, and N. Sarkar, "Autonomous robot-mediated imitation learning for children with autism," in *Robotics and Automation (ICRA), 2014 IEEE International Conference on*, 2014, pp. 2707-2712.

[27] M. Kanoh, Y. Oida, Y. Nomura, A. Araki, Y. Konagaya, K. Ihara, T. Shimizu, and K. Kimura, "Examination of practicability of communication robot-assisted activity program for elderly people," *Journal of Robotics and Mechatronics,* vol. 23, p. 3, 2011.

[28] D. Feil-Seifer and M. J. Mataric, "B³IA: A control architecture for autonomous robot-assisted behavior intervention for children with Autism Spectrum Disorders," in *Robot and Human Interactive Communication, 2008. RO-MAN 2008. The 17th IEEE International Symposium on*, 2008, pp. 328-333.

[29] J. Chan and G. Nejat, "Promoting engagement in cognitively stimulating activities using an intelligent socially assistive robot," in *Advanced Intelligent Mechatronics (AIM), 2010 IEEE/ASME International Conference on*, 2010, pp. 533-538.

[30] J. Chan and G. Nejat, "A learning-based control architecture for an assistive robot providing social engagement during cognitively stimulating activities," in *Robotics and Automation (ICRA), 2011 IEEE International Conference on*, 2011, pp. 3928-3933.

[31] H. M. Gross, K. Debes, E. Einhorn, S. Mueller, A. Scheidig, C. Weinrich, A. Bley, and C. Martin, "Mobile Robotic Rehabilitation Assistant for walking and orientation training of Stroke Patients: A report on work in progress," in *Systems, Man and Cybernetics (SMC), 2014 IEEE International Conference on*, 2014, pp. 1880-1887.

[32] D. O. Johnson, R. H. Cuijpers, J. F. Juola, E. Torta, M. Simonov, A. Frisiello, M. Bazzani, W. Yan, C. Weber, and S. Wermter, "Socially Assistive Robots: A comprehensive approach to extending independent living," *International Journal of Social Robotics,* vol. 6, pp. 195-211, 2014.

[33] M. Malfaz, Á. Castro-González, R. Barber, and M. A. Salichs, "A biologically inspired architecture for an autonomous and social robot," *Autonomous Mental Development, IEEE Transactions on,* vol. 3, pp. 232-246, 2011.

[34] C. Jayawardena and A. Sarrafzadeh, "An alternative approach for developing socially assistive robots," in *Biomedical Robotics and Biomechatronics (2014 5th IEEE RAS & EMBS International Conference on*, 2014, pp. 573-578.

[35] J. Cohen-Mansfield, M. S. Marx, L. S. Freedman, H. Murad, N. G. Regier, K. Thein, and M. Dakheel-Ali, "The comprehensive process model of engagement," *The American Journal of Geriatric Psychiatry,* vol. 19, pp. 859-870, 2011.

[36] D. Bohus and E. Horvitz, "Models for multiparty engagement in open-world dialog," in *Proceedings of the SIGDIAL 2009 Conference: The 10th Annual Meeting of the Special Interest Group on Discourse and Dialogue*, 2009, pp. 225-234.

[37] M. Cummings. (18 November 2015). *Simon Says as a Teaching Tool*. Available: https://www.youtube.com/watch?v=RewIoHJ9RdM

[38] J. Fan, J. W. Wade, B. Dayi, A. P. Key, Z. E. Warran, L. C. Mion, and N. Sarkar, "A Step Towards EEG-based Brain Computer Interface for Autism Intervention," presented at the 37th Annual International Conference of the IEEE Engineering in Medicine and Biological Society (EMBS), in press, 2015.

[39] D. Bian, J. Wade, A. Swanson, Z. Warren, and N. Sarkar, "Physiology-based affect recognition during driving in virtual environment for autism intervention," in *2nd international conference on physiological computing system (Accepted, 2015)*, 2015.

[40] N. Sarkar, "Psychophysiological control architecture for human-robot coordination-concepts and initial experiments," in *Robotics and Automation, 2002. Proceedings. ICRA'02. IEEE International Conference on*, 2002, pp. 3719-3724.

[41] C. BenMessaoud, H. Kharrazi, and K. F. MacDorman, "Facilitators and barriers to adopting robotic-assisted surgery: contextualizing the unified theory of acceptance and use of technology," *PloS one,* vol. 6, p. e16395, 2011.

[42] M. Chaouachi, P. Chalfoun, I. Jraidi, and C. Frasson, "Affect and mental engagement: towards adaptability for intelligent systems," in *Proceedings of the 23rd International FLAIRS Conference, Daytona Beach, FL. http://citeseerx. ist. psu. edu/viewdoc/download*, 2010.

[43] F. G. Freeman, P. J. Mikulka, L. J. Prinzel, and M. W. Scerbo, "Evaluation of an adaptive automation system using three EEG indices with a visual tracking task," *Biological psychology,* vol. 50, pp. 61-76, 1999.

[44] N. Sharkey and A. Sharkey, "The eldercare factory," *Gerontology,* vol. 58, pp. 282-288, 2012.

[45] T. Körtner, "Ethical challenges in the use of social service robots for elderly people," *Zeitschrift für Gerontologie und Geriatrie,* pp. 1-5, 2016.