Collaboration of an assistive robot and older adults with dementia

Momotaz Begum PhD[a]
Rajibul Huq PhD[b]
Rosalie Wang PhD[c]
Alex Mihailidis PhD[c]

[a]Department of Computer Science, University of Massachusetts Lowell, MA, USA, E: mbegum@cs.uml.edu [b]The Mathworks, MA, USA, E:rajib.huq@mathworks.com; [c]Intelligent Assistive Technology and Systems Lab (IATSL), University of Toronto and Toronto Rehabilitation Institute, University Health Network, ON, Canada, E: Alex.Mihailidis@utoronto.ca

M. Begum, R. Huq, R. Wang, A. Mihailidis. Collaboration of an assistive robot and older adults with dementia, Gerontechnology 2015;13(4):405-419; doi:10.4017/gt.2015.13.4.005.00 **Objective** Assistive robots that help older adults with dementia (OAwDs) to carry out daily activities or socially interact with them need to be designed to account for their unique interaction patterns and cognitive limitations. We report on some of the challenges and recommendations involved in the design of a collaborative human-robot interaction (HRI) framework for assistive robots that help OAwDs in daily activities. **Method** An observational study was conducted with 10 OAwDs and their familial caregivers in a simulated home environment. OAwDs completed a tea-making task in collaboration with a tele-operated assistive robot. The robot guided each OAwD to the kitchen, provided assistance (through prompting and answering questions), engaged in social conversation when appropriate, and guided the OAwD back to the caregiver. Participants were interviewed to solicit their opinions about the interaction. All study activities were video recorded. **Results** The recorded robot-OAwD interactions and interviews were analyzed using behavioral coding techniques to identify specific interaction behaviors of OAwDs that may present challenges to the design of a collaborative HRI framework. Reported are five different behaviors (interactiveness, natural dialogue, team behavior, emotion, cognition and memory) that relate to four key human factors (trust, grounding, communication, and situational awareness). Preliminary recommendations for future development include conducting a large study to better understand the needs of the target population and designing an intelligent robot control interface capable of working collaboratively with OAwDs. **Conclusion** Design of a collaborative HRI framework may require intelligent modifications to existing machine learning, speech recognition, and natural language processing algorithms.

Keywords: Human-robot interaction, human-robot collaboration, assistive robot, dementia

With a globally declining caregiver-older adult ratio, designing assistive robots that help older people and people with physical and cognitive disabilities in their everyday lives has become an important topic of study[1-7]. For such assistive robots human-robot interaction (HRI) design plays a key role in the robots' capability, success, and overall acceptance by targeted users[8]. The required autonomy of robots to maintain a long-term and proximate interaction, as necessary to help people in their daily activities in a realistic manner, is far from being an imminent reality. To address this limitation, human-robot collaboration (HRC) is considered an effective approach for assistive robot operation[9]. Collaboration is a type of HRI where a human and a robot work as a team to reach a common goal (for instance, completing a daily activity) through sharing task knowledge, exchanging ideas, and dynamically adjusting plans and actions[10-13]. Collaborative interactions, therefore, are more goal-oriented compared to other forms of HRI. This article will use the terms collaborative HRI and HRC interchangeably. HRC enables formation of a synergistic team between the robot and the human partner, where limitations of the robot (for instance, limited autonomy, perceptual abilities) and the human partner (for instance, cognitive impairment, in the case of older adults with dementia (OAwDs)) can be compensated[14].

Designing collaborative HRI for assistive robots to serve OAwDs in everyday activities is a tremendous challenge because traditional human-robot team interactions expect the human partner to be 'cognitively intact' and may not be designed to accommodate the cognitive limitations of OAwDs. For instance, abstract thinking ability is required to lay out a collaborative-task plan executable by the robot (given its limited autonomy and/or perceptual abilities)[15], or owing to attentional deficits, the OAwD may not be able to maintain his or her commitment to the collaborative task[16]. Although dementia leads to various cognitive impairments[17], we believe that older adults in the early stages of dementia, with the help of a carefully designed HRC framework, can work effectively with an assistive robot to complete various activities of daily living (ADLs)[18]. The outcome of this technology can give OAwDs better control over their lives, take some burden off caregivers, and enable OAwDs to remain living in their own homes for longer. The HRC framework for assistive robots needs to be designed to accommodate the interaction patterns resulting from the various cognitive impairments presented by OAwDs.

How the cognitive limitations of OAwD may influence the dynamics of HRC is not well-explored in contemporary HRI research. There exist only a handful of research projects involving robotic assistance for people with dementia. The roles of these robots are to provide companionship and cognitive stimulation[5,19-23]. These robots can stimulate different senses (for instance, pleasure, relaxation) in OAwDs through triggering context-appropriate social cues (for instance, smiling back when the OAwD smiles at the robot)[5,19-21], or verbally encourage OAwDs to engage in different activities (for instance, playing games, eating healthy food, doing exercise) [22,23]. Goal-oriented interactions are unlike cognitive stimulation and companionship scenarios. For effective HRC to achieve a common goal, the human and the robot need to be aware of each other's abilities and limitations. Currently there is no literature which reports the issues involved in HRC when the human partner has cognitive limitations resulting from dementia. The purpose and major contribution of this paper is to report some of the key challenges involved in HRI design when an assistive robot needs to collaborate with OAwDs to accomplish a certain goal, and to identify preliminary recommendations for future design of collaborative interaction frameworks for assistive robots for OAwDs.

The challenges and recommendations were identified in an observational study where an assistive robot was fully tele-operated to provide need-based, step-by-step guidance (in the form of audio or audio-visual prompts) to OAwDs as they made a cup of tea. Tea making was selected for the study based on findings of an online survey of 106 familial caregivers that indicated that tea making was an important ADL tasks to be incorporated in future smart home systems for OAwDs[24]. From an HRC perspective, tea-making involves several subtasks, and to complete the tea-making task the OAwD needs to interact with the robot. The HRI during the tea-making task was of the non-contact type and the robot's role in the collaboration was to provide the OAwD with appropriate task knowledge when necessary. The robot factors that generally influence the performance of a human-robot team (for instance, perception, communication, task performance, cognitive abilities) maintained a satisfactory standard through tele-operation of the robot. This allowed focus on and analysis of different human factors such as the OAwDs' interaction patterns with the robot and how these can influence the performance and dynamics of a human-robot team. Observations from the study were analyzed with respect to human factors described in the literature. Several HRI studies on human-robot collaborative task execution identified a number of human factors that have influence on the performance of a human-robot team[10-14, 25-34]. These factors are described in the following section.

Theoretical background

The dynamics of a human-robot team and metrics to evaluate its performance are emerging topics in HRI research, although no complete model is yet available[31]. There are factors associated with both the robot and the human that contribute to the performance of a human-robot team in a collaborative endeavor. Our current research is more focused on the human factors, and assumes that reasonably good performance of the robot (with respect to perception, communication, task performance, cognitive abilities, etc.) will be achieved through skilled tele-operation. A literature survey on the performance metrics for HRI suggests the following four human factors as the key to the performance of a human-robot team: trust, grounding, communication and situational awareness[11-14, 25-34].

Trust

Inspired by the definition of trust in automation, trust in robots can be defined as "the attitude that an agent will help achieve an individual's goals in a situation characterized by uncertainty and vulnerability"[35]. Trust in robots has profound impact on the effectiveness of a HRC. The human must have an appropriate level of trust in the abilities of the robot and the guidance it provides to collaboratively accomplish a common goal[32,33,36,37]. Lack of trust in robots has negative influences on a human partner's collaborative attitude, for instance, his or her willingness to exchange information with the robot, to follow the robot's suggestions, or to use information supplied by the robot[38]. Excessive trust, on the other hand, might result in reliance on the robot beyond its capacity. All of these undermine the true value of a robot and make the necessity of assistive robots somewhat questionable. There are several factors associated with the robot and the human that govern the development of trust in a human-robot team. A preliminary analysis of these factors is available[36]. In a human-robot team, the trust of a human in his/her robotic partner can be manifested in a variety of ways, e.g. expressions of positive emotion toward the robot[38], interactiveness[39], or reliance on the robot[35,38]. The exact manifestation depends on the type of task and the human's personality[36].

Grounding
Common ground between a human and a robot in a collaborative activity can be defined as "the knowledge, beliefs, and suppositions they believe they share about the activity"[40]. Common ground enables a human partner to convey necessary information to a robot in his or her team in the most effective way, such that the robot understands the information correctly and makes the best use of it to achieve the goal[41]. Forming a common ground with a robot requires the human to develop a mental model of the robot, where the term 'mental model' refers to the organized set of knowledge that the human possesses about the robot (for instance, how the robot works, its abilities, shortcomings, performance and reliability with respect to a given task)[33,42,43]. The human's mental model of a robot is dynamic and should change over time as the human-robot team goes through common experiences. How accurately a human can develop and adjust over time a mental model of the robot depends on several human factors such as personality, education, attitude toward technology, and cognitive abilities (for instance, knowledge, perception, reasoning, communication ability)[9,44,45].

Communication
Communication between team members has a crucial role to sustain collaboration until the common goal is achieved. Transparent communication enables team members to understand each other's intention and commitment to achieve a common goal, and to devise plans for the execution of collaborative action. To work collaboratively with a robot, the human must understand the communication signals delivered by the robot as well as send signals that the robot understands[12,13,38]. A human's accurate mental model of a robot emerges through transparent, bidirectional communication in a human-robot team[46]. There are several ways a human-robot team can communicate, for instance, natural speech-based communication, non-verbal cues (for instance, head nod, hand gesture, gaze, facial cues), and force feedback. Natural speech, however, has been proven to be the most effective way of communication in a human-robot team[9,13].

Situational awareness
Situational awareness indicates the knowledge someone has about their surroundings, and can be formally defined as "the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning and the projection of their status in the near future"[47]. In the context of HRI, situational awareness of a human refers to his or her awareness about the current status of the robot (with respect to its location, possible actions, and the robot's world model) as well as the environment where a task is being carried out by the human-robot team[14,25,33]. The human generally achieves his or her situational awareness through an integrated process of attention, perception, comprehension and knowledge-based prediction[14]. Proper situational awareness enables a human to fully utilize the ability of the robot to achieve the goal of a HRC.

Method
The data presented in this paper are from an observational usability study aimed at exploring the use of and design requirements of an assistive robot to provide need-based, step-by-step guidance to OAwDs to complete daily activities. The study design and small sample size accommodates many of the challenges inherent in conducting complex assistive technology development studies with OAwD[63]. The study methods included behavioral observations, semi-structured interviews, and questionnaires which facilitated collection of in-depth and diverse data to inform the design of an assistive robot for OAwDs. The study was carried out in a simulated home setting in the Toronto Rehabilitation Institute – University Health Network, and was approved by the Research Ethics Board of the same institution.

Subjects
As the focus of this paper is on the OAwDs and their collaboration with the assistive robot, descriptions of the caregivers will be included only when relevant. OAwDs were included in the study according to the following criteria: 55 years or older, fluent in English, can hear normal levels of speech, have a diagnosis of Alzheimer disease by their physician, have a family member or privately hired caregiver who provides care, have difficulty completing common sequences of steps (as reported by the caregiver), and are able to give informed consent or assent, and/or have a substitute decision maker give informed consent. OAwDs were excluded if they did not meet the inclusion criteria. The caregivers were all family members knowledgeable about the abilities of the OAwDs. A recruitment target of 5-10 dyads of OAwDs and their caregiver was set for the observational usability study. Ten were recruited and consecutively enrolled through a local, community-based medical clinic specializing in the diagnosis and treatment of Alzheimer disease and related disorders.

Study procedures
OAwDs and their caregivers were study subjects, so both signed informed consent forms before participating in the study. The consent information was reviewed with the OAwD and his or her caregiver and the study protocol and risks and benefits of participating were discussed prior to their signing. Through signing the consent forms the participants provided permission to use the audio and video recordings collected during the study in research, reports, publications, presentations, or documentation with the condition that the participants' identities would be made secret by blocking out their faces and any other distinguishing visual features. To comply with, these faces of the OAwDs have been blocked out in all images presented in this paper.

A Mini-Mental State Exam (MMSE)[48] was performed with each OAwD following informed consent procedures to screen their level of cognitive impairment. The MMSE score, however, was not used as a criterion to determine eligibility to participate in the study.

A semi-structured interview was conducted with the OAwDs and their caregivers to collect demographics and social, health and functional history (*Table 1*).

OAwDs and their caregivers were introduced to the tele-operated assistive robot "Ed" (*Figure 1*).

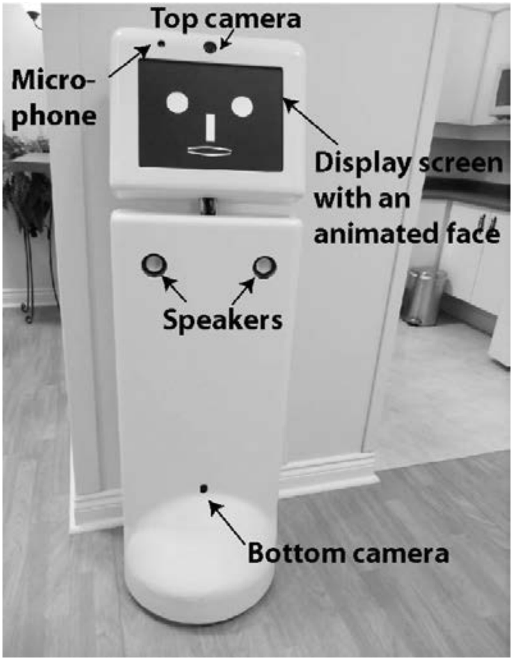

Figure 1. Robot Ed used in the study

The OAwDs did not have to follow any specific protocol during the interactions with the robot. They were informed that the robot's movements, speech and other behaviors are controlled by a researcher (tele-operated). The OAwDs were asked to interact with the robot, which included having the OAwDs make a cup of tea in the kitchen of the simulated home, with the robot helping him or her if needed. The OAwDs were able to do or say anything they wanted in order to communicate or collaborate with the robot while performing the tea-making task. They were also informed that they could stop the interaction and study at any time, take breaks as needed, and their caregivers and the researchers monitored them for signs of discomfort or stress that warranted stopping the study. During the tea-making task, the robot guided the OAwDs to the kitchen, provided assistance (through prompting and answering questions) as necessary (*Figure 2*), engaged in social conversations when appropriate, and guided them back to their caregivers once the task was completed.

The caregivers were asked to observe the interaction, but refrain, as much as possible, from interjecting. Following the tea-making task, OAwDs and their caregivers were interviewed by the researchers separately to ask their opinions about the assistive robot that the OAwDs collaborated with and their general expectations from such a robot. The robot-OAwD collaborative interactions and all interviews were video recorded. Additional details about the study protocol can be found in[18]. The duration of the study for each OAwD was approximately 2.5 hours. The duration of the collaborative tea-making task was different for each OAwD and depended on the amount of assistance required from the robot. The average duration for the tea-making task, however, was 12 minutes.

The robot was tele-operated throughout the task. The tele-operator continuously monitored the task progress and the overall affective state of the OAwDs in a video stream sent by the robot. The tele-operator initiated social conversation, asked task-related questions, provided confirmations, and delivered prompts to guide the OAwDs toward successful completion of the tea-making task. The prompts consisted of simple sentences or simple sentences and video demonstrations that were structured, according to our previous studies, to be easy to follow by people with cognitive impairment[49]. The tea-making task was broken down into subtasks, for instance, go to kitchen, turn water faucet on, fill kettle with water, boil water, put teabag into cup, pour hot water into cup, and put teabag into garbage bin (*Table 2*). Audio or audio-video prompts corresponding to each of these

Table 1. Demographics, daily activities and care needs of subjects with dementia (OA); MMSE=Mini-Mental State Exam, maximum score 30

Subject	Gender	Age, Years	MMSE	Daily activities and care needs
OA01	F	76	9	-Son helps with turning on shower, setting up meals, gives reminders of activities -Needs to walk more; has arthritis -Goes to seniors' day centre 2 times/week -Other family member visits and helps 3 times/week
OA02	M	86	24	-Carries out daily routine on own, eats breakfast, goes for walks, drives car -Wife cues him to change his clothes -Prepares meals and goes grocery shopping with wife -Visits with children
OA03	M	88	25	-Does most of his own care - shower, shave, makes coffee and breakfast -Goes for walks, uses treadmill, reads, makes bed, does laundry, watches sports on TV -Daughter helps him and his wife with shopping and brings him to medical appointments
OA04	F	77	25	-Does own self-care -Takes care of grandchildren, cleans, cooks -Daughter takes her to appointments, gives her reminders and phones her
OA05	F	59	18	-Requires reminders for most daily activities -Believed she was teaching children in school and driving to work (no longer the case) -Watches TV and sleeps -Prepares meals and does groceries with husband -Husband does heavy work
OA06	M	63	23	-Wife provides daily reminders, answers his questions, repeats questions a lot -Independent with shaving, toileting and showering -Needs guidance for dressing -Plays math games on computer -Walks 3 miles - 5 days a week outside or in a gym -Watches TV, does chores, goes to appointments -Does groceries with family
OA07	F	77	25	-Does own bathing and other self-care -Does most daily activities with husband -Goes out sometimes, knows bus routes -Cooks supper with assistance from husband -Husband does most of heavy work, laundry, housekeeping -Watch TV together -Daughter visits 1 day a week; takes her out for day
OA08	F	83	19	-Does most of her own daily care, but requires prompting -5 days a week attends a day program -Prepares meals with son and family -Takes care of dog -Son and family help her with shopping, medications, driving to appointments, help her to organize clothes and finances
OA09	F	84	25	-Does cooking and cleaning (also has housekeeper - 1x/week) -Showers, makes bed -Watches TV, plays solitaire on computer -Goes out, but not on own -Daughter helps with groceries, paying bills, some banking, drives her (7-10 h/week of care)
OA10	M	85	15	-Sleeps in, makes breakfast, cleans a bit, goes for walks, reads paper -Wife reminds him of things; he does own shower but needs reminders to change clothes, takes medications on own, may need reminders of dates or times for doing things -2 days/week he and his wife take care of grandchildren, sometimes grandchildren stay overnight or for weekends -Tires easily because of physical health conditions -Meets friends for lunch, watches TV after dinner -Wife has own physical health conditions, so she goes to exercise -Wife goes food shopping in afternoon, cooks meals, does washing

Figure 2. Robot Ed and subjects with dementia during the tea-making task in the kitchen of a simulated home

subtasks were recorded previously. An audio prompt is a speech-based direction to complete a subtask while a video prompt is an example display of how a specific subtask can be performed. For each subtask, the prompts have three different levels of assistance: minimal (MN), maximal (MX), and maximal with video (MXV). The MN prompt is a high level speech-based instruction to complete a subtask. The MX prompt provides more directive instruction (rather than suggestive) and is delivered along with the subject's name in order to attract his or her attention[49]. The MXV prompt is the MX audio prompt executed along with a corresponding video display.

The robot observed the following rules while collaborating with the OAwDs:

(i) The robot allowed the OAwDs to initiate subtasks and waited for them to initiate a subtask as they wished.

(ii) When an OAwD looked around or asked about directions, the robot delivered the appropriate prompt for the subtask.

(iii) When an OAwD replied that s/he would like to do things in his or her own way, the robot agreed with that as long as the OAwD did not skip an essential subtask .

(iv) When an OAwD asked a question about the location of an item specific to the subtask, the robot provided a full-body gesture by physically orienting itself toward the 'sought for' item.

(v) During water boiling, the robot asked the OAwD to put sugar and/or milk and a tea bag in the cup. If that was done or the OAwD did not want these items, and there was more time, the robot engaged in a social conversation with the OAwD, for instance,asking about the weather. The robot initiated only two social questions with the OAwDs and used pre-defined sentences for that.

(vi) When an OAwD asked a question for which the prerecorded outputs did not work, the robot either responded by giving the correct answer (through the tele-operator using a text-to-speech (TTS) platform) or said "I don't know", depending on the question.

Table 2. Example of steps and prompts for the tea-making task; MN=minimal; MX=maximal; MXV= MX+video

Step	Prompt
Turn water on	MN: Can you turn the water on now? MX: Try pulling the silver lever toward you MXV: MX+ Video (Model turns on the water)
Fill kettle with water	MN: Can you fill the kettle with water now? MX: Try filling the kettle under the water MXV: Model picks up the kettle and fills the kettle with water

Behavioral analysis

Considering trust, grounding, communication, and situational awareness as the performance determining human factors of a human-robot team, we performed a behavioral analysis using the tea-making interaction and post-interaction interview data from OAwDs. The analysis was conducted to gain a preliminary understanding of patterns in the OAwDs' behaviors that might influence the dynamics of a HRC and effect team performance. The findings suggest trends that may well be applicable to designing a robot-OAwD collaborative interaction framework and that we used to make recommendations to tackle perceived challenges.

The videos of the tea-making task and the interviews of the OAwDs were manually scored by three co-authors of this manuscript. Two co-authors have a robotics background and one has clinical experience working with OAwDs. Five behaviors of the OAwDs were coded from the video data that are related to trust, grounding, communication, and situational awareness: interactiveness, natural dialogue, team behavior, emotion, cognition and memory. These five behaviors are chosen based on previous HRI studies that shed light on human factors that might influence the success of a human-robot team in a collaborative task[10-14,25-34]. Although all of these HRI studies involved individuals with intact cognition, we decided to rely on these five key indicators found in the literature as there is no known report on human factors that can influence the performance of a human-robot team in a collaborative task such as tea making. We also coded a number of small scale behaviors under these five categories based on behavioral trends in people with dementia (*Table 3*).

Two co-authors performed the behavioral coding and the third author performed a 20% cross-check. The authors discussed the coded results until they reached agreement.

Two quantitative metrics were used:
(i) Percentage of observation, *X*: This indicates the percentage of the sampled population who showed a certain behavior and is calculated as follows:

$$X = \frac{\text{Number of OAwDs with the Behavior}}{\text{Sample Size}} \text{ x } 100 \quad [1]$$

X was calculated for all behaviors.
(ii) Frequency of observation, *f*: This indicates the average number of times a certain behavior was observed in the sampled population and is calculated as follows:

$$f = \frac{\sum_x Number\ of\ observations\ in\ x}{|x|} \quad [2]$$

Where $x = \{OAwDs\ who\ showed\ the\ behavior\}$

Table 3. Mapping between coded behaviors and human factors[10-14, 25-34]

Behavior	Human factors
Interactiveness	Trust, communication
Natural dialogue	Communication
Team behavior	Trust
Emotion	Trust
Cognition and memory	Trust, grounding, situational awareness

f was calculated for the behaviors examined from the tea-making task (i.e., interactiveness, team behavior, and emotions), but not for those extracted from the interviews (i.e., natural dialogue, and cognition and memory). This was done because identifying the presence or absence of these behaviors is more meaningful than the exact number of times the behaviors were actually observed. For example, the behavior 'Confabulation' is when a person fabricates, distorts, or misinterprets memories about him or herself or about others. A single occurrence of confabulation during the interview of an OAwD triggers the need that a HRC interface should be aware of situations where the information provided by an OAwD to a robot might not be fully reliable.

The quantities X and f convey valuable information about the consistency of a behavior in the sampled population. For a certain behavior, high values of X and f indicate that the behavior was frequently observed in most of the OAwDs who participated in this pilot work and may indicate a trend in behavior for the general target population. A high value of X and a low value of f indicate a stable behavior of the sampled population. A low value of X and a high value of f indicate person-specific behavior. Finally, low values of X and f indicate a discrete behavior that is less likely to be representative of the target population.

Qualitative coding of a behavior involves the coders' assessment and agreement about the presence or absence of that behavior. Qualitative coding was done for the behaviors examined from the interviews (i.e., natural dialogue, and cognition and memory), but not for those extracted from the tea-making task (i.e., interactiveness, team behavior, and emotions). This was because while eliciting data directly from the tea-making task was considered to be most valuable, the few verbal exchanges between the robot and OAwD during the short tea-making task did not allow for meaningful qualitative coding. However, the post-task interview did.

Definitions of the coded behaviors and how they are related to different human factors described above are discussed below.

Interactiveness
Interactiveness of an OAwD during the tea-making task is coded through observations of the following behaviors:
(i) Verbal engagement: The OAwD provides verbal responses to questions or comments delivered by the robot. Such questions or comments can be task-related (for instance, "do you like sugar in your tea?") or of social type (for instance, "how do you find the weather

today?"). If the OAwD, however, talks to himself or herself, that is not considered verbal engagement. The behavior is coded quantitatively.
(ii) Initiating conversation: The OAwD takes the initiative to start a conversation with the robot and the topic might not be directly related to the tea-making task. Any conversation will fall in this category. If the OAwD provides follow-up comments or responds to the robot's non-task related questions or comments, these are not considered as initiating conversation. The behavior is coded quantitatively.
(iii) Non-verbal cues: The OAwD directs any kind of non-verbal cues (for instance, smile, touch, gaze, or gestures) toward the robot. The behavior is coded quantitatively.

Previous research on human-robot teaming in collaborative tasks show that Interactiveness of a human is an indication of his or her willingness to consider the robot as an interaction partner and is related to trust in the robot[39]. Similarly, verbal responses and non-verbal cues are directly related to the communication ability of a person to express his or her intention or commitment to the robot[13, 50].

Natural dialogue
The spoken dialogue of OAwDs shows one or more of the following four characteristics commonly observed in people with dementia[17, 51]. The four coded behaviors are as follows:
(i) Long pause: When asked any question, the OAwD waits for an unusually long time before responding, or does not respond at all.
(ii) Problem with word finding: The OAwD has a difficult time finding the correct word for objects or people.
(iii) Confusion: The OAwD expresses signs of confusion about a person, object, or the purpose of his/her own presence in the study (for instance, the OAwD confuses the robot with the caregiver while speaking about his or her recent experience with the robot).
(iv) Confabulation: The OAwD provides non-factual information about him or herself or his or her experience with the robot (that s/he perceives to be true).

Previous research shows that spoken dialogue is the most powerful way of communication between a human and a robot in a human-robot team[62]. Natural dialogue is a direct measure of an OAwD's communication ability to convey information to the robot in an easily understandable manner. The behavior is coded qualitatively.

Team behavior
Three team behaviors were observed and coded:
(i) Status update: The OAwD updates the robot with the current task status about which the robot might be unaware of (for instance, informing the robot that "water is boiling now"). The behavior is coded quantitatively.
(ii) Turning toward the robot: The OAwD spontaneously turns toward the robot when s/he encounters a problem with completing the task. For instance, due to unfamiliarity with the kitchen, the OAwD could not find a tea bag and spontaneously asked the robot about where to find a tea bag. The behavior is coded quantitatively.
(iii) Turning toward the caregiver: The OAwD encounters a problem during the tea-making task and, instead of asking the robot, s/he turns to the caregiver for a possible solution. For instance, the OAwD could not install the kettle and s/he asked the caregiver about how to do that. The behavior is coded quantitatively.

Previous research on human-robot team performances shows that various team-oriented behaviors (for instance, status updating, asking for help, etc.) are linked to the mutual trust of team-members[38]. The team behaviors defined here are direct indications of the trust that the OAwD has in the robot during collaborative task execution.

Emotion
The Observed Emotion Rating Scale[52] designed to rate the affect of people with dementia is used to code the affective responses of the OAwDs during the tea-making task. The emotions observed in OAwDs were reported under two categories: positive emotions, for instance, different signs of pleasure such as laughing, smiling, singing, gently touching the robot, reaching out warmly to the robot, and negative emotions, for instance, signs of anger (e.g. pursing lips, drawing eyebrows together, yelling), anxiety or fear (for instance, restlessness, repeated or agitated movement, line between eyebrows, line across forehead, hand wringing), or sadness (for instance, frowning, sighing).

To be coded, an affective response does not have to be directed particularly toward the robot. Rather, any affective response that indicates the general emotional state of the OAwD when s/he is doing the tea-making task with the robot is considered here. The behavior is coded quantitatively. It was difficult to measure the exact duration of each affective response but the majority of the responses were short lived (2-5s) while a few of them lasted longer (10-20s). Previous research on HRI shows that emotion is a key factor that influences the performance of a team[53] and is an indication of the presence or absence of trust in a human-robot team[36].

Cognition and memory

Four behaviors of OAwDs related to cognitive abilities and memory performance were coded:

(i) Lack of attention: The OAwD fails to search for cues or attend to available cues, or is unable to follow the guidance provided by the robot to complete the tea-making task. For instance, the OAwD could not hold his or her attention to the video prompt shown by the robot and was unable to proceed with the task. The behavior is coded quantitatively.

(ii) Lack of comprehension: The OAwD is confused about what s/he is doing, cannot comprehend the purpose of the robot or the purpose of the whole study. The behavior is coded qualitatively.

(iii) Lack of abstract thinking ability: The OAwD could not imagine situations (other than the one s/he recently went through) where the robot could be useful to him or her or to other people. Also, the OAwD could not propose some features or attributes of the robot that s/he thinks would be nice to have in such a robot. The behavior is coded qualitatively.

(iv) Poor short-term memory: The OAwD shows signs that s/he has partly or completely forgotten his or her experience with the robot, instructions or prompts that were delivered or an incident that happened during the collaborative interaction with the robot. OAwDs generally have issues with short-term memory, although it might not manifest during the short duration of the tea-making task or interview. The behavior is coded qualitatively.

Cognitive ability has been identified by previous research as a factor involved in the ability of a person to trust a robotic partner[36], develop an accurate mental model of the robot[45] (which, in turn, facilitates grounding), and finally, gain situational awareness of his or her surroundings[14].

Results

Data from videos of the tea making task and from the post tea-making interviews were coded and scored using the methods described above (*Table 4*).

The following sections provide an overview of our interpretation of information -trust, grounding, communication, and situational awareness- that are key to the performance of a human-robot team. This research constitutes an exploratory pilot study conducted with the intention of gaining familiarity with the application of personal robots to assisting OAwDs with daily tasks. As such, data analysis is conducted at a high- evel and the results are general observations to reflect the small number of OAwDs completing a single task. In essence, this research is intended to give a 'feel'

Table 4. Analysis of interaction behaviors of subjects (n=10); [a]'Observed' indicates the subject with dementia exhibited that behavior one or more times, and 'unable to judge' if the coders were unable to ascertain the presence or absence of the behavior; [b]For the tea-making task, behaviors were either 'observed' or 'unobserved'; [c]For the post-task interviews, behaviors were either 'observed', 'unable to judge', or 'unobserved'

Behavior		**Data source**	**Measurement**		
			Qualitative[a]	**Quantitative[b,c]**	
				X, %	**f**
Interactiveness	Verbal engagement	Tea making	Observed	80	7.1
	Initiating conversation	Tea making	Observed	10	2.0
	Non-verbal cues	Tea-making	Observed	100	15.1
Natural Dialogue	Long pause	Post-task interview	Observed	10	-
			Unable to judge	0	-
	Problem in word finding	Post-task interview	Observed	60	-
			Unable to judge	10	-
	Confusion	Post-task interview	Observed	30	-
			Unable to judge	40	-
	Confabulation	Post-task interview	Observed	30	-
			Unable to judge	20	-
Team behavior	Status updating	Tea-making	Observed	80	3.9
	Turning toward the robot	Tea-making	Observed	10	4.0
	Turning toward the caregiver	Tea-making	Observed	90	4.2
Emotion	Positive	Tea-making	Observed	80	7.1
	Negative	Tea-making	Observed	100	9.1
Cognition and Memory	Lack of attention	Tea-making	Observed	60	4.0
	Lack of comprehension	Post-task interview	Observed	40	-
			Unable to judge	20	-
	Lack of abstract thinking ability	Post-task interview	Observed	50	-
			Unable to judge	10	-
	Poor short-term memory	Post-task interview	Observed	40	-
			Unable to judge	20	-

for what human-robot interventions look like for OAwDs in order to direct future research efforts.

Trust

An interesting picture of trust in the robot emerges when we look at the interactiveness and team behaviors of the OAwDs. Eight out of ten OAwDs (X=80%) verbally communicated often when the robot approached them with questions or comments (f=7.1). Even though the robot was not capable of generating non-verbal cues such as gestures or smiles in response to the OAwDs, all OAwDs (X=100%) frequently directed different non-verbal communication cues toward the robot (f=15.1). Some of them even touched the robot affectionately, burst into laughter when talking to it and passed critical comments to it for being slow in movement (these are discrete observations and the related X and f are not listed in *Table 4*).

We observed the same attitude in the OAwDs when they updated the robot with the current task status (assuming that the robot might be unaware of the status). Although such status updating did not occur at a very high frequency behavior (f=3.9), it was observed more than once in eight out of ten OAwDs during the short duration of the tea-making task. These observations indicate that the OAwDs had some level of trust in the robot to accept it as an interaction partner who might have abilities to help in the current task.

The level of trust, however, was not so high that they turned to the robot for help to solve problems that they were unable to resolve. Although nine out of ten OAwDs encountered different types of difficulties while performing the tea-making task (for instance, difficulty in installing the kettle properly to boil the water, finding the tea bags), only one of them (X=10%) spontaneously turned toward the robot for solutions in different occasions (f=4.0). Nine out of ten OAwDs (X=90%) turned to the caregivers to solve problems. Some of them even showed signs of hesitation when asked to direct their query toward the robot instead of the caregiver. In addition, OAwDs' hesitation to accept the robot as a peer is expressed in the behavior that only one of them (X=0%) took the initiative to start a conversation with the robot, although the robot stood by them during the entire tea-making task and initiated more than one social conversation (that was unrelated to the tea-making task). With respect to the emotional state of the OAwDs, signs of negative emotion were observed more frequently in all of the OAwDs (X=100%, f=9.1) than signs of positive emotion (X=80%, f=7.1). In general it was observed that OAwDs seemed more comfortable with the robot toward the end of the tea-making task, especially after having a social conversation with the robot.

Grounding

The behavioral analysis presents a complex picture of the grounding ability of OAwDs. During the collaborative task, eight out of ten OAwDs occasionally (f=3.9) updated the robot about their task status and provided the robot with perceptual information that the robot might be unaware of (for instance, letting the robot know that the water is boiling). This indicates that OAwDs were, to some level, aware of the robot's purpose to assist them in the task and the robot's perceptual limitations. All of these are necessary for common grounding with the robot and also to develop an accurate mental model of the robot. But the hesitation observed in nine out of ten OAwDs (X=90%, f=4.3) to turn toward the robot for problem solving is one indication that their mental model of the robot was not very informative and did not emerge over time - i.e., during the short duration of the study. In addition, during the interview, five out of ten OAwDs were unable to report on the overall goal of the study, the purpose of the robot, or its abilities and limitations. In the case of people with intact cognition, accurate mental models (and hence the ability for grounding) emerge over time as the human-robot team goes through common experiences[36,41]. The cognitive impairment of OAwDs might make the process of time evolution of a correct mental model longer, if not impossible.

Communication

OAwDs were generally very comfortable with non-verbal communication with the robot (X=100%, f=15.1). Non-verbal cues, however, might have limited abilities to convey information, especially in a task-oriented setting. Eight out of ten OAwDs (X=80%) were quick in verbal communications and based on the content of the communication appeared to enjoy social conversation with the robot. However, the number of verbal responses (from OAwDs) during the tea-making task (f=7.1) was not very high for the analysis of spoken dialogue. Interviews with the OAwDs, on the other hand, involved many verbal exchanges and revealed the characteristics of the spoken dialogue of the OAwDs in terms of the ability to convey information to the robot.

Six out of ten OAwDs (X=60%) had difficulty finding the correct words when referring to objects, people, or their feelings. Three out of ten OAwDs showed clear signs of confusion as they were answering questions related to the robot and their experiences with it (coders were unable to clearly categorize the signs of confusion in four OAwDs). Most significantly, three OAwDs (OA2, OA6, OA7) were confabulating while describing their experiences with the robot (coders were unable to clearly categorize this behavior in OA3, OA10). All of these present a complex picture of the OAwDs' communication ability through natural dialogue.

Natural speech has been previously demonstrated to be the most powerful tool for human-robot dialogue and information exchange in a collaborative HRI. The information conveyed to the robot through natural dialogue during assisted completion of tasks, however, must be factual, narrative, and clearly understandable. Otherwise, the robot, with its limited perception and cognition, will not be able to use the information provided by the human partner. Confabulation, confusion, word-finding difficulty can significantly affect the flow and quality of information exchanged between OAwDs and a robot through natural dialogue.

Situational awareness

Within the limited time of the tea-making task, most of the OAwDs showed some level of situational awareness as they responded to the robot's questions in a reasonable manner (X=80%, f=7.1), provided the robot with status updates (X=80%, f=3.9), and frequently directed affective cues toward the robot (X=100%, f=15.1). Many of them, however, failed to attend to the cues provided by the robot that could be helpful for the completion of the tea-making task. For instance, six OAwDs either overlooked the video prompt shown by the robot (f=4.0) or could not use the information even after looking at it. During the interview, many of the OAwDs showed signs of comprehension difficulty (X=40%, coders were unable to clearly categorize for two OAwDs: OA9, OA10), short-term memory (X=40%, coders were unable to clearly categorize for two OAwDs: OA7, OA6), and abstract thinking ability (X=50%, coders were unable to clearly categorize for one OAwD: OA2). All of these have potential to greatly hinder the OAwDs' ability to gain situation awareness during a long-term collaboration with the robot.

Discussion

Designing robots for any assistive application is already an open challenge for robotics researchers due to the demand for highly sophisticated robotic perception, action, cognition and HRI abilities. Cognitive impairment in the target user adds an additional dimension to this challenge. Based on the results reported above, we have identified key challenges and preliminary recommendations within three areas, namely, collaborative control, human-robot dialogue, and learning. Note that our focus is on the non-contact type of robot-OAwD collaboration which is achieved (from the robot's side) through in-time delivery of task knowledge to OAwDs.

Collaborative control

OAwDs, in our current scenario, have the final authority to accept or decline the guidance, suggestion or assistance offered by the robot. Trust calibration is one of the key challenges to designing this kind of collaborative framework as, no matter how intelligent the robot is, an inappropriate level of trust will make the robot's expertise useless to the OAwDs. This will lead to poor team performance. It has been reported in the literature that familiarity leads to better understanding about a robot (even for users with intact cognitive abilities) and trust in robots emerges as a result of the bidirectional interaction between familiarity and understanding[38]. Familiarity is also an antecedent of developing an accurate mental model of the robot[45] and an accurate mental model helps to develop a proper level of trust in robots[36]. OAwDs can gain familiarity with the robot through spending more time with it in natural settings. This is generally termed as operator training and is a recommended way of improving users' trust in robots[9].

Training OAwDs with new concepts, skills, or devices, however, might not be trivial. While OAwDs have been shown to be able to learn some new skills via preserved procedural memory, training needs to be carefully structured to optimize learning and success, and to ensure the safety and well-being of OAwDs.

A health economic analysis, therefore, is necessary to justify the cost of developing and use of such assistive robots for OAwDs. Aside from trust issues, assistive robots for OAwDs will generally require higher situational awareness (for instance, improved perception, cognition, scene-analysis ability, and a correct mental model of the u ser) than robots in other assistive applications. In the case of OAwDs, the human collaborator might not always be the source of accurate and reliable information as traditionally expected in HRC[11]. Access to ambient sensor networks can help a robot to achieve improved perceptual awareness[2]. For improved awareness in executive functions (for instance, planning, scene understanding, solving complex problems related to the task), it is possible to include a caregiver in the robot-OAwD team where the caregiver will be in a supervisory role and will only be contacted in case of emergency. Defining the dynamics (for instance, role, authority, flow of information, HRI) of a mixed team with multiple members is complicated[10, 33] and might require the caregiver to go through special training processes.

Human-robot dialogue

Dialogue is one of the most effective ways to resolve ambiguity in a team that works in a dynamic environment[62]. OAwDs in our study showed impressive performance in non-verbal communication. Non-verbal cues, however, have limited abilities to convey information, especially in a task-oriented setting. Our data suggest that OAwDs can be very fluent in their verbal communication, although the information they deliver through their speech might not be factual and the speech itself might not be narrative and easily understandable. It was, however, frequently observed during the study that OAwDs can accurately respond to carefully phrased simple questions and follow instructions delivered through such sentences[18].

The natural dialogue management system of the assistive robot for OAwDs, therefore, should be equipped with a number of sophisticated abilities. For instance, the automatic speech recognizer (ASR) should be tolerant to the special features commonly present in the spoken dialogue of OAwDs (for instance, long pauses). Appropriate tuning of language and acoustic models can enable an ASR to exhibit such characteristics. In addition to this, the natural language processing (NLP) system will require the ability to investigate to what extent the speech is factual, relevant, and informative. Research in NLP has not yet achieved this level of sophistication for any application. In the case of this specific application, for making such high level inferences an NLP system will require expert analysis of the speech of OAwDs in order to discover common patterns. There are few preliminary initiatives to create a database of spoken dialogue by OAwDs during everyday activities[54]. Such a database can be used to conduct research in this direction. Finally, the natural language generation system of the assistive robot should rely on sentences which are carefully constructed to be understandable by people with cognitive impairments in order to ensure meaningful communication[49].

Learning

In the case of long-term HRI, robots need to be designed with interactive learning and adaptation abilities, although the learning and adaptation occur naturally in humans[55,56,57]. Mutual learning and adaptation in the case of robot-OAwD interaction, however, can be complicated. The learning patterns of OAwDs are different from others with intact cognitive abilities. In addition, humans take an active role to interactively teach the robot different skills[58] and tasks[59]. Interactive learning processes generally require an accurate mental model of the robot. The limited cognition of OAwDs (for instance, abstract thinking ability, situational awareness, short term memory) might restrict their abilities to take an active role in the robot's learning. It is, however, possible to design sophisticated interactive learning mechanisms that impose less cognitive load on the teacher (i.e. OAwDs). For instance, self-directed learning abilities in the robot[60] can be a good choice to implement such learning mechanisms where the robot will proactively come up with 'good questions' in order to strengthen its knowledge[61]. Of course the questions should be phrased in ways that are easily understandable by people with cognitive impairments[49].

The results of this pilot work indicate that an assistive robot will need highly sophisticated artificial intelligence in order to make a collaborative task with OAwDs successful. AI robotics has made tremendous progress in the past decade but we are still not in a stage where off-the-shelf AI algorithms can directly be employed to solve many of the real-life issues discussed above (for instance, understanding autonomously that an OAwD is confabulating, etc.). Collaborative control, human-robot dialogue, and learning are three primary areas that will need to advance through robotics and HRI research before an assistive robot can complement the interaction patterns demonstrated by OAwDs.

Limitations of the study

There were several limitations to the study. The data analyzed in this paper were from a study conducted with a small number of participants (n=10) interacting with one robot in one situation. Generalizability of the findings to the larger population of OAwDs with respect to interaction behaviors with robots may be limited. The challenges and recommendations presented in this in-depth analysis are, however, grounded in observations of OAwDs interacting in a fairly unstructured, realistic setting doing a common daily activity. Data of this nature with OAwDs are rare in the current literature, and findings from this analysis establish a foundation for hypothesis generation and future development. The diversity of abilities in our sample provides a reasonable base for observing a range of behaviors, and many of the abilities and behaviors we observed were consistent with those of people with Alzheimer's disease and other dementias. Observation of a breadth of abilities allows identification of more challenges, and arguably can better inform design decisions and directions. In spite of this diversity, the OAwDs were all able to hear normal levels of speech (as part of the inclusion criteria). Further research will be necessary to include OAwDs who have hearing deficits, as this is common for older adults, and to examine communication requirements for this subset of the population.

Another limitation of this study is the duration of human-robot interaction. The average duration of the tea-making task was 12 minutes and that is the time when OAwDs actually interacted with the robot. Therefore, it is not possible to investigate whether novelty effect had any influence on the behaviors of OAwDs while interacting with the robot.

Conclusion

In spite of the ever increasing need for assistive robots to serve people with cognitive impairments, research on how cognitive impairments might influence the dynamics of HRI is not a well-explored domain. To address this gap, this paper reports on the challenges involved in the design of collaborative HRI for an assistive robot that will work with OAwDs in everyday activities. The data are from a study we conducted where an assistive robot was fully tele-operated to provide need-based step-by-step guidance (in the form of audio or audio-visual prompts) to a group of OAwDs as they made a cup of tea in the kitchen of a simulated home. We performed an exploratory behavioral analysis on our pilot study data to identify a set of interaction behaviors of OAwDs that can make the design of collaborative HRI challenging, for instance, inappropriate amount of trust in the robot, inability to properly communicate with the robot and convey necessary information, and failure to develop a correct mental model of the robot. Our analysis suggests that OAwDs might be able to work collaboratively with an assistive robot if the robot offers enough sophistication (especially with respect to HRI) to accurately address their unique requirements. The paper provided a few recommendations to tackle these challenges, for instance, designing intelligent HRI interface for OAwD-robot collaboration, advanced natural language recognition and understanding framework, and sophisticated learning and adaption algorithms for the robot. Studies with more OAwDs, however, are required to solidify the findings presented in this paper and we are currently focusing on that.

Acknowledgements

This project was funded through the Pilot Project Program by the Canadian Institutes of Health Research (CIHR). We wish to thank Colin Harry and Yani Ioannou for their technical assistance, Drs. Jennifer Boger and Goldie Nejat for contributing to the design of the study, and Vara Parameswaran and Dr. Sharon Cohen at the Toronto Memory Program for their feedback on the robot and assistance in recruiting subjects.

References

1. Tobe F. Progress report on eldercare robots. The Robot Report, November 2012; www.robotics-businessreview.com/article/progress_report_on_eldercare_robots; retrieved January 12, 2014
2. Torta E, Oberzaucher J, Werner F, Cuijper RH, Juola JF. Attitude towards socially assistive robots in intelligent homes: Results from laboratory studies and field trials. Journal of Human-Robot Interaction 2012;1(2):76-99; doi:10.5898/JHRI.1.2.
3. Sharkey A, Sharkey N. Granny and the robots: ethical issues in robot care for the elderly. Ethics and Information Technology 2012;14():27-40; doi:10.1007/s10676-010-9234-6
4. Borenstein J, Pearson Y. Robot caregivers: harbingers of expanded freedom for all? Ethics and Information Technology 2010;12():277-288; doi:10.1007/s10676-010-9236-4
5. Shibata T, Wada K. Robot therapy: A new approach for mental healthcare of the elderly; a mini-review. Gerontology 2011;57(4):378-386; doi:10.1159/000319015
6. Wu Y, Faucounau V, Boulay M. Robotic agents for supporting community-dwelling elderly people with memory complaints: Perceived needs and preferences, Health Informatics Journal 2010;17(1):33-40; doi:10.1177/1460458210380517
7. Bemelmans R, Gelderblom G, Jonker P, Witte L. Socially assistive robots in elderly care: A systematic review into effects and effectiveness. Health Informatics Journal 2012;13(2):114-120; doi:10.1016/j.jamda.2010.10.002
8. Heerink M, Kr? A VOWEL SEEMS TO BE MISSING se B, Evers V, Wielinga B. Assessing acceptance of assistive social agent technology by older adults: the Almere model. International Journal of Social Robotics 2010;2(4):361-375; doi:10.1007/s12369-010-0068-5
9. Goodrich MA, Schultz AC. Human-robot interaction: A survey. Foundations and Trends in Human-Computer Interaction 2007;1(3):203-275; doi:10.1561/1100000005
10. Hoffman G, Breazeal C. Collaboration in human-robot teams. In: Proceedings of the AIAA 1st Intelligent Systems Technical Conference 2004; doi:10.1.1.111.1039
11. Fong T, Thorpe C, Baur C. Collaboration, dialogue, and human-robot interaction. In: Proceedings of the International Symposium of Robotics Research 2001; doi:10.1.1.16.7415
12. Bauer A, Wollherr D, Buss M. Human-robot collaboration: A survey. International Journal of Humanoid Robotics 2008;5(1):47-66; doi:10.1142/S0219843608001303
13. Green SA, Billinghurst M, Chen X, Chase JG. Human-robot collaboration: A literature review and augmented reality approach in design. International Journal Advanced Robotic Systems 2008;5(1):1-18; doi:10.5772/5664
14. Scholtz J. Theory and evaluation of human robot interactions. In: Proceedings of the IEEE Conference on System Sciences 2003; doi:10.1109/HICSS.2003.1174284
15. Grosz BJ. Collaborative systems. AI Magazine 1996;17(2):67-85; doi:10.1609/aimag.v17i2.1223
16. Cohen PR, Levesque HJ. Teamwork. Nofis 1991;

25(4):487-512
17. Delirium, dementia, and amnestic and other cognitive disorders. Chapter 2 in Diagnostic and Statistical Manual of Mental Disorders, 4th Edition, Text Revision (DSM-IV-TR). Arlington: American Psychiatric Association; 2000
18. Begum M, Wang R, Huq R, Mihailidis A. Performance of daily activities by older adults with dementia: The role of an assistive robot. In: Proceedings of the IEEE International Conference on Rehabilitation Robotics 2013; doi:10.1109/ICORR.2013.6650405
19. Wu Y, Chetouani M, Cristancho-Lacroix V, Matre J, Jost C, Pevedic B, Duhaut D, Granata C, Rigaud A. ROBADOM: an assistive robot for the elderly with mild cognitive impairment: System design and users' perspective. In: 5th Companion Robotics Institute Workshop AAL User-Centric Companion Robotics, France; 2011; doi:3D10.1.1.393.2892
20. Sakai Y, Nonaka Y, Yasuda K, Nakano YI. Listener agent for elderly people with dementia. In: Proceedings of IEEE/ACM International Conference on Human-Robot Interaction 2012; pp 199–200; doi:10.1145/2157689.2157754
21. Huang H, Matsushita H, Kawagoe K, Sakai Y, Nonaka Y, Yasuda K, Nakano YI. Toward a memory assistant companion for the individuals with mild memory impairment. In: Proceedings of the IEEE International Conference on Cognitive Informatics and Cognitive Computing 2012; pp 295-299; doi:10.1109/ICCI-CC.2012.6311164
22. Tapus A, Tapus C, Mataric MJ. Music therapist robot for people suffering from dementia: Longitudinal study. In: Proceedings of the International Conference on Alzheimer's Disease 2009; doi:10.1016/j.jalz.2009.04.580
23. McColl D, Nejat G. A human-robot interaction study with a meal-time socially assistive robot and older adults at a long-term care facility. Journal of Human Robot Interaction 2012;2():275-294; doi:10.5898/JHRI.2.1.McColl
24. Czarnuch S, Mihailidis A. The design of in-home assistive technologies: Assessing the needs of older adults with dementia and their caregivers. Gerontechnology 2011;10(3):165-178; doi:10.4017/gt.2011.10.3.005.00
25. Drury JL, Scholtz J, Yanco HA. Awareness in human-robot interactions. In: Proceedings of the IEEE Conference on Systems, Man and Cybernetics 2003; pp 111-119; doi:10.1109/ICSMC.2003.1243931
26. Weiss A, Bernhaupt R, Lankes M, Tscheligi M. The USUS evaluation framework for human-robot interaction. In: Proceedings of the Symposium on New Frontiers in Human-Robot Interaction 2009; doi:10.1075/ais.2.07wei
27. Steinfeld A, Lewis M, Fong T, Scholtz J. Common metrics for human-robot interaction. In: Proceedings of the 1st ACM SIGCHI/SIGART conference on Human-robot interaction 2006; pp 33-40; doi:10.1145/1121241.1121249
28. Murphy R, Schreckenghost D. Survey of metrics for human-robot interaction. In: Proceedings of the 8th ACM/IEEE international conference on Human-robot interaction 2013; pp 197-198; doi:10.1109/HRI.2013.6483569
29. Olsen DR, Goodrich MA. Metrics for evaluating human-robot interactions. In: Proceedings of Performance Metrics for Intelligent Systems Workshop 2003; http://icie.cs.byu.edu/Papers/RAD.pdf ; retrieved January 12, 2014
30. Burghart C, Haeussling R. Evaluation criteria for human-robot interaction. In: Workshop on Robotic Companions AISB; 2005
31. Singer SM, Akin DL. A survey of quantitative team performance metrics for human-robot collaboration. In: Proceedings of International Conference on Environmental Systems 2011; pp 1–19; doi:10.2514/6.2011-5248
32. Saleh JA, Karray F. Towards generalized performance metrics for human-robot interaction. In: Proceedings of the International Conference on Autonomous and Intelligent Systems 2010; pp 1-6; doi:10.1109/AIS.2010.5547049
33. Pina P, Cummings ML, Crandall JW, Penna MD. Identifying generalizable metric classes to evaluate human-robot teams. In: Proceedings of Metrics for Human-Robot Interaction workshop, ACM/IEEE International Conference on Human-Robot Interaction 2008; pp13- 20
34. Nikolaidis S, Shah J. Human-robot cross-training: Computational formulation, modeling and evaluation of a human team training strategy. In: Proceedings of the IEEE/ACM International Conference on Human-Robot Interaction 2011, pp 33-40; doi:10.1109/HRI.2013.6483499
35. Lee JD, Moray N. Trust, control strategies and allocation of function in human-machine systems. Ergonomics 1992;35(10):1243-1270; doi:10.1080/00140139208967392
36. Hancock PA, Billings DR, Oleson KE, Chen JYC, Visser ED, Parasuraman R. A meta-analysis of factors influencing the development of human-robot trust. Technical Report ARL-TR- 5857. Adelphi: US Army research laboratory; December 2011; doi:10.1177/0018720811417254
37. Yagoda RE, Gillan DJ. You want me to trust a robot? The development of a human-robot interaction trust scale. International Journal of Social Robotics 2012;4(3):235-248; doi:10.1007/ s12369-012-0144-0
38. Freedy A, Visser ED, Weltman G, Coeyman N. Measurement of trust in human-robot collaboration. In: Proceedings of the International Conference on Collaborative Technologies and Systems 2007; pp 17-24; doi:10.1109/CTS.2007.4621745
39. Jung MF, DePalma N, Chernova S, Hinds PJ, Breazeal C. Human-robot collaboration: Bids and bytes. In: Proceedings of the ACM/IEEE International Conference on Human-Robot Interaction, 4th Annual Human-Agent-Robot Teamwork Workshop, 2012; http://bradshawfamily.net/~samuel/zzz/hart2012/pdf/Jung.pdf; retrieved: January 12, 2014

40. Clark H, editor. Using Language, Lecture Notes in Statistics. Cambridge: Cambridge University Press; 1996
41. Stubbs K, Wettergreen D, Hinds PJ. Autonomy and common ground in human-robot interaction: A field study. IEEE Intelligent Systems 2007;22(NUMBER IS MISSING):42-50; doi:10.1109/MIS.2007.21
42. Kiesler S. Fostering common ground in human-robot interaction. In: Proceedings of the International Symposium on Robot and Human Interactive Communication 2005; pp 729- 734; doi:10.1109/ROMAN.2005.1513866
43. Nikolaidis S, Shah J. Human-robot cross-training: computational formulation, modeling and evaluation of a human team training strategy. In: Proceedings of the ACM/IEEE International Conference on Human-Robot Interaction 2013; pp 33-40; doi:10.1109/HRI.2013.6483499
44. Briggs G, Scheutz M. Facilitating mental modeling in collaborative human-robot interaction through adverbial cues. In: Annual Meeting of the Special Interest Group on Discourse and Dialogue 2011; pp 239-247; doi:10.1.1.207.5277
45. Lee SL, Lau IYM, Kiesler S, Chiu CY. Human mental models of humanoid robots. In: Proceedings of theIEEE International Conference on Robotics and Automation 2005; pp 2767-2772; doi:10.1109/ROBOT.2005.1570532
46. Burke J, Murphy R. Situation awareness, team communication, and task performance in robot-assisted technical search: Bujold goes to Bridgeport. CMPSCI Tech. Rep. CRASAR-TR2004-23. Tampa: University of South Florida; 1999
47. Endsley MR, Garland DJ, editors. Situation Awareness Analysis and Measurement. Lecture Notes in Statistics. Mahwah: Erlbaum; 2000; doi:10.1002/hfm.1021
48. Folstein MF, Folstein SE, White T, Messer MA. Mini-Mental State Examination user's guide. Odessa: Psychological Assessment Resources; 2001
49. Wilson R, Rochon E, Mihailidis A, Leonard C. Examining success of communication strategies used by formal caregivers assisting individuals with Alzheimer's disease during an activity of daily living. Journal of Speech, Language, and Hearing Research 2012;55(2):328-341; doi:10.1044/1092-4388(2011/10-0206)
50. Breazeal C, Kidd CD, Thomaz A, Hoffman G, Berlin M. Effects of nonverbal communication on efficiency and robustness in human-robot teamwork. In Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems 2005; pp 708- 713; doi:10.1109/IROS.2005.1545011
51. Attali E, Anna FD, Dubois B, Barba GD. Confabulation in Alzheimer's disease: poor encoding and retrieval of over-learned information. Brain 2009;132(Pt1):204-212; doi:10.1093/brain/awn241
52. Lawton MP, Haitsma KV, Perkinson M, Ruckdeschel K. Observed affect and quality of life in dementia: Further affirmations and problems. Journal of Mental Health and Aging 1999; 5(1):69-81
53. Isen AM, Daubman KA, Nowicki GP. Positive affect facilitates creative problem solving. Journal of Personality and Social Psychology 1987; 52(6):1122-1131
54. Davis B, Pope C. Carolina conversations collection: password-protected multimedia web portal at the medical university of South Carolina: two cohorts (alztalk, 200+ conversational interviews and older adults, 200+ conversational interviews). Rockville Pike: NIH/National Library of Medicine, 2001; http://carolinaconversations.musc.edu/about/; retrieved January 12, 2014
55. Gockley R, Bruce A, Forlizzi J, Michalowski M, Mundell A, Rosenthal S, Sellner B, Simmons R, Snipes K, Schultz AC, Wang J. Designing robots for long-term social interaction. In: Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems 2005; doi:10.1109/IROS.2005.1545303
56. Stubbs K, Bernstein D, Crowley K, Nourbakhsh IR. Long-term human-robot interaction: The personal exploration rover and museum docents. In: Proceedings of the International Conference on Artificial Intelligence in Education 2005; doi:10.1.1.417.3540
57. Martinho LC, Paiva A. Social robots for long-term interaction: A survey. International Journal of Social Robotics 2013; 5(2):291-308; doi: 10.1007/s12369-013-0178-y
58. Asada M, MacDorman KF, Ishiguro H, Kuniyoshi Y. Cognitive developmental robotics as a new paradigm for the design of humanoid robots. Robotics and Autonomous Systems 2001;37(2):185-193; doi:10.1016/S0921-8890(01)00157-9
59. Argall BD, Chernova S, Veloso M, Browning B. A survey of robot learning from demonstration. Robotics and Autonomous Systems 2009;57(5):469-483; doi:10.1016/j.robot.2008.10.024
60. Begum M, Karray F. Integrating visual exploration and visual search in robotic visual attention: The role of human-robot interaction. In: Proceedings of the IEEE International Conference on Robotics and Automation 2011; pp 3822–3827; doi:10.1109/ICRA.2011.5980376
61. Cakmak M, Thomaz A. Designing robot learners that ask good questions. In: Proceedings of the ACM/IEEE International Conference on Human-Robot Interaction 2012; pp 17-24; doi:10.1145/2157689.2157693
62. Kruijff GJM, Janicek M, Zender H. Situated communication for joint activity in human-robot teams. IEEE Intelligent Systems 2012; 27(2):27-35; doi:10.1109/MIS.2012.8
63. Wang RH, Viswanathan P, Czarnuch S, Boger J, Nejat G, Mihailidis A. Developing advanced assistive technologies for older adults with dementia: Lessons learned. In: Proceedings of RESNA. Bellevue, USA, 2013