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Brian 2.1
A Socially Assistive Robot for the Elderly and Cognitively Impaired

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Introduction

As the world's elderly population continues to grow, so does the number of individuals diagnosed with cognitive impairments. By 2050, it is estimated that 115 million people will have age related memory loss [1]. The number of older adults who have difficulties performing self-care and independent living activities increases significantly with the prevalence of cognitive impairment. This is especially true for the population over 70 years of age [2]. Cognitive impairment, as a result of dementia, severely affects a person's ability to independently initiate and perform daily activities as cognitive abilities can be diminished [3]. If a person is incapable of performing these activities, continuous assistance from others is necessary. In 2010, the total worldwide cost of dementia (including medical, social and informal care costs) was estimated to be $604 billion USD [1].

Recent studies have supported the positive effects that cognitive training interventions can have on the cognitive functioning of older adults [4]. However, more research is needed as these therapies still have inadequate ecological validity and unproven outcomes. Moreover, the implementation of such interventions requires considerable resources and people. Due to the fast-growing demographic trends, the available care needed to provide supervision and coaching for cognitive interventions is already lacking and on a recognized steady decline [5]. There exists an urgent need to further investigate the potential use of cognitive training interventions as a tool to aid the elderly.

The goal of our research is to advance knowledge in cognitive/social interventions for elderly individuals suffering from cognitive impairments via the development of robotic technology [6,7]. We aim to design human-like socially assistive robots capable of providing cognitive assistance and social interaction in self-maintenance (i.e., eating, dressing and grooming) and activities of daily living (i.e., cognitively and socially stimulating leisure activities). These robots focus on the core impairments of dementia and the ability to support working memory, attention, awareness and focus on task behavior, in order to reduce a person's dependence on caregivers and provide him/her with social interaction during the course of these activities. Our long-term goal is to study how such robots can contribute to therapeutic protocols aimed at improving or maintaining residual social, cognitive and global functioning in persons suffering from dementia.

In this article, we present the development of our unique expressive *human-like* socially assistive robot Brian 2.1, Fig. 1, that can engage elderly individuals in both self-maintenance and cognitively stimulating leisure activities. The robot is able to determine its appropriate assistive behaviors based on the state of the activity and a person's user state. The social abilities of the robot play an important role in creating engaging and motivating interactions customized for individual users. In addition, we present the results of human-robot interaction (HRI) studies conducted with elderly users at a long-term care facility to investigate the overall acceptability of such a human-like robot for the intended activities. Namely, the study consisted of observing user engagement and compliance during interactions with Brian 2.1, as well as obtaining user feedback regarding acceptance of the robot as an assistive tool via a questionnaire administered after the interactions.

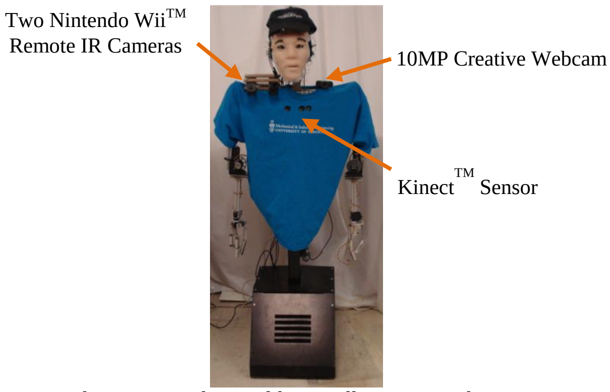

Fig. 1. The expressive human-like socially assistive robot Brian 2.1.

Related Work

Limited research has been conducted on the use and benefits of social robots as therapeutic aids or assistants for activities of daily living for the elderly. However, such robots have the potential to bring a new interaction tool to a vulnerable population that would otherwise lack resources. They also appear to make existing care cheaper and more effective [8]. For example, the seal-like robot Paro has been designed to engage elderly persons in animal therapy scenarios by learning which

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behaviors are desired by the way a person pets, holds, or speaks to it. Studies performed with Paro have shown that the robot can improve users' mood and stress levels, as well as facilitate interaction between users by creating a comfortable and sociable atmosphere [9]. The Pearl robot was developed to perform tasks in assisted living facilities such as providing a person with reminders, guiding him/her to appointments and/or providing information assistance [10]. Experiments with a group of six elderly people verified the robot's ability to autonomously and effectively complete the guidance task. A music game study performed with the child-like robot Bandit II and three elderly participants with cognitive impairments showed an improvement in cognitive attention and task performance over a six month period [11]. The same robot was also used in [12] as an exercise instructor. A feasibility study with eleven elderly participants showed that the robot could motivate these individuals to perform simple physical exercises. The novelty of our robot Brian 2.1 with respect to the aforementioned robots is in its increased human-like social abilities. Namely, the robot can determine both user engagement and activity state during HRI and, in turn, use this information in real-time to determine its own emotional assistive behaviors. We also propose two new assistive interaction activities for the robot: meal eating and a card game.

To date, the majority of outcomes that have been utilized to study HRI with interactive robots and the elderly have focused primarily on task performance. A handful of studies have also collected detailed data on the acceptance and attitudes towards a robot and its social behaviors, however, they have been mainly focused on animal-like robots such as Paro [9], and iCat [13]. In this article, we investigate assistive HRI with an expressive human-like robot, in order to determine if the robot's human-like assistive and social characteristics would promote activity engagement and also result in the elderly having positive attitudes towards the robot as well as accepting it.

One-on-One Cognitive Intervention Scenarios with Brian 2.1

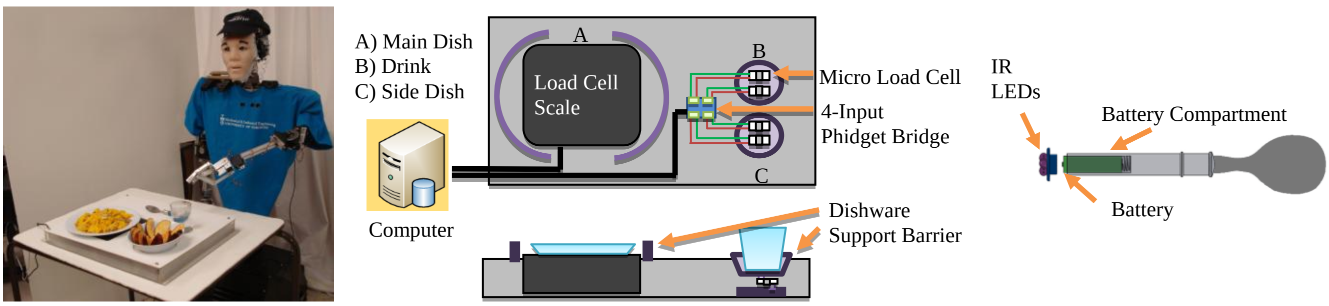
Research has found that individuals with cognitive impairments who reside in nursing homes have low activity levels and are at a higher risk for understimulation because they lack the initiative to begin or sustain activities of daily living [14]. These findings were vital to designing Brian 2.1 and the cognitive interventions that the robot can provide. For our exploratory work, the two interventions that we considered include: 1) the self-care activity of eating, and 2) a leisure memory card game. Both activities can significantly contribute to the quality of life of older adults.

The Human-like Socially Assistive Robot Brian 2.1

Brian 2.1 has been designed to have similar functionalities to a person from the waist up. The robot can display body language, gestures and facial expressions using: 1) a 3 degrees of freedom (DOF) neck capable of life-like head motions; 2) two arms that have four DOFs each; that allow Brian 2.1 to point to different objects; 3) a 2 DOF waist that allows the robot to turn left and right, and also lean forward and backwards; and 4) a 5 DOF facial muscle system capable of displaying emotions such as happy, neutral and sad. The robot is also able to communicate verbally using speech and vocal intonation using a synthesized voice. Multiple sensing modalities are used by the robot to determine the state of the two activities as well as the user during HRI. These inputs are then used to determine the robot's assistive behavior.

Meal Eating Activity Assistance

Nutritional well-being can be compromised with dementia as there exists a reduced ability to consume foods without constant prompting (more than 65% of nursing home residents have unintentional weight-loss and under-nutrition due to cognitive disabilities [15]). The objective is for Brian 2.1 to improve the independent eating habits of elderly individuals and to enhance their overall meal time experience by providing prompts, encouragement, and orientating statements, Fig. 2(a).



(a) (b) (c)

Fig. 2. Meal assistance scenario.

Eating is monitored through the use of a utensil tracking system and a meal tray that we have designed with embedded weight sensors to track changes in the weight of food in plates/bowls and liquids in glasses. A schematic of the meal tray is shown in Fig. 2(b). We consider the contents of the meal to consist of a main dish, side dish, and beverage. The meal tray consists of the following embedded sensors: 1) a DYMO M10 Scale to measure the weight changes of the main dish; and 2) two pairs of Phidgets shear micro load cells for the side dish and beverage. To account for data acquisition delays, sensor noise and errors caused by a user exerting pressure onto the sensors with his/her utensil, a median filtering algorithm is utilized. The robot will focus a person's attention to a particular dish or the beverage on the meal tray based on a meal plan provided by the caregiver.

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The sensing platform is calibrated using the weight of empty dishes prior to its use. The meal tray sensing platform is used to monitor the following activities: 1) food has been picked up (decrease in weight), 2) the cup has been lifted up (decrease in cup weight to zero), 3) the beverage in the cup has been consumed (decrease in cup weight), 4) a meal item has been finished (weight of meal item is zero), and 5) food has not been eaten for an extended period of time (no weight change). Based on the food and beverage levels, the robot can determine which stage of the meal-time scenario the user is in.

The utensil tracking system consists of: 1) two Nintendo Wii™ Remote IR Camera's with resolutions of 1024x768 pixels mounted on Brian 2.1's right shoulder (Fig. 1); 2) a Kinect™ depth sensor (Fig. 1), and 3) three 940 nm IR LEDs which are affixed to the utensil (Fig. 2(c)). The IR cameras are utilized with the IR LEDS to determine the 3D position of a utensil via infrared stereo vision. The Kinect™ depth sensor [16] is utilized to locate the 3D position of the user's head during the meal eating activity. Tracking of both the 3D positions of a user's head and the utensil allows the robot to determine three location states for the utensil: at the mouth, on the tray or between the tray and mouth. To detect the direction of motion of the utensil (i.e., towards the mouth, towards the tray or no motion), the location of the utensil is tracked to observe utensil state transitions. Tracking the utensil's movement allows the robot to estimate the eating task the user is performing.

Memory Card Game Activity

The memory game is a one-on-one game consisting of matching pairs of picture cards. This intervention consists of Brian 2.1 engaging an older adult in the game by providing targeted encouragement, motivation and control over the game via verbal and non-verbal cues, Fig. 3(a). Eight pairs of picture cards are turned face down in a 4x4 grid formation at the start of the game. The objective is to flip over two cards in each round and match the pictures on the cards. The game is over when all cards have been matched. The game uses large (9.5cm x 9.5cm) and easy to manipulate (thickness of 0.75 cm) cards that we have designed, Fig 3(b). A 1.3MP Logitech camera is used as an overhead camera to determine the number, location and identify of cards that have been flipped over in a round of the game. A card recognition and localization approach that utilizes SIFT (Scale-Invariant Feature Transform) [17] has been developed to identify flipped over cards. Pairs of picture cards have a large number of unique SIFT keypoints allowing them to be distinguished from other cards. A database of the keypoints for each picture card is utilized to identify the cards that have been flipped over during the game.

This game was chosen so that the intervention can be designed to match varying levels of cognitive functioning abilities and thus, provide appropriate opportunities for different individuals to participate. The memory functions within the brain that will be trained during this game include both the visual memory and the working memory. The pictures on the cards also provide an opportunity to evoke personal memories of the objects.

(a) (b)

Fig. 3. (a) Memory game scenario, and (b) sample cards used in the game.

User State

People suffering from dementia can easily be distracted from a particular task at hand due to limited attention span and concentration, or other diversions in their environment [18]. The objective, herein, is for the robot to recognize this distracted state in order to re-engage the person in an activity. User state is defined to be either distracted or attentive to the robot or activity. To determine these states, a combination of face orientations and body language are used.

Face Orientations

Face orientation is detected and tracked from a 10MP Creative webcam, mounted on the robot's left shoulder (Fig. 1), by determining the distances between the eyes and nose of the user to identify if the person is looking towards the robot, the activity or has turned away from both. The facial feature tracking system is based on Haar feature-based cascade classifiers, [19], which are used to locate the face, eyes and nose. An identified facial feature is denoted by a bounding box. Namely, the feature is assumed to be at the centroid of the bounding box. Face orientation is defined in the horizontal (looking left or right) direction.

The face orientation angle, θ, is determined utilizing the location of the eyes and nose:

$$\theta = \sin^{-1}\left(\frac{l_{en} - r_{en}}{r_{en} + l_{en}}\right) \quad \text{if } \theta > 0 \text{ then angle is to the right, if } \theta < 0 \text{ then angle is to the left,} \qquad (1)$$

where r_{en} is the distance from the center of right eye to the center of the nose and l_{en} is the distance from the center of the left eye to the center of the nose, Fig. 4(a). If θ is greater than 45° in either the left or right direction, the face is presumed to be oriented away from the interaction, Fig. 4(b) and (c). The choice of 45° is based on empirical results that have shown the

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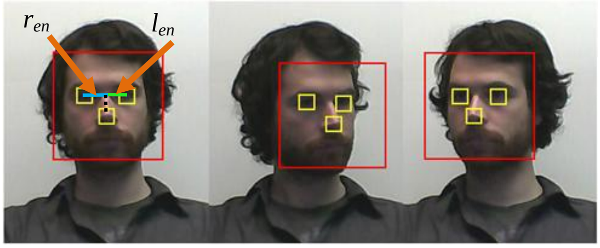
difficultly in having a gaze direction towards the robot or activity when the head has been oriented at this angle or angles larger than 45°. If facial features are occluded for a long period of time, i.e., because only the profile of the face is observable or if a facial feature has been occluded by an object, we utilize the last detected face orientation.



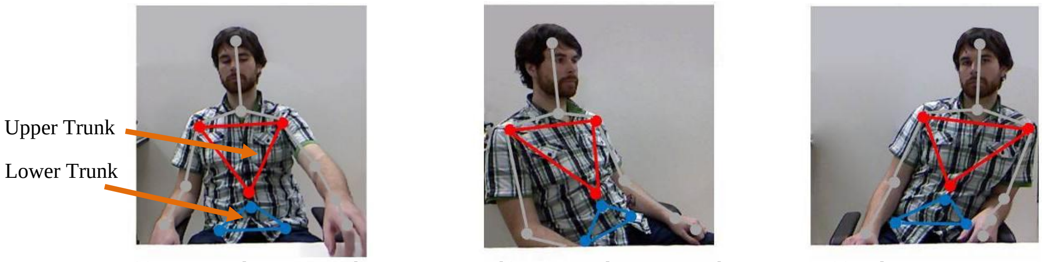
(a) Centered Horizontal (b) Left and away (c) Right and away

Fig. 4. Face orientation examples.

Body Language

A person's fluctuations in rapport, stress, involvement, and affective state can be determined by analyzing static body poses during one-on-one interactions [20]. During the proposed HRI scenarios, the robot can determine how accessible (i.e., open) a person is to the activity and interaction based on trunk orientations and leans of these static poses. Herein, a body pose is defined to be static if it is held for at least four seconds [20].

The 3D Kinect™ skeleton model [16] is used to track the trunk orientations of users. We utilize the planes generated from the three joint points of the skeleton model representing the left and right shoulders and the spine (in the middle of the torso along the back) to determine the orientation of the upper trunk, and the three joint points that represent the left, right and center hip locations to define the orientation of the lower trunk. Fig. 5(a) shows an example of the skeleton for a person sitting at the card game scenario. Trunk lean is determined from the hip and shoulder joint points, if the right/left shoulder joint is less than 30% of the hip width (defined as the distance between the left and right hip joints) to the right/left of the right/left hip joint, then the participant is considered to be in an upright stance. If the angle between the upper and lower trunk planes is more than 10°, the user is considered to be leaning forward. These parameters have been verified by the authors through empirical testing of numerous different individuals in different leaning poses. These trunk orientations and leans are then categorized utilizing the Davis Nonverbal State Scale (DNSS) [20]. DNSS is a coding method developed to investigate body poses displayed by a person during an interaction in order to directly correlate a person's body language to his/her reaction during one-on-one conversations [20]. The DNSS relates upper and lower trunk orientations/leans to a person's level of accessibility. Using DNSS, trunk orientations are defined as: towards (T), when oriented between 0° and 3° from the robot; neutral (N), when oriented between 3° to 15° from the robot; and away (A), when oriented more than 15° from the robot. Fig. 5(b) and (c) show examples of trunk orientations and leans. Table I shows the combinations of trunk orientations and leans for each accessibility level from level I corresponding to the least accessible static pose to level IV most accessible static pose.



(a) Upper and Lower Trunk Orientations Towards the Activity (b) Upper and Lower Trunk Orientations Away from the Activity (c) Sideways Lean

Fig. 5. Example Kinect™ skeletons overlaid on Kinect™ 2D images of a person with different trunk orientations/leans.

Once the face and trunk orientations have been classified individually, a person's overall user state, distracted or attentive towards the robot or activity, is determined based on the combination of body language and face orientations, Table II. These user states are based on studies that have shown that the lower body parts such as the lower/upper trunks define the dominant direction of involvement of a person over the head [21]. Different combinations of face and trunk orientations may indicate that a user is attempting to be involved in multiple courses of actions and could lead to short-term or long-term distraction (where the latter is simply defined in Table II as distracted) [21].

Robot Behavior Deliberation

Currently, a finite state machine is used to determine the assistive behaviors of Brian 2.1 based on the activity and user state inputs. To promote the social dimensions of an activity, Brian 2.1 greets a person, tells jokes and provides general positive statements about the interaction or the activity. Since the robot will interact with elderly persons with different interaction preferences and/or varying degrees of cognitive impairment, it has the ability to personalize its actions based on the person's user state and task compliance.

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TABLE I: ACCESSIBILITY LEVELS

Trunk Orientation	*Accessibility Level*
Upper/Lower trunk: T/N or N/T combined with upright or forward leans, T/T with all possible leans	IV
Upper/Lower trunk: T/N or N/T except positions that involve upright or forward leans	III
Upper/Lower trunk: N/N, A/N, N/A, T/A, A/T with all possible leans	II
Upper/Lower trunk: A/A with all possible leans	I

TABLE II: USER STATE

Face Orientation	*Accessibility*	*User State*
Towards Robot or Activity	I	Distracted
Towards Robot or Activity	II	Distracted
Towards Robot or Activity	III	Attentive
Towards Robot or Activity	IV	Attentive
Away from Robot or Activity	I	Distracted
Away from Robot or Activity	II	Distracted
Away from Robot or Activity	III	Short-term Distracted
Away from Robot or Activity	IV	Short-term Distracted

Robot Behaviors for the Meal Eating Activity

The robot's behaviors for the meal eating activity are based on the objective to motivate a user to eat or drink while promoting the social dimensions of eating (i.e., telling jokes). The behaviors are categorized into prompts to: 1) obtain food from a dish or lift a beverage, and 2) to eat food or drink a beverage. The task graph for the meal eating activity is shown in Fig. 6(a). Two techniques are used to motivate the person to complete a given meal task: *Encourage* and *Orient*. *Encouraging* behaviors are positive reasoning tactics that are provided along with prompts to convince the user to perform a meal task. *Orienting* actions are designed to provide general awareness of the activity and the environment. The robot provides encouraging behaviors using a happy emotional state, while orientating behaviors are provided in a neutral emotional state. When a user becomes (long-term) distracted, the robot provides orientating behaviors in a sad emotional state. Example robot behaviors are presented in Table III and Fig. 7(a) and (b).

Robot Behaviors for the Memory Card Game

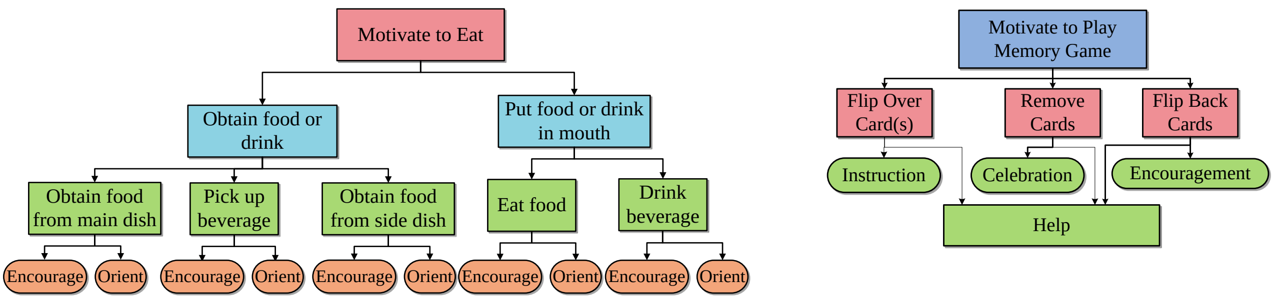
The robot's behaviors for the memory card game activity are based on the overall objective to identify and check that all pairs of cards have been matched correctly, and are categorized into providing: 1) instructions - guiding a user to flip over cards; 2) celebration - congratulating a user on finding a matching pair of cards; 3) encouragement- reinforcement to try again when a match is not found; and 4) help - identifying the location of a matching card when *n* rounds have been played without a match. For the study presented, herein, we chose *n* to be 2 in order to allow users to frequently experience success with the robot and build up confidence in their abilities to use it. The task graph for the card game is shown in Fig. 6(b). Examples of these types of behaviors are presented in Table IV and Fig. 7(c) and (d). The instruction and encouragement behaviors of the robot are implemented in a neutral emotional state, except when the user becomes (long-term) distracted, at which time instructions are provided in a sad emotional state (i.e., sad facial expression and voice). Celebration behaviors are implemented in a happy emotional state. A happy voice is characterized by a higher pitch and a faster speaking rate than the neutral voice and a sad voice is characterized by a slower speaking rate and lower pitch than the neutral voice.

TABLE III: EXAMPLE ROBOT BEHAVIORS FOR MEAL EATING ACTIVITY

Behavior Type	*Example Behavior*
Encourage to obtain food from main dish	"The main dish smells amazing. Why don't you pick up some food with your spoon."
Orient to obtain food from side dish	"Your side dish is located at the bottom right corner of your tray." (while pointing to the side dish)
Encourage to eat food	"What you have on your spoon looks delicious. Why don't you take a bite and see how it tastes."
Joke and positive statements	"Why did the cookie go to the doctor? She was feeling crummy." (robot chuckles and puts one hand in front of its mouth)

TABLE IV: EXAMPLE ROBOT BEHAVIORS FOR CARD GAME ACTIVITY

Behavior Type	*Example Behavior*
Instruction	"Let's play a round of the memory game. Please flip over a card."
Celebration	"Congratulations, you have made a successful match. Please remove the cards from the game."
Encouragement	"Those are interesting cards that you have flipped over, but they are not the same. Please flip back the cards and try again. I know you can do this!"
Help	"The matching card is located here." (while pointing to the card location)



(a) Meal eating activity (b) Memory card game

Fig. 6. Activity task graphs.

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(a) Brian 2.1 happy while encouraging a user to pick up food.

(b) Brian 2.1 sad while orienting a distracted user.

(c) Brian 2.1 and user laughing at the robot's joke.

(d) Brian 2.1 providing celebration for matching cards.

Fig. 7. Example robot behaviors during HRI.

HRI Studies at a Long-Term Care Facility

We conducted a preliminary study at a local long-term care facility to observe potential user interactions with the robot, Fig. 8. The robot was placed in a public space at the facility for two days. Brian 2.1 would introduce itself and ask if individuals would be interested in playing the memory game with it. It would also explain how it could monitor a meal-eating activity by cueing individuals to pick up and move the utensil, and pick up and place the beverage on the tray. Members of the research team were present to observe the interactions, answer questions about the robot and administer questionnaires.

The measured variables for this HRI study were: (a) duration of interaction, (b) engagement in the interaction as defined by the frequency and type of participant interaction (i.e., manipulation of cards and/or utensil and cup, attention towards the activity or robot), (c) compliance with the robot (i.e., person's cooperative behaviors with respect to the robot's behaviors), and (d) acceptance and attitudes towards the robot. In order to obtain feedback on their experience with Brian 2.1 a user acceptance questionnaire was administered to participants after the interactions. The questionnaire, Table V, included nine constructs from the technology acceptance model developed by Heerink et al. [13]. Participants were instructed to indicate their agreement with each statement using a five point Likert scale (5=strong agreement, 3=neutral, 1=strong disagreement). They were also asked to identify the characteristics of the robot they liked the most. Demographic information, and experience with computers and robots were collected to describe the questionnaire results. A number of participants also engaged in open dialogue about the robot with our research team.

Fig. 8. Brian 2.1 interacting with individuals at the long-term care facility.

Results and Discussions

During the two days, we were able to observe the interactions of forty elderly participants having mild Alzheimer's disease, mild cognitive impairments and normal cognitive controls. We also obtained twenty-two completed questionnaires from participants ranging in age from 57 to 100 years old. For this exploratory study we did not categorize the results for different cognition levels due to the short-term nature of the interactions, but rather focused on how older adults interacted with a human-like robot to obtain feedback in order to optimize robot design. User engagement was observed for each interaction of an activity to identify the presence/non-presence of the engagement indicators presented above (manipulation of objects and attention towards activity/robot). Each interaction is defined to include a robot detecting a user's action (which updates the activity state) as well as the corresponding robot's reaction. The results were then categorized into a participant being engaged: all the time (constant presence of engagement indicators); some of the time (at least one or more instances where non-presence of engagement indicators is detected); or none of the time (constant non-presence of engagement indicators). A similar approach was utilized to determine compliance. The results showed that 33 participants were engaged all the time and 7 were engaged some of the time. With respect to compliance: 35 participants complied with the robot all the time, 4 participants complied some of the time and 1 participant did not comply. Hence, the majority of participants were both engaged and complied with Brian 2.1. The participant that did not comply with the robot stated that its voice was causing interference with his hearing aid. Since the robot was placed in a large space with a lot of background noise, we used an amplifier to increase the volume of the robot's voice. Even though the participant had this issue, he sat with and watched the robot for approximately 5 minutes before letting one of the research team members know about the interference. The average length of time participants interacted with Brian 2.1 was 12.6 minutes. There were no observable differences between the two activities for engagement and compliance during the interactions. We also observed participant reactions to both the happy and sad emotional behaviors of Brian 2.1. When the robot was happy, we found that 82% of the participants either smiled back at the robot or laughed. For the 7 participants that were distracted at least once during the interactions, at which time the robot displayed a sad state, it was found that 57% were re-engaged by looking at Brian 2.1 and verbally responding back to the robot's emotion empathetically. The remaining 43% were re-engaged by bringing their focus of attention back to the robot and activity.

Three participants interacted with Brian 2.1 on two different occasions and one participant interacted with the robot on four different occasions during the course of the two days. In general, the majority (31 participants) were polite to the robot, greeting it before interactions, thanking the robot for its help and saying good-bye to the robot. Six participants talked to the robot by asking questions regarding their progress throughout the memory game activity, for example "How am I doing Brian?" and "What do you think about these two cards?" One of these participants actively asked the robot to provide her with encouragement after she did not get a matching pair of cards. Other participants commented to Brian 2.1 about the pictures on the cards. For example, one male participant wearing a tie told the robot that his tie was similar to the tie on one of the cards. Similar to other HRI studies in public places, the robot promoted interactions between the participants and other elderly individuals as well as their caregivers. Participants discussed the robot's behaviors with on-lookers or laughed with them when the robot smiled or told a joke.

Post-Interaction Questionnaire Results

The demographic and background information of the twenty-two participants who completed the questionnaire is presented in Table VI. Cronbach's alpha was determined for the constructs in the questionnaire that had multiple questions in order to verify inter-reliability between them for the participant group. Alpha values are presented in Table V under the appropriate constructs. In general, values of at least 0.5 are considered to be acceptable for such short instruments [22]. The descriptive statistics for the individual questions of the questionnaire are also presented in Table V. Based on the results, it is worth noting that Brian 2.1 scored high on questions related to the participants' attitudes towards using the robot, their perceived enjoyment during interactions with the robot and the robot's perceived sociability. Furthermore, they found the robot easy to use and would use it again. Participants were also trusting of the advice the robot would provide them. In general, participants had a positive experience with the robot, which influenced their motivation to use it again. The memory card game appeared to be the most enjoyable activity for the participants based on open feedback provided on the questionnaire.

TABLE V: USER ACCEPTANCE QUESTIONNAIRE

Construct	Statement	Min	Max	Mean	Std. Dev.
Attitude Towards Using the Robot (alpha=0.64)	1. I think it's a good idea to use the robot.	3.0	5.0	4.71	0.58
	2. The robot would make my life more interesting.	1.0	5.0	4.35	1.11
Intent to Use	3. I would use the robot again.	2.0	5.0	4.53	0.94
Perceived Adaptability	4. I think the robot can help me with what I need.	1.0	5.0	3.59	1.41
Perceived Enjoyment	5. I enjoy the robot talking to me.	4.0	5.0	4.65	0.49
Perceived Ease of Use	6. I find the robot easy to use.	2.0	5.0	4.53	0.79
Perceived Sociability (alpha=0.50)	7. I find the robot pleasant to interact with.	2.0	5.0	4.47	0.94
	8. I feel the robot understands me.	1.0	5.0	3.88	1.16
	9. I think the robot is nice.	4.0	5.0	4.76	0.43
Perceived Usefulness (alpha=0.84)	10. I think the robot is useful to me.	1.0	5.0	3.53	1.50
	11. It would be convenient for me to have the robot.	1.0	5.0	3.24	1.60
	12. I think the robot can help with many things.	1.0	5.0	3.56	1.45
Social Presence (alpha=0.62)	13. When interacting with the robot I felt like I'm talking to a real person.	1.0	5.0	3.18	1.42
	14. It sometimes felt as if the robot was really looking at me.	2.0	5.0	4.18	0.91
	15. I can imagine the robot to be a living creature.	1.0	5.0	3.12	1.5
	16. Sometimes the robot seems to have real feelings.	1.0	5.0	3.37	1.45
Trust (alpha=0.86)	17. I would trust the robot if it gave me advice.	1.0	5.0	3.37	1.40
	18. I would follow the advice the robot gives me.	1.0	5.0	3.68	1.25

TABLE VI: DEMOGRAPHIC AND BACKGROUND INFORMATION OF QUESTIONNAIRE PARTICIPANTS

Age	Sex	Participants' Experience with Computers	Participants' Experience with Robots
57-100	14 Females (F) 8 Males (M)	8 (7 F and 1 M): **No experience**	19 (13 F and 6 M): **No experience**
		2 (1 F and 1 M): **Beginner** (email, use simple programs)	2 (1 F and 1 M): **Beginner** (seen robots at museums/science centers or stores, or have watched shows on real/physical robots)
		1 (M): **Intermediate** (internet, chat)	1 (M): **Intermediate** (have worked with/used commercial robots)
		11 (6 F and 5 M): **Advanced** (editing documents, use complex programs)	0: **Advanced** (have worked on robot developmental aspects including hardware/software design)

Table VII summarizes the participants' responses with respect to the most liked characteristics of the robot. The responses are based on a ranking of the total number of responses for each characteristic. The robot's ability to display different emotions through facial expressions and tone of voice was ranked the highest for the most-liked characteristic. This concurs with the results of the questionnaire and the observations of the interactions which found that a large number of participants smiled or laughed when the robot would smile at them or when the robot told a joke and subsequently laughed itself.

Influence of Gender and Experience with Computers

We conducted a non-parametric Mann-Whitney test on the Intent to Use and Perceived Enjoyment constructs to investigate if gender influenced these constructs for the *human-like* robot Brian 2.1. For both constructs, we found that there was no statistically significant difference between the two genders. Spearman ρ was used to determine if a correlation exists between computer experience and Perceived Ease of Use of Brian 2.1 with our study participants. We identified a ρ of 0.237, which showed no significant correlation between these two factors for our participants for an α=0.05. Namely, we found that both the male and female participants regardless of their computer experience found the robot easy to use.

TABLE VII: MOST LIKED ROBOT CHARACTERISTICS

Ranking	Robot Characteristics
1st (82% of participants)	The robot expressing different emotions through facial expressions and different tones of voice
2nd (77% of participants)	The robot's human-like voice
2nd (77% of participants)	The robot's life-like appearance and demeanor
3rd (68% of participants)	The companionship the robot provides by just being there

Conclusions

This research focuses on providing a needed assistant for cognitive/social interventions for elderly individuals via the development of the expressive human-like robot Brian 2.1. We have designed Brian 2.1 to provide assistance for two interventions: a meal eating activity and a leisure memory card game. The robot uses various sensor modalities to identify activity and user states in order to determine its assistive behaviors. We conducted a preliminary study with Brian 2.1 at a long-term care facility to observe potential user interactions with the robot. We found that the large majority of the elderly participants were both engaged in the interaction and complied with the robot's prompts during interaction. The user acceptance questionnaire showed that Brian 2.1 scored high on questions related to participants' attitudes towards using the robot, their perceived enjoyment during the interactions and the robot's perceived sociability. The robot's display of emotions was highly liked by the participants. We also found no significant difference between males and females for their intent to use the robot and perceived enjoyment. Regardless of the level of computer experience, participants also found the robot easy to use. In general, the results of the HRI study presented show promise for the use of a human-like robot for cognitive interventions, and motivate further development and long-term testing of the robot.

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