Brian 2.1

A Socially Assistive Robot for the Elderly and Cognitively Impaired

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As the world's elderly population continues to grow, so does the number of individuals diagnosed with cognitive impairments. It is estimated that 115 million people will have age-related memory loss by 2050 [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 US$604 billion [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

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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 humanlike, 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, to reduce a person's dependence on caregivers and provide him/her 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, humanlike, socially assistive robot, Brian 2.1 (Figure 1). Brian 2.1 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 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.

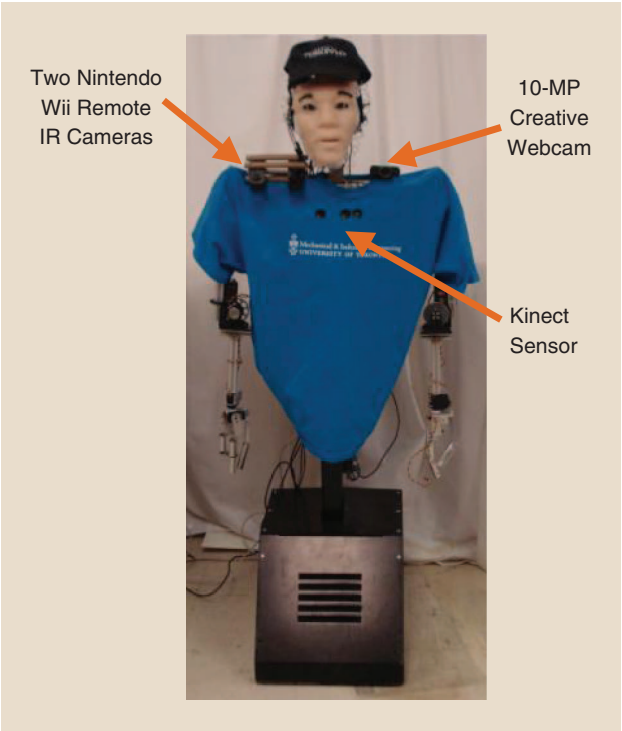


Figure 1. The expressive, humanlike, socially assistive robot, Brian 2.1.

Related Work

To date, limited research has been conducted on the use and benefits of social robots as therapeutic aids or assistants 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 the elderly in animal therapy by learning which behaviors are desired from 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 the 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 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 childlike 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 the 11 elderly participants showed that the robot could motivate these individuals to perform simple physical exercises.

The number of older adults who have difficulties performing self-care and independent-living activities increases significantly with the prevalence of cognitive impairment.

The novelty of Brian 2.1 with respect to the aforementioned robots is its increased humanlike 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: eating and playing 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 toward 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 humanlike robot to determine whether the robot's humanlike assistive and social characteristics would promote activity engagement and also result in the elderly having positive attitudes toward 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 the design of Brian 2.1 and the cognitive interventions that it 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 robot is able to determine its appropriate assistive behaviors based on the state of the activity and a person's user state.

Brian 2.1's Design

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 lifelike head motions, 2) two arms that have 4 DoF each, allowing Brian 2.1 to point to different objects, 3) a 2-DoF waist that allows the robot to turn left and right and to lean forward and backward, 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 undernutrition 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 [Figure 2(a)].

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 Figure 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 microload cells for the side dish and beverage. To account for data-acquisition delays, sensor noise, and errors caused by a user exerting pressure on 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 on the basis of the meal plan provided by the caregiver.

The meal-tray-sensing platform is calibrated using the weight of empty dishes prior to its use. The 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)
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.

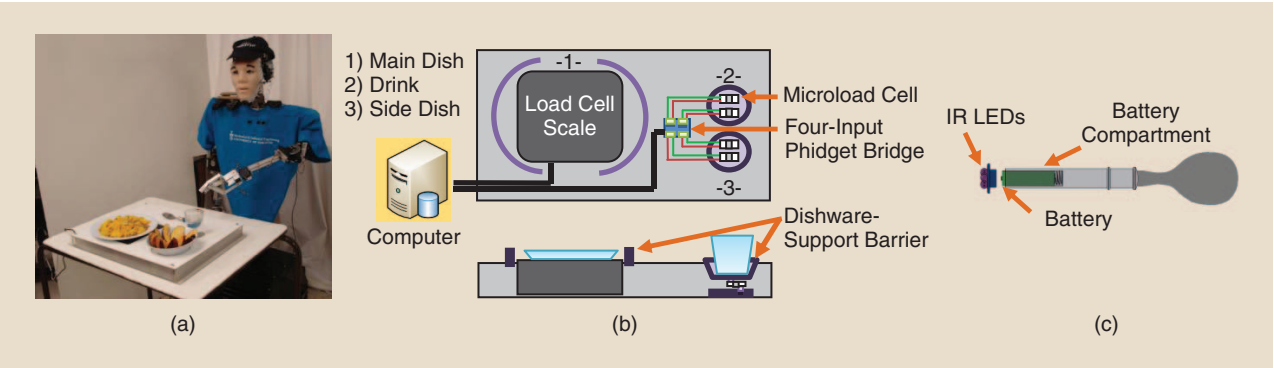


Figure 2. (a) Meal-eating scenario, (b) meal tray with embedded sensors, and (c) a utensil with IR LEDs.

The utensil-tracking system consists of: 1) two Nintendo Wii Remote infrared (IR) cameras with resolutions of 1024 ×768 pixels mounted on Brian 2.1's right shoulder (Figure 2), a Kinect depth sensor (Figure 1), and three 940-nm IR LEDs, which are affixed to the utensil [Figure 2(c)]. The IR cameras are utilized with the IR LEDS to determine the three-dimensional (3-D) position of a utensil through IR stereo vision. The Kinect depth sensor [16] is used to locate the 3-D position of the user's head during the meal-eating activity. Tracking of both the 3-D 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., toward the mouth, toward 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 that the user is performing.

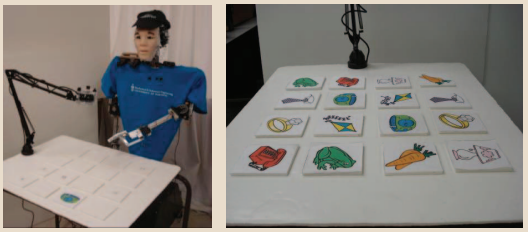
Memory Card Game Activity

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 nonverbal cues [Figure 3(a)]. Eight pairs of picture cards are turned face down in a 4 ×4 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 (9.5 cm × 9.5 cm) and easy to manipulate (thickness of 0.75 cm) cards that we have designed [Figure 3(b)]. A 1.3-MP Logitech camera is used as an overhead camera to determine the number, location, and identity of cards that have been flipped over in a round of the game. A card recognition and localization approach that utilizes scale-invariant feature transform (SIFT) [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 function 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 and working memory. The pictures on the cards also provide an opportunity to evoke personal memories of the objects.

User State

People suffering from dementia can easily be distracted from a particular task due to limited attention span and concentration or other diversions in their environment [18]. The objective is for the robot to recognize this distracted state to reengage the person in an activity. The 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.



(a) (b)

Figure 3. (a) A memory game scenario and (b) the sample cards used in the game.

Face Orientations

The face orientation is detected and tracked from a 10-MP Creative webcam, mounted on the robot's left shoulder (Figure 1), by determining the distances between the eyes and nose of the user to identify whether the person is looking toward 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. The face orientation is defined in the horizontal (looking left or right) direction.

The user state is defined to be either distracted or attentive to the robot or activity.

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

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

where r_{en} is the horizontal distance from the center of the right eye to the center of the nose, and l_{en} is the horizontal distance from the center of the left eye to the center of the nose [Figure 4(a)]. If θ is greater than 45° in either the left or the right direction, the face is presumed to be oriented away from the interaction [Figure 4(b) and (c)]. The choice of 45° is based on empirical results that have shown the difficulty in gazing toward the robot or activity when the head has been oriented at an angle of 45° or greater. If facial features are occluded for a long period of time, i.e., because only the profile of the face is observable or when a facial feature has been occluded by an object, we utilize the last detected face orientation.

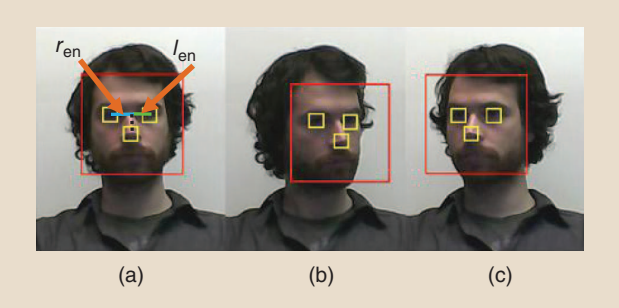


Figure 4. Face orientation examples: (a) centered horizontal, (b) left and away, and (c) right and away.

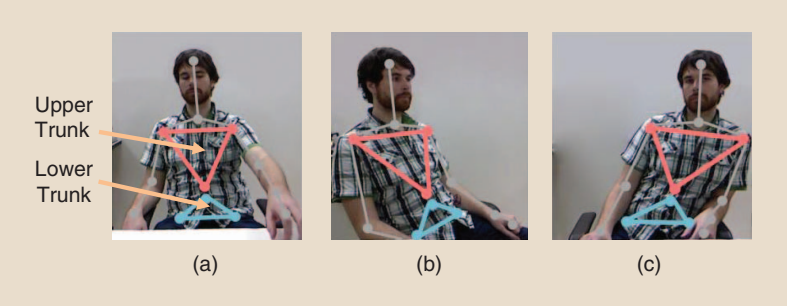


Figure 5. Example Kinect skeletons overlaid on Kinect 2-D images of a person with different trunk orientations/leans: (a) upper- and lower-trunk orientations toward the activity, (b) upper-and lower-trunk orientations away from the activity, and (c) sideways lean.

Table 1. 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 2. User state.

Face Orientation	Accessibility	User State
Toward robot or activity	I	Distracted
Toward robot or activity	II	Distracted
Toward robot or activity	III	Attentive
Toward 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

Body Language

A person's fluctuations in rapport, stress, involvement, and affective state can be determined by analyzing their 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 on the basis of the trunk orientations and leans of these static poses. Herein, a body pose is defined to be static if it is held for at least 4 s [20].

The 3-D Kinect skeleton model [16] is used to track the trunk orientations of users. We use 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. Figure 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]. The DNSS is a coding method developed to investigate body poses displayed by a person during an interaction to directly correlate a person's body language to his/her reaction during one-on-one conversations [20]. The DNSS relates the upper and lower trunk orientations/leans to a person's level of accessibility. Using DNSS, the trunk orientations are defined as: toward (T), when oriented between 0° and 3° from the robot; neutral (N), when oriented between 3° and 15° from the robot; and away (A), when oriented more than 15° from the robot. Figure 5(b) and (c) shows examples of the trunk orientations and leans. Table 1 shows the combinations of the trunk orientations and leans for each accessibility level from level I (least accessible static pose) to level IV (most accessible static pose).

Once the face and trunk orientations have been classified individually, a person's overall user state (distracted or attentive to the robot or activity) is determined based on the combination of body language and face orientations (Table 2). These user states are based on studies that have shown that the lower body parts such as the lower/upper trunk define the dominant direction of involvement of a person rather than the

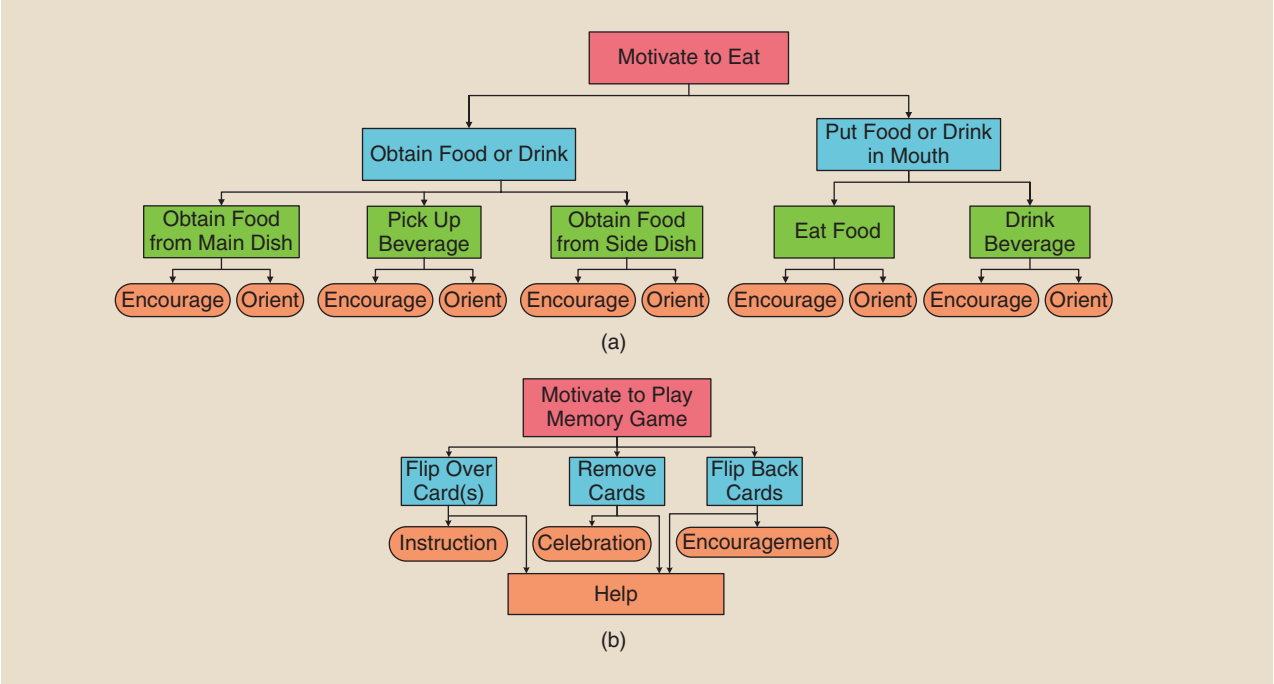


Figure 6. Activity task graphs for (a) the meal eating activity and (b) the memory card game.

head [21]. Different combinations of face and trunk orientations may indicate that a user is attempting to be involved in multiple courses of action, which could lead to short-term or long-term distraction (where the latter is simply defined in Table 2 as distracted) [21].

Robot Behavior Deliberation

Currently, a finite-state machine is used to determine the assistive behaviors of Brian 2.1 on the basis of 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 people with different interaction preferences and/or varying degrees of cognitive impairment, it has the ability to personalize its actions on the basis of the person's user state and task compliance.

Robot Behaviors for the Meal-Eating Activity

The robot's behaviors for the meal-eating activity are based on the objective of motivating a user to eat or drink while promoting the social dimensions of eating (i.e., telling jokes). The behaviors are categorized into prompts to obtain food from a dish or lift a beverage and to eat food or drink a beverage. The task graph for the meal-eating activity is shown in Figure 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 3 and Figure 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 of identifying and checking that all pairs of cards have been matched correctly. The behaviors are categorized into providing: 1) instructions—guiding a user to flip 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

Table 3. 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." (The robot points 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." (The robot chuckles and puts one hand in front of its mouth.)

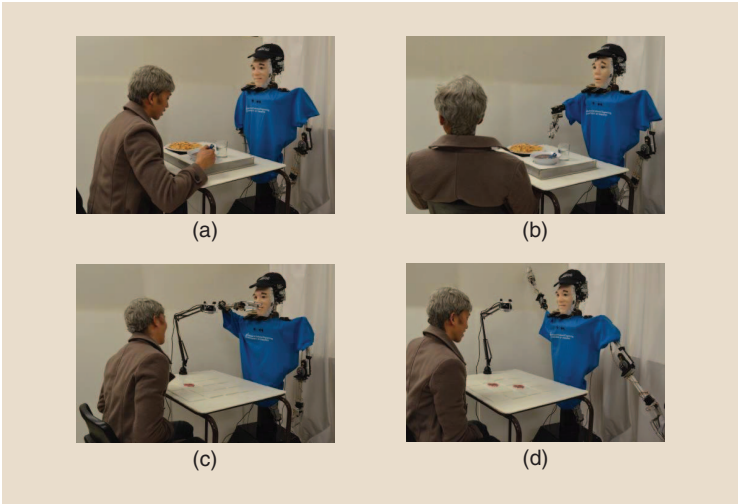


Figure 7. Examples of robot behaviors during HRI. (a) Brian 2.1 is happy while encouraging a user to pick up food, (b) Brian 2.1 is sad while orienting a distracted user, (c) Brian 2.1 and user laughing at the robot's joke, and (d) Brian 2.1 providing celebration for matching cards.

Table 4. Example robot behaviors for the 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." (The robot points to the card location.)

Figure 8. Brian 2.1 at the long-term care facility: (a) a one-on-one interaction and (b) a group of participants observing the robot.

chose n to be 2 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 Figure 6(b). Examples of these types of behaviors are presented in Table 4 and Figure 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.

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. The robot was placed in a public space at the facility for two days (see Figure 8). 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: 1) duration of interaction, 2) 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 to the activity or robot), 3) compliance with the robot (i.e., the person's cooperative behaviors with respect to the robot's behaviors), and 4) acceptance and attitudes toward the robot. To obtain feedback on their experience with Brian 2.1, a user-acceptance questionnaire was administered to participants after the interactions. The questionnaire (Table 5) 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, and 1 = strong disagreement). They were also asked to identify the characteristics of the robot they liked the most. Demographic information and information about users' experience with computers and robots were collected to describe the questionnaire results.

Table 5. User-acceptance questionnaire.

Statement	Construct	Minimum	Maximum	Mean	Standard Deviation
1) I think it's a good idea to use the robot. 2) The robot would make my life more interesting.	Attitude toward using the robot ($\alpha = 0.64$)	1.0	5.0	4.53	0.89
3) I would use the robot again.	Intent to use	2.0	5.0	4.53	0.94
4) I think the robot can help me with what I need.	Perceived adaptability	1.0	5.0	3.59	1.41
5) I enjoy the robot talking to me.	Perceived enjoyment	4.0	5.0	4.65	0.49
6) I find the robot easy to use.	Perceived ease of use	2.0	5.0	4.53	0.79
7) I find the robot pleasant to interact with. 8) I feel the robot understands me. 9) I think the robot is nice.	Perceived sociability ($\alpha = 0.50$)	1.0	5.0	4.37	0.96
10) I think the robot is useful to me. 11) It would be convenient for me to have the robot. 12) I think the robot can help with many things.	Perceived usefulness ($\alpha = 0.84$)	1.0	5.0	3.44	1.50
13) When interacting with the robot, I felt like I'm talking to a real person. 14) It sometimes felt as if the robot was really looking at me. 15) I can imagine the robot to be a living creature. 16) Sometimes the robot seems to have real feelings.	Social presence ($\alpha = 0.62$)	1.0	5.0	3.46	1.39
17) I would trust the robot if it gave me advice. 18) I would follow the advice the robot gives me.	Trust ($\alpha = 0.86$)	1.0	5.0	3.53	1.32

A number of participants also engaged in open dialogue about the robot with our research team.

Results and Discussion

During the two days, we were able to observe the interactions of 40 elderly participants having mild Alzheimer's disease, mild cognitive impairments, and normal cognitive control. We also obtained 22 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 because of the short-term nature of the interaction but rather focused on how the older adults interacted with a humanlike robot to obtain feedback to optimize the robot design.

User engagement was observed for each interaction of an activity to identify the presence/nonpresence of the previously mentioned engagement indicators (manipulation of objects and attention to the activity/robot). An interaction was defined as including the robot detecting the user's action (which updates the activity state) as well as the corresponding reaction from the robot. 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 nonpresence of engagement indicators is detected), or none of the time (constant nonpresence of engagement indicators). A similar approach was used to determine compliance. The results showed that 33 participants were engaged all the time and seven were engaged some of the time. With respect to compliance, 35 participants complied with the robot all the time, four participants complied some of the time, and one participant did not comply. Hence, the majority of participants both engaged and complied with Brian 2.1. The participant who 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. Although the participant had this issue, he sat with and watched the robot for approximately 5 min 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 min. There were no observable differences between the two activities for engagement and compliance during the interactions.

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.

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 seven participants who were distracted at least once during the interactions, at which time the robot displayed a

Table 6. 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 (e-mail, 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 7. 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 humanlike 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

sad state, it was found that 57% were reengaged by looking at Brian 2.1 and verbally responding back empathetically to the robot's emotion. The remaining 43% were reengaged by bringing their focus of attention back to the robot and activity.

The robot provides encouraging behaviors using a happy emotional state, while orientating behaviors are provided in a neutral emotional state.

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 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 asked 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 onlookers or laughed with them when the robot smiled or told a joke.

Post-Interaction Questionnaire Results

The demographic and background information of the 22 participants who completed the questionnaire is presented in Table 6. Cronbach's alpha (α) was determined for the constructs in the questionnaire that had multiple questions to verify interreliability between them for the participant group. Alpha values are presented in Table 5 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 constructs are also presented in Table 5. Based on the results, it is worth noting that Brian 2.1 scored high on questions related to the participants' attitudes toward using the robot, their perceived enjoyment during interactions with the robot, and the robot's perceived sociability. Furthermore, the participants found the robot easy to use and would use it again. The participants were also trusting of the advice the robot would provide them. In general, the 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 feedback provided in the questionnaire.

Table 7 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 nonparametric Mann–Whitney test on the intent to use and perceived enjoyment constructs to investigate whether gender influenced these constructs for the humanlike robot Brian 2.1. For both constructs, we found that there was no statistically significant difference between the two genders. Spearman's ρ was used to determine whether a correlation exists between computer experience and the 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 $\alpha = 0.05$. Namely, we found that both the male and female participants, regardless of their computer experience, found the robot easy to use.

Conclusions

This article focuses on providing a needed assistant for cognitive/social interventions for elderly individuals via the development of the expressive, humanlike robot, Brian 2.1. We designed Brian 2.1 to provide assistance for two interventions: a meal-eating activity and a leisure memory card game. The robot used various sensor modalities to identify activity and user states 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 the participants' attitudes toward 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 in their intent to use the robot and perceived enjoyment. Regardless of the level of computer experience, the participants found the robot easy to use. In general, the results of the HRI study presented show promise for the use of a humanlike robot for cognitive interventions and motivate further development and long-term testing of the robot.

References

[1] A. Wimo and M. Prince, "World Alzheimer's report 2010: The global economic impact of dementia," Alzheimer's Disease Int., London, U.K., Tech. Rep., 2010.

[2] National Academy on an Aging Society, "Caregiving: Helping the elderly with activity limitations," *Challenges for the 21st Century: Chronic Disabling Conditions*, no. 7, pp. 1–6, May 2000.

[3] E. F. LoPresti R. C. Simpson, N. Kirsch, D. Schreckenghost, and S. Hayashi, "Distributed cognitive aid with scheduling and interactive task guidance," *J. Rehab. Res. Develop.*, vol. 45, no. 4, pp. 505–522, 2008.

[4] K. Ball, D. B. Berch, K. F. Helmers, J. B. Jobe, M. D. Leveck, M. Marsiske, J. N. Morris, G. W. Rebok, D. M. Smith, S. L. Tennstedt, F. W. Unverzagt, and S. L. Willis, "Effects of cognitive training interventions with older adults," *J. AMA*, vol. 288, no. 18, pp. 2271–2281, 2002.

[5] M. Matarić, A. Okamura, and H. Christensen, "A research roadmap for medical and healthcare robotics," in *Proc. NSF/CCC/CRA Roadmapping for Robotics Workshop*, 2008, pp. 1–30.

[6] G. Nejat and M. Ficocelli, "Can I be of assistance? The intelligence behind an assistive robot," in *Proc. IEEE Int. Conf. Robotics Automation, 2008*, pp. 3564–3569.

[7] J. Chan, G. Nejat, and J. Chen "Designing intelligent socially assistive robots as effective tools in cognitive interventions," *Int. J. Humanoid Robot.*, vol. 8, no. 1, pp. 103–126, 2011.

[8] D. Feil-Seifer, K. Skinner, and M. J. Matarić, "Benchmarks for evaluating socially assistive robotics," *Interaction Stud.*, vol. 8, no. 3, pp. 423–439, 2007.

[9] S. Shibata and K. Wada, "Robot therapy: A new approach for mental healthcare of the elderly—A mini review," *Gerontology*, vol. 57, no. 4, pp. 378–386, 2010.

[10] M. Montemerlo, J. Prieau, S. Thrun, and V. Varma, "Experiences with a mobile robotics guide for the elderly," in *Proc. AAAI National Conf. Artificial Intelligence*, 2002, pp. 587–592.

[11] A. Tapus, C. Tapus, and M. J. Matarić, "Long term learning and on-line robot behaviour adaptation for individuals with physical and cognitive impairments," in *Field Service Robotics* (Springer Tracts in Advanced Robotics), 1st ed. Heidelberg, Germany: Springer-Verlag, 2010, pp. 389–398.

[12] J. Fasola and M. Matarić, "Robot exercise instructor: A socially assistive robot system to monitor and encourage physical exercise for the elderly," in *Proc. IEEE Int. Symp. Robot Human Interactive Communication*, 2010, pp. 416–421.

[13] M. Heerink, B. Krose, V. Evers and B. Wielinga, "Measuring acceptance of an assistive social robot: A suggested toolkit," in *Proc. IEEE Int, Symp, Robot Human Interactive Communication*, 2009, pp. 528–533.

[14] J. Cohen-Mansfield, M. S. Marx, M. Dakheel-Ali, N. G. Regier, and K. Thein, "Can persons with dementia be engaged with stimuli?" *Amer. J. Geriatr. Psych.*, vol. 18, no. 4, pp. 351–362, 2010.

[15] D. Sullivan and D. Lipschitz, "Evaluation and treatment of nutritional problems in older patients," *Clin. Geriatr. Med.*, vol. 13, no. 4, pp. 753–768, 1997.

[16] Microsoft. (2010). Kinect for windows programming guide. [Online]. Available: http://msdn.microsoft.com/en-us/library/hh855348.aspx

[17] D. G. Lowe, "Distinctive image features from scale-invariant keypoints," *Int. J. Comput. Vision*, vol. 60, no. 2, pp. 91–110, 2004.

[18] M. C. Silveri, G. Reali, C. Jenner, and M. Puopolo, "Attention and memory in the preclinical stage of dementia," *J. Geriatr. Psych. Neurol.*, vol. 20, no. 2, pp. 67–75, 2007.

[19] P. Viola and M. Jones, "Rapid object detection using boosted cascade of simple features," in *Proc. IEEE Conf. Computer. Vision Pattern Recognition*, 2001, pp. 511–518.

[20] M. Davis and D. Hadiks, "Non-verbal aspects of therapist attunement," *J. Clin. Psychol*, vol. 50, no. 3, pp. 393–405, 1994.

[21] A. Kendon, "Behavioral foundations for the process of frame-attunement in face-to-face interaction," in *Conducting Interaction: Patterns Behavior Focused Encounters*. Cambridge, U.K.: Cambridge University Press, 1990, pp. 239–262.

[22] J. Kehoe, "Basic item analysis for multiple-choice tests," *Practical Assessment Res. Evaluat.*, vol. 4, no. 10, pp. 1–2, 1995.

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