

To the Graduate Council:

I am submitting herewith a thesis written by Fengpei Yuan entitled “Development and Feasibility Studies of AI-powered Socially Assistive Robotics to Promote Wellbeing of Persons with Alzheimer’s Disease and Related Dementias.” I have examined the final paper copy of this thesis for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Mechanical Engineering.

Xiaopeng Zhao, Major Professor

We have read this thesis
and recommend its acceptance:

Xiaopeng Zhao

Subhadeep Chakraborty

Caleb Rucker

Hairong Qi

Joel G. Anderson

Wenjun Zhou

Accepted for the Council:

Dixie L. Thompson

Vice Provost and Dean of the Graduate School

To the Graduate Council:

I am submitting herewith a thesis written by Fengpei Yuan entitled “Development and Feasibility Studies of AI-powered Socially Assistive Robotics to Promote Wellbeing of Persons with Alzheimer’s Disease and Related Dementias.” I have examined the final electronic copy of this thesis for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Mechanical Engineering.

Xiaopeng Zhao, Major Professor

We have read this thesis
and recommend its acceptance:

Xiaopeng Zhao

Subhadeep Chakraborty

Caleb Rucker

Hairong Qi

Joel G. Anderson

Wenjun Zhou

Accepted for the Council:

Dixie L. Thompson

Vice Provost and Dean of the Graduate School

(Original signatures are on file with official student records.)

Development and Feasibility Studies
of AI-powered Socially Assistive
Robotics to Promote Wellbeing of
Persons with Alzheimer's Disease and
Related Dementias

A Dissertation Presented for the

Doctor of Philosophy

Degree

The University of Tennessee, Knoxville

Fengpei Yuan

May 2024

© by Fengpei Yuan, 2024
All Rights Reserved.

Dedication

For every person living with Alzheimer's disease and related dementias, and their caregivers. Your strength, courage, and resilience inspire every page of my work.

Acknowledgements

I would like to express my heartfelt thanks to my family, friends, mentors, and colleagues for their unwavering love and support throughout my PhD journey. Special thanks to my family—particularly my dad, mom, and aunt—who made it possible for me to come to the US and pursue my graduate studies five years ago. I am also immensely grateful to my friends in Knoxville, especially my boyfriend, Hao Ye. Their support and encouragement have not only made my PhD journey more enjoyable but also given me the courage to persevere during the most challenging times.

My deepest appreciation goes to my PhD mentor, Dr. Xiaopeng Zhao, for his support not only in my research projects but also in shaping my mindset and attitude towards life. There were moments when I doubted my research capabilities, and it was Dr. Zhao who consistently reminded me of my potential, offering invaluable guidance and encouragement to keep moving forward.

I would also like to extend my gratitude to my other mentors—Dr. Joel Anderson, Dr. Marie Boltz, Dr. Ran Zhang, Dr. Wenjun Zhou, and Dr. Dania Bilal. Their insights and feedback have been instrumental in enabling me to conduct my PhD work on robot-assisted dementia care comprehensively. I am also thankful to my dissertation committee members, Dr. Subhadeep Chakraborty, Dr. Caleb Rucker, Dr. Hairong Qi, Dr. Joel G. Anderson, and Dr. Wenjun Zhou, for their valuable suggestions on my dissertation topics and the broader field of robot-assisted dementia care, which have enriched both my current and future research endeavors.

Furthermore, I am thankful to all my study participants, particularly the persons with dementia, their families, and the staff at the collaborating centers, including Genesis Neuroscience Clinic, O'Connor Senior Center, and the Smart Home at University of Tennessee. Their support, input, and cooperation in my robotic studies for dementia care were indispensable. Without them, conducting such a comprehensive study would have been impossible.

Abstract

The prevalence of Alzheimer’s Disease and Related Dementias (ADRD) continues to increase, with projections indicating a rise from 6.9 million individuals in 2024 to about 14 million by 2060. This trend underscores a critical challenge: the escalating demand for quality dementia care, both from informal and professional caregivers. My dissertation explores the development of socially assistive robotics (SAR) designed to supplement care for persons living with ADRD (PLWDs). This technology aims to enhance the cognitive, social, emotional, and physical well-being of PLWDs and their family caregivers by providing companionship, assistance, rehabilitation, monitoring, and entertainment.

A focal point of my research is robot-mediated reminiscence therapy using the state-of-the-art humanoid robot, Pepper. I developed and evaluated a robot-mediated reminiscence exercise for its acceptability, feasibility, and user experience among PLWDs and their caregivers. Furthermore, we innovated a reinforcement learning algorithm to tailor the robot’s conversational strategy, ensuring adaptive and personalized interaction with PLWDs based on their emotional and cognitive states.

Another cornerstone of my dissertation is the development of SAR to assist PLWDs with their activities of daily living, aiming to enhance their independence, safety, and adequacy. Employing teleoperation as a preliminary step, this method led to a pilot study with individuals exhibiting mild cognitive impairment and dementia. The insights gained have been pivotal in creating a portable robotic platform,

adaptable for use across various settings and expanding the possibilities for PLWD-robot interaction studies. Moreover, in collaboration with occupational therapists, we devised a comprehensive framework to assess these interactions, striving to establish a new benchmark for future SAR research in dementia care. This interdisciplinary approach underscores the potential of robotic technologies to meet the intricate needs of PLWDs, advocating for more inclusive and adaptable dementia care solutions. Furthermore, my work extends into employing reinforcement learning to enable SAR to offer adaptive assistance for daily activities, further emphasizing the innovative and user-centered design of our approach.

Table of Contents

1	Introduction	1
1.1	Literature Review on Robotic Rehabilitation for Cognitive Training .	2
1.1.1	Enabling Technologies	4
1.1.2	Experimental Studies	11
1.1.3	Robot Products	15
1.1.4	Discussions	15
1.1.5	Conclusion	25
1.1.6	Summary	26
2	Understanding User Acceptance and Needs of Robotic Dementia Care	27
2.1	Methods	29
2.1.1	Participants	29
2.1.2	Instrument	29
2.1.3	Data analysis	30
2.2	Results	31
2.2.1	Demographic information	31
2.2.2	Perceptions of robot among people with MCI or ADRD	32
2.2.3	Perception of robot among caregivers and the general public .	34
2.2.4	Ethical concerns	34
2.2.5	Open-ended questions	35

2.3	Discussion	38
2.3.1	Robot acceptance	38
2.3.2	User needs and requirements	40
2.3.3	Ethical concerns	42
2.3.4	Limitations and future work	43
2.4	Summary	45
3	Robot-assisted Conversational Engagement	46
3.1	Development of a Pre-programmed Robot-mediated Reminiscence Activity	48
3.1.1	General Reminiscence Knowledge Base	49
3.1.2	A Prototype of Robot-Mediated Reminiscence Therapy	50
3.2	Usability Study of Robot-mediated Reminiscence Therapy	52
3.2.1	Study Design and Participant Recruitment	52
3.2.2	Experimental Procedure	53
3.2.3	Data Collection	54
3.2.4	Data Analysis	56
3.2.5	Results	57
3.2.6	Discussion	59
3.2.7	Summary	66
3.3	Adaptive Robot-Assisted Reminiscence Therapy	67
3.3.1	Simulation Model for a Person with Dementia (PwD)	68
3.3.2	Adaptive Robot-Assisted Reminiscence Therapy	70
3.3.3	Results and Discussion	74
3.4	Causal Structural Learning of Conversational Engagement for Socially Isolated Older Adults	76
3.4.1	Materials and methods	77
3.4.2	Results	80
3.4.3	Discussion and Summary	82

4	Robotic Assistance for Activities of Daily living	84
4.1	A Platform of Robot-guided PASS at Smart Home	87
4.1.1	Ten PASS tasks	88
4.1.2	Teleoperation	88
4.1.3	Experimenter Interface	89
4.1.4	Tammy Agent	90
4.1.5	Multimodal Data Collection During PASS	91
4.1.6	Prototype Verification and Refinement	92
4.2	Usability Study of Robot-guided PASS Platform	93
4.2.1	Experimental Procedure	94
4.2.2	Evaluation of Acceptability and User Experience	95
4.2.3	Privacy Protection	96
4.2.4	Results and Discussion	97
4.2.5	User Acceptance and Experience	98
4.2.6	Limitation and Future Work	99
4.2.7	Summary	102
4.3	Portable Robot-assisted PASS Platform	103
4.3.1	Robotic Assistance	104
4.3.2	Experimental Design of Portable Robot-assisted PASS	104
4.4	Evaluation Framework for PLWD-robot Interaction	108
4.4.1	Development of Holistic Framework for PLWD-robot Interaction	109
4.4.2	Results	111
4.4.3	Discussion	111
4.5	Reinforcement Learning for Adaptive Robotic Assistance of PLWDs During Activities of Daily Living	112
4.5.1	SIMULATOR OF A PERSON WITH DEMENTIA	113
4.5.2	Reinforcement Learning Framework	117
4.5.3	Action Space	118
4.5.4	Results	121

4.5.5	Discussion and Summary	121
5	Robot-assisted Psycho-Education for Dementia Caregivers	124
5.1	Background	124
5.2	Development of a Social Robot-assisted Psycho-educational Program	126
5.2.1	Psycho-educational Materials for Dementia Caregivers	126
5.2.2	Prototype of a Social Robot-assisted Psycho-educational Program	128
5.2.3	Prototype Verification and Refinement	130
5.3	Usability Study	131
5.3.1	Study Design and Participants	131
5.3.2	Experimental Procedure	131
5.3.3	Data Collection	132
5.4	Results	134
5.5	Discussion	135
5.5.1	User Experience and Satisfaction	135
5.5.2	Open-ended Comments from caregivers	137
5.5.3	Limitations and Future Work	137
5.6	Summary	138
6	Conclusion	139
	Bibliography	142
A	Appendix: Tables and Figures	181
A.1	Study of Understanding User Acceptance and Needs	181
A.2	Study of Robot-assisted Conversational Engagement	198
A.3	Tables and Figures from Study of Robot-assisted Activities of Daily Living	214
A.4	Tables and Figures from Study of Robot-assisted Psycho-education	227
Vita		234

List of Tables

A.1	Response distribution of participants within US	181
A.2	Demographic information of participants	183
A.3	Percentage of responses by people with MCI or ADRD.	185
A.4	Percentage of responses to questions about robot acceptance by the caregivers and the general public.	186
A.5	Percentage of responses to questions about robotic functionality by the caregivers and the general public.	188
A.6	Percentage of responses to questions about usability and ethical concerns of robots for ADRD care by caregivers and the general public.	193
A.7	The top 10 frequently mentioned words in open-ended comment by caregivers and the general public	195
A.8	Items to evaluate user experience for the RMRT usability study . . .	198
A.9	Descriptive statistics of participants	199
A.10	Participants' responses to Items Q1-Q12 about system usability and user experience	200
A.11	Count of functions participants hoped the robot Tammy to have . . .	201
A.12	Videos coding for the participant's interaction with the robot during RMRT for Participant P1.	202
A.13	Videos coding for the participant's interaction with the robot during RMRT for Participant P2	204

A.14 Videos coding for the participant's interaction with the robot during RMRT for Participant P3	205
A.15 Reward components w.r.t. response relevance in reward function R_1 and R_2	205
A.16 The PwD-robot interaction during a reminiscence therapy.	206
A.17 Summary statistics of participants' response features	208
A.18 Causal relationship between participants' current response X_t and the backward-looking dialogue act Z_{tb} taken by the moderator occurred more than 5 time in the causal graphs	208
A.19 Causal relationship between participants' current response X_t and the forward-looking dialogue act Z_{tf} taken by the moderator occurred more than 5 time in the causal graphs	208
A.20 Causal relationship between participants' current response X_t and following response Y_t occurred more than 5 time in the causal graphs	209
A.21 Causal relationship between backward-looking dialogue act Z_{tb} from the moderator and participants' following response Y_t occurred more than 5 time in the causal graphs	209
A.22 Causal relationship between forward-looking dialogue act Z_{tf} from the moderator and participants' following response Y_t occurred more than 5 times in the causal graphs	209
A.23 Items to Evaluate User Experience and Satisfaction for the Robot-assisted PASS	214
A.24 Percentage of responses to Items Q1-Q13 about user experience and satisfaction.	215
A.25 Evaluation Framework for PwD-robot-task-environment transaction during activities of daily living	216
A.26 Example of Coding Task Breakdown	217
A.27 Terms and Definitions used in our Simulating Context	218
A.28 Definitions and Examples of Assistance Types	219

A.29 Probabilistic Transition of PLWD’s cognitive and affective status without external assistance	220
A.30 Weight of each reward component	220
A.31 Example of follow-up questions and comments during robot-assisted psycho-educational intervention	227
A.32 Items to evaluate user experience and satisfaction for the robot-assisted psychoeducation	228
A.33 Descriptive statistics of participants	229
A.34 Example of follow-up questions and comments	231

List of Figures

A.1	Disease distribution among patient group	196
A.2	Functions participants with MCI or ADRD hoped the robot would help with. F1 = Help call family and friends; F2 = Help contact medical services; F3 = Help do shopping; F4 = Help order food; F5 = Help prevent falling; F6 = Remind to turn off stove top; F7 = Remind to take medicine; F8 = Emergency call service; F9 = Keep me company; F10 = Other.	196
A.3	Correlation map among responses from people with MCI or ADRD. Please See Supplementary Appendix 1 for Items Q1-Q9. Asterisks denote statistically significant relationships between responses to two items (* at 0.05 level, ** at 0.01 level, *** at 0.001 level).	197
A.4	Examples of photos that could be used to assist reminiscing sports. However, the first two pictures on the left could be distracting to PLWD. Comparatively, the picture on the right is appropriate for PLWD during reminiscence.. . . .	209
A.5	Screenshot of touchscreen design in the robot for RMRT: (a) The touchscreen design for the topic selection layer. (b) An example of a PLWD-robot conversation.	210
A.6	The flowchart of the robot-mediated reminiscence activity.	210
A.7	Experimental procedure for the usability study of robot-mediated reminiscence therapy.	210

A.8	The learning process by ϵ -greedy Q-learning with reward function R_1 .	211
A.9	The most nearly optimal policy π'_* learned by ϵ -greedy QL.	211
A.10	The occurrence of DA tags with backward-looking function in I-CONNECT conversational dataset.	211
A.11	The occurrence of DA tags with forward-looking function in I-CONNECT conversational dataset.	212
A.12	Example of PDAG learned for three participant-moderator conversation sessions. This graph implies that the participant's status of disgust (D) and neutral (N) at turn t has causal effect on the dialogue act of H and $ConC$ taken by the moderator. And the moderator's dialogue action, including $ConC$, H , AcD , CoC and $DYNQ$ has causal effect on the participant's emotional status and length of utterance at following turn $t + 1$	212
A.13	Example of PDAG learned for three participant-moderator conversation sessions. This graph implies that the participant's status of anger (A), and disgust (D) at turn t has causal effect on the moderator's dialogue action of $ConC$ and OrC . And the moderator's dialogue action of $DYNQ$ and OrC has causal effects on participant's following status of sadness (nSa) and fear.	213
A.14	Example of PDAG learned for three participant-moderator conversation sessions. This graph implies that participant's current emotions of anger has causal effects on moderator's action of <i>hedge</i> , The edge from F to nD and from Su to nA implies that the participant's emotion of <i>fear</i> and <i>surprise</i> has causal effect on the participant's following emotion of Disgust (nD) and anger (nA), respectively.	213
A.15	Representation of three JSON branches in the Firebase Realtime Database.	221
A.16	Experimenter Interface at Startup.	221

A.17 A screenshot of the graphical user interface in the app Tammy Agent on the robot's tablet.	222
A.18 The diagram illustrating the tele-operated robot-assisted PASS platform.	222
A.19 Illustration of positions of the participant, the robot, and the experimenter during experiments.	222
A.20 Participants and the Pepper robot during PASS tasks observed through the cameras equipped at Smart Home. The corresponding PASS tasks from left to right are bed mobility, changing bed linen, medication management, and making a sandwich. Participants' faces were clearly recorded, while their faces were blurred here.	223
A.21 Participants during PASS tasks observed through the camera equipped in the robot's tablet. The corresponding PASS tasks from left to right are changing bed linen, obtaining information from a poster, and making a sandwich. Participants' faces were clearly recorded, while their faces were blurred here.	223
A.22 Examples of scenarios of the robot provide assistance to remind and/or support persons with dementia during daily routine tasks.	223
A.23 Examples of scenarios of the robot provide assistance to redirect persons with dementia from performance breakdown during daily routine tasks.	224
A.24 Examples of scenarios of the robot chatting with a person with dementia during daily routine tasks.	224
A.25 Illustration of experimental procedure using our robotic platform to guide and assist a person with dementia to perform daily routine tasks.	224
A.26 A graph illustration of how the dynamics of PLWD's status <i>Forgetfulness</i> is simulated. The same mechanics applied to the other three statuses, <i>Confusion</i> , <i>Angry</i> , and <i>Disengagement</i>	225

A.27 Average Return from 40 Experiments Using Temporal Optimal Policy π' at the 10th Episode during the training process. This graph compares the performance of constant-epsilon RL (blue), decaying-epsilon RL (pink), and random action selection strategies (green). The returns are calculated by applying the temporal optimal policy extracted at the 10th episode of each epoch, with each strategy's performance averaged over 40 experimental runs.	225
A.28 The optimal policy learned by the decaying epsilon greedy RL agent (right) and the constant-epsilon greedy RL agent (left).	226
A.29 A user testing the psycho-educational program.	231
A.30 Module selection layer (left) and topic selection layer (right) in the FAIR REACH app.	232
A.31 Schematic flowchart of the FAIR-REACH app.	232
A.32 Screenshots of the GUI design on robot's tablet during presenting psycho-educational materials.	232
A.33 Experimental procedure for the usability study of robot-assisted psycho-educational program.	232
A.34 Participants' responses about user experience and satisfaction towards the robot-assisted psycho-educational intervention. Please see Table A.32 for Items Q1-Q12. 1= <i>strongly disagree</i> , 2= <i>somewhat disagree</i> , 3= <i>neither agree nor disagree</i> , 4= <i>somewhat agree</i> , 5= <i>strongly agree</i>	233

Nomenclature

PLWD	Person living with Alzheimer's Disease and Related Dementia
SAR	Socially assistive robotics

Chapter 1

Introduction

As the number and proportion of people aged 65 or older continue to increase worldwide, the number of adults living with dementia is also growing. In 2022, an estimated 6.5 million adults live with Alzheimer’s disease and related dementias (ADRD) in U.S. ([Alzheimer’s Association, 2022](#)). Individuals with ADRD may have a substantial limitation in their capacity for functional mental tasks, including conceptualizing, planning, sequencing thoughts and actions, remembering, interpreting subtle social cues, and manipulating numbers and symbols ([LoPresti et al., 2008](#)). This vulnerable population is usually associated with significant distress or disability in their social, occupational, or other important activities. According to 2022 Alzheimer’s Disease Facts and Figures report, more than 11 million unpaid caregivers (e.g., family members, friends and relatives) provided care for people with ADRD in 2020 ([Alzheimer’s Association, 2022](#)). This long-duration, time-intensive care can negatively impact caregivers’ physical and mental health and contribute to increased risk for depression and poor health ([Brodaty and Donkin, 2009](#)). With the advancement of robotics and information and communication technologies (ICTs), social robots have become one of the most common forms of assistive technology to support people with ADRD ([Kruse et al., 2020](#); [Woods et al., 2021a](#); [Yuan et al., 2021e,a](#); [Liu et al., 2021](#)). As an augmentation of human caregivers with respect to

the substantial health care labor shortage and the high burden of caregiving, robots may provide care with high repeatability and without any complaints or fatigue (Taheri et al., 2015b). Moreover, a meta-analysis by Li (Li, 2015) comparing how people interacted with physical robots and virtual agents showed that physically present robots were found to be more persuasive, perceived more positively, and resulted in better user performance compared to virtual agents. Furthermore, robots can facilitate social interaction, communication, engagement, and positive mood to improve the performance of the system (Shibata, 2012). For example, a recent study (Pino et al., 2020) showed that older adults with mild cognitive impairment (MCI) who received memory training through a humanoid social robot (NAO) achieved more visual gaze, fewer symptoms of depression, and better therapeutic behavior. In a study (Manca et al., 2021) to investigate the impact of how humanoid robots support older adults with MCI in serious games, which are games aimed to go beyond mere entertainment, but for helping cognitive assessment, stimulation and rehabilitation (McCallum and Boletsis, 2013), the same music-based memory serious game was implemented using a robot (i.e., Pepper) and a tablet. Older adults with MCI reported higher engagement in the games with the robot than those using the tablet. The results also suggested the robot produced more empathetic and emotional responses from the participants than the tablet.

1.1 Literature Review on Robotic Rehabilitation for Cognitive Training

In this section, we conducted a literature review on robot-assisted cognitive training. To date, the most researched application of robots in cognitive training is to improve individual social communication skills, which may include joint attention skills, imitation skills, turn-taking skills and other social interaction skills. For example, (Kajopoulos et al., 2015) designed a robot-assisted training protocol based on response

to joint attention for children with ASD. The training protocol used a modified attention cueing paradigm, where the robot’s head direction cued children’s spatial attention to a stimulus presented on one side of the robot. The children were engaged in a game that could be completed only through following the robot’s head direction. To aid in the training of imitation skills in children with ASD, (Taheri et al., 2020) proposed a reciprocal gross imitation human–robot interaction platform, in which ASD children are expected to imitate the robot body gestures, including a combination of arms, feet, neck and torso movements. Robot-assisted cognitive training showed increased cognitive capabilities for people with limited social capabilities, such as children with ASD (Huijnen et al., 2016; Esteban et al., 2017; Marino et al., 2019) and people with dementia (Sung et al., 2015; Yu et al., 2015; Otaki and Otake, 2017). Due to cognitive impairment, individuals with dementia may also show deficits in social functioning, such as social withdrawal (Dickerson, 2015; Havins et al., 2012). In the pilot study by (Sung et al., 2015) about robot-assisted therapy using socially assistive pet robot (PARO), institutionalized older adults showed significantly increased communication and interaction skills and activity participation after receiving 4-week robot-assisted therapy. Another robotic application is to provide intervention to enhance people’s impaired cognitive function, such as memory (Paletta et al., 2018), attention (Lins et al., 2019) and concentration (Tleubayev et al., 2019), or reduce their negative psychophysiological feelings, such as stress (Aminuddin et al., 2016) and anxiety (Ab Aziz et al., 2015). Additionally, a few studies adopted the robots to facilitate learning and educational activities for people with cognitive disabilities, such as children with dyslexia (Andruseac et al., 2015) or Traumatic Brain Injury (TBI) (Barco Martelo and Fosch Villaronga, 2017).

1.1.1 Enabling Technologies

This section presents a summary on a few important enabling technologies that foster the advancement of robotic rehabilitation for cognitive training, including multimodal perception, multimodal feedback, gamification, virtual and augmented reality, and artificial intelligence.

Design of Physical Appearance

A robot can have a human-like (Taheri et al., 2019; Peleka et al., 2018; Miskam et al., 2015), animal-like (Sung et al., 2015; Cao et al., 2015), or unfamiliar appearance (Scassellati et al., 2018). Besides the appearance, the size, softness and comfort of the robot can also have an impact on users' perception, affection, cognitive load, and gaze following during interaction (Kohori et al., 2017), and thus the effectiveness of cognitive training. It remains unclear how users' perception is specifically affected by the robot's appearance. On the one hand, the human-like appearance was indicated to significantly positively affect users' perception of anthropomorphism, animacy, likeability and intelligence towards robots, compared to a snowman-like appearance (Haring et al., 2016). On the other hand, increasing human-like appearance was found not to necessarily increase performance in human-robot interaction. For example, in the survey of expectation about the robots' appearance in robot-assisted ASD therapy, zoomorphic robots were indicated to be less ethically problematic than robots that looked too much like humans (Coeckelbergh et al., 2016). Some of their participants (i.e., parents, therapists or teachers of children with ASD) worried about the possibility that the robot is perceived by the child as a friend, or that the robot looks too human-like. The relation between robots' human-like appearance and people's reaction to them may relate to the uncanny valley theory (Mori et al., 2012), which describes that people's familiarity (or affinity) with robots increases as the robots appear more human-like but when the robots are almost human, people's response would shift to revulsion. (Tung, 2016) observed an uncanny valley between

the degree of anthropomorphism and children’s attitudes toward the robots. In the review paper to study factors affecting social robot acceptability in older adults including people with dementia or cognitive impairment, (Whelan et al., 2018) found that there is a lack of consensus regarding to the optimal appearance of social robots and that the uncanny valley concept varies between individuals and groups.

Multimodal Sensing

Having a good understanding of a user’s cognitive state, affective state and surrounding environment, which is termed as multimodal perception, is a prerequisite step for robots to provide cognitive training. Usually the concept of multimodal perception involves two stages, multimodal sensing and perception. Further details on these two techniques in previous publications are individually discussed in the following. Various sensors have been adopted to facilitate a robot to achieve multimodal sensing, based on system requirements, end-user population, cost-effectiveness, etc. Among different sensing technologies, visual and auditory sensing are the most popular modalities. We summarize the multiple modalities for sensing in the following aspects.

1. *Visual sensing.* During human-robot interaction, visual sensors are a very popular, useful and accessible channel for perception. The advancement of technologies, such as manufacturing and ICTs, enabled researchers to integrate small, high-resolution and affordable cameras into their rehabilitation robotic system. Some studies placed cameras in the environment along with the robot (Melo et al., 2019). Other studies included cameras in the robotic mechanical system. For example, in the social robot Pepper, there were 2D and 3D cameras attached to the head (Paletta et al., 2018). With computational approaches, such as computer vision, the robots analyzed the video/images from the cameras and recognized users’ critical states, such as their environment, facial expression, body movements, and even emotion and attention (Rudovic et al., 2018; Peleka et al., 2018; Mois et al., 2020; Paletta et al., 2018), which led to a better perception of users (Johal et al., 2015).

2. *Auditory sensing.* Another popular modality adopted during robot-assisted cognitive training is auditory sensing. Researchers analyzed users' auditory signals in terms of the lexical field, tone and/or volume of voice for speech recognition, emotion detection, and speaker recognition in robots (Rudovic et al., 2018; Paletta et al., 2018; Peleka et al., 2018). Due to the natural and intuitive nature for users behind the auditory sensing, some end users, such as older adults preferred this sensing channel to the touch input during interaction with the robot (Zsiga et al., 2018).

3. *Physiological sensing.* Besides visual and auditory sensing, physiological modalities have been incorporated into the robotic system, in order to have a better understanding of users' states (e.g., affective states). Previous studies show that human-robot interaction may be enhanced using physiological signals, such as heart rate, blood pressure, breathing rate, and eye movement (Lopez-Samaniego and Garcia-Zapirain, 2016; Ahn et al., 2017; Ozcana et al., 2016; Alimardani and Hiraki, 2017; Sonntag, 2015). For example, (Rudovic et al., 2018) employed wearable sensors to detect children's heart-rate, skin-conductance and body temperature during their robot-based therapy for children with ASD, to estimate children's levels of affective states and engagement. When studying robot-assisted training for children with ASD, (Nunez et al., 2015) used a wearable device of electromyography (EMG) sensors to detect smiles from children's face.

4. *Neural sensing.* The inclusion of brain-imaging sensors provides capabilities to measure and/or monitor a user's brain activity and to understand the user's mental states (Ali et al., 2019). This was especially useful when considering the user's cognitive states, such as level of attention and task engagement (Alimardani and Hiraki, 2017; Tsiakas et al., 2018). Neural sensing may also be meaningful to users who have difficulty in expressing their intention and feeling because of their physical and/or cognitive limitations, such as the older adults with Alzheimer's disease. Currently, among all candidates of brain-imaging sensors, EEG and functional near-infrared spectroscopy (fNIRS) are two popular modalities due to their advantages of non-invasiveness, portability and cost-effectiveness. For example, (Lins et al., 2019)

developed a robot-assisted therapy to stimulate the attention level of children with cerebral palsy and applied electroencephalogram (EEG) sensors to measure children's attention level during the therapy.

Multimodal Feedback

After perceiving its user and environment, a robot shall entail multimodal feedback to interact (e.g., display its behaviors and feedback) with its user in a comfortable, readable, acceptable and effective way (Melo et al., 2019). Multimodal feedback is particularly meaningful when the end users are unfamiliar with technologies or are limited in cognitive capabilities, such as older adults with dementia. Examples of feedback include voice, video, gesture, and physical appearance, all of which can affect users' perception of the robot during their interaction and thus the effectiveness of cognitive training/rehabilitation (Rabbitt et al., 2015; Ab Aziz et al., 2015). The following list shows popular modalities for robotic feedback during interaction with human users.

1. *Visual feedback.* One of the most widely-used overt feedback modalities is visual feedback or graphical user interface (GUI), displaying two-dimensional information. During robot-assisted cognitive training, visual feedback was delivered through an additional computer screen (Taheri et al., 2019; Mois et al., 2020; Salvador et al., 2016), or a touchscreen embodied in the robot (Peleka et al., 2018; Paletta et al., 2018). Some principles and/or issues on the design of GUI for robot-assisted training were suggested in previous studies. For example, a few studies recommended a larger screen and a simpler interface associated with each function choice for GUI to better facilitate visual feedback during cognitive training (Ahn et al., 2017).

2. *Auditory feedback.* Another widely used modality for feedback or interaction is auditory output, like speech during human-human interaction. This intuitive auditory communication can reduce the unfamiliarity with robotic technologies and increase the usability of system in the vulnerable population, such as the elderly population (Zsiga et al., 2018). Among previous studies, this feedback was delivered in one or

combined form of beep (Nault et al., 2020), speech (Ab Aziz et al., 2015; Miskam et al., 2015; Peleka et al., 2018; Taheri et al., 2019), and music (Nunez et al., 2015). With auditory output, the robot provided daily communication and medication reminder, instructed cognitive training, and made emergent warning (e.g., short of battery) to the user (Orejana et al., 2015).

3. *Nonverbal feedback.* We refer to nonverbal feedback as all non-verbal communication cues by a robotic body, such as hand gestures and other body movements (Miskam et al., 2015; Taheri et al., 2019), eye gaze (Taheri et al., 2019), eye colors (Miskam et al., 2015; Taheri et al., 2019), and facial expression. Animation, similar to verbal language, makes a significant contribution to improving robot-assisted cognitive training. Moreover, the robot’s animation can particularly introduce social interaction to a user, which is meaningful to individuals with impairments in social interaction skills.

4. *Haptic feedback.* Haptic feedback, by simulating the sense of touch and motion, may play important role during robot-assisted cognitive training due to the importance of touch in everyday life (Beckerle et al., 2017; Cangelosi and Invitto, 2017). Tactile feedback is one type of haptic feedback. During robot-assisted cognitive training, haptic feedback can also be introduced using vibration via wearable devices. For example, (Nault et al., 2020) developed a socially assistive robot-facilitated memory game elaborated with audio and/or haptic feedback for older adults with cognitive decline. Although there was no significant difference in participants’ game accuracy, preference and performance in their system pilot study, the results provided insight into future improvements such as increasing the strength of haptic feedback to increase the ease of being perceived and make the system more engaging. One notable robot, Paro, with the combination of soft, plush surface and additional encouraging haptic feedback (e.g. small vibration) creates a soothing presence. In a pilot study for institutionalized older adults by (Sung et al., 2015), the communication and social skills of participants were improved by the robot-assisted therapy using Paro.

Gamification

Recently, game technology is becoming a popular way to motivate, engage and appeal to users in cognitive tasks, since traditional cognitive tasks are usually effortful, frustrating, repetitive and disengaging. Serious games and brain training games are a growing research field for cognitive training (Heins et al., 2017). Integration between gaming and robotic technologies has attracted increasing amount of interest in research and application, to further enhance users' engagement in cognitive training. A few types of relationships between robots and games have been developed in the literature. For example, a robot can lead or accompany users through the game for cognitive training by providing instructions on how to perform the task (Ioannou et al., 2015; Nault et al., 2020; Tleubayev et al., 2019; Taheri et al., 2019; Scassellati et al., 2018; Chu et al., 2017; Tsardoulas et al., 2017; Sandygulova et al., 2019) or playing a role of an active player in the game (Melo et al., 2019; Tariq et al., 2016). Additionally, a robot can provide various types of feedback (see details in Section 1.1.1) to encourage users to engage in the game (Lopez-Samaniego and Garcia-Zapirain, 2016; Taheri et al., 2015a). Often, games associated with cognitive training can be integrated into the robotic systems through a GUI (Paletta et al., 2018; Peleka et al., 2018; Ahn et al., 2017).

Virtual and Augmented Reality

Combining robot-assisted cognitive training with virtual reality (VR) and/or augmented reality (AR) techniques offers a cost-effective and efficient alternative to traditional training settings. The incorporation of VR/AR allows for replication of the tasks and environments in a more convenient and affordable way. Researchers also explored robotic cognitive training using mixed reality technology in cognitive training. For example, (Sonntag, 2015) presented an intelligent cognitive enhancement platform for people with dementia, where a mixed reality glass was

used to deliver the storyboard (e.g. serious game for active memory training) to the user and a NAO robot served as a cognitive assistant for “daily routine”. Bozgeyikli et al. used virtual reality in a vocational rehabilitation system, which included six different modules such as money management in a virtual grocery store, to provide vocational training for persons with ASD and TBI (Bozgeyikli et al., 2015).

Artificial Intelligence

Artificial Intelligence plays a significant role in the field of robot-assisted cognitive training/rehabilitation, including applications in multimodal perception and feedback, personalization and adaptability (Rudovic et al., 2018; Ab Aziz et al., 2015). Given multimodal sensing, a successful multimodal perception further requires robots to integrate signals across multiple modalities of input sensors. To date, a great progress has been made thanks to the advancement of machine learning and deep learning. Multi-modal signals enable the robot with a good interpretation and understanding of its users, including their needs, intention, emotions, and surrounding environment (Paletta et al., 2018). (Rudovic et al., 2018) implemented deep learning in a robot for ASD therapy to automatically estimate children’s valence, arousal and engagement levels. (Javed et al., 2018) utilized multimodal perception, including the analyses of children’s motion, speech and facial expression, to estimate children’s emotional states. Using multiple feedback modalities may overload users with redundant information, increase task completion time, and reduce the efficiency of cognitive training (Taranović et al., 2018). Additionally, users may favor certain modalities over others due to personal preference or cognitive disability. (Taranović et al., 2018) designed an experiment of adaptive modality selection (AMS) in robot-assisted sequential memory exercises and applied artificial intelligence to learn the strategy that selects the appropriate combination and amount of feedback modalities tailored to different situations (e.g., environments and users). An appropriate strategy is crucial to successful long-term robot-assisted cognitive intervention. Specifically, reinforcement learning, an area of machine learning, is a promising approach to adapt

and personalize the intervention to each individual user as well as to optimize the performance of robot-assisted cognitive training, due to its capability of allowing a robot to learn from its experience of interaction with users (Sutton and Barto, 2018). For example, (Tsiakas et al., 2016) used interactive reinforcement learning methods to facilitate the adaptive robot-assisted therapy, that is, adapt the task difficulty level and task duration to users with different skill levels (e.g., expert or novice user), in the context that users need to perform a set of cognitive or physical training tasks. (Javed et al., 2018) developed a Hidden Markov model (HMM) in their adaptive framework for child-robot interaction, aiming to enable a child with ASD to engage in robot-assisted ASD therapy over long term. In their HMM, the states took into consideration a child’s emotional state or mood, and the actions were the robot’s behaviors or other audiovisual feedback. (Clabaugh et al., 2019) utilized reinforcement learning to personalize instruction challenge levels and robot feedback based on each child’s unique learning patterns for long-term in-home robot interventions. Although reinforcement learning may suffer the problem of sample inefficiency, the slowness of reinforcement learning can be overcome using techniques such as episodic memory and meta-learning (Botvinick et al., 2019).

1.1.2 Experimental Studies

Many experimental studies have been conducted to evaluate the important properties of robotic rehabilitation, such as feasibility, safety, usability, performance, etc. On the one hand, exploratory studies including surveys and interviews with users (e.g., patients, caregivers, and therapists) have been conducted to inform the next stage of study (Darragh et al., 2017; Salichs et al., 2016; Korchut et al., 2017; Rabbitt et al., 2015; Law et al., 2019; Kohori et al., 2017; Coeckelbergh et al., 2016). On the other hand, researchers have conducted experimental studies to verify and/or validate robot-assisted cognitive training systems. Up to date, majority of the experimental studies were conducted in a controlled lab setting, and only a few studies were

conducted in an environment simulating daily activities in real world (Scassellati et al., 2018).

Study Design

Most experimental studies included three phases: pre-training assessment (i.e., baseline assessment), robot-assisted cognitive training, and post-training assessment (Kajopoulos et al., 2015; Sung et al., 2015; Kim et al., 2015; Alemi et al., 2016; Taheri et al., 2019; Scassellati et al., 2018; Marino et al., 2019; Yu et al., 2015; Taheri et al., 2016; van den Heuvel et al., 2017). The effectiveness of robot-assisted training was evaluated by the comparison of pre- and post-training assessments using machine learning or statistical methods (Kim et al., 2015; Taheri et al., 2019; Scassellati et al., 2018; Marino et al., 2019; Yu et al., 2015).

Most studies adopted the group-based design where participants were randomly assigned to control or intervention groups (Sung et al., 2015; Kim et al., 2015; Marino et al., 2019; Yu et al., 2015). Some researchers employed single-case designs (or single-subject designs) to investigate the impact of social robots on cognitive training (Ioannou et al., 2015; Taheri et al., 2015a; David et al., 2018). For example, (Ioannou et al., 2015) conducted the single-case study to explore the potential role of co-therapist of humanoid social robot, NAO, during autism therapy session with one child with ASD. In their study, there are four intervention sessions, and one follow-up, post-intervention therapy session to examine the effectiveness of the therapy with NAO.

Sample sizes vary dramatically in the literature (Ioannou et al., 2015; Rudovic et al., 2018; Sung et al., 2015; Kajopoulos et al., 2015; Kim et al., 2015; Chu et al., 2017; Khosla et al., 2017), where some studies were conducted with hundreds of participants whereas some studies included only a few participants. Challenges to recruitment included accessibility of participants and their caregivers, participants' disability, and ethical issues (e.g., privacy).

In terms of the intensity and duration of robot-assisted cognitive training, due to the variety of applications and end users, there was also a great variation in the total number of training sessions as well as the session duration. For example, with respect to one single training session, it took from about 20 min (Tleubayev et al., 2019; Shukla et al., 2015) to 90 min (Kim et al., 2015). Corresponding to the total cognitive training period, it varied from a few days (Bharatharaj et al., 2017) to more than 5 years (Chu et al., 2017).

Evaluation

Researchers employed subjective and/or objective evaluation metrics to evaluate the performance of robots in cognitive training. Subjective measurement include qualitative observation, interviews and questionnaires. Objective measurements evaluate the performance from a behavioral or neurophysiological level.

1. *Observation.* During the experiments or recorded video, the experimenters or professional therapists observed and evaluated participants' behaviors, such as affective feelings, eye contact, communication and other related interactions, based on their knowledge and experience (Ioannou et al., 2015; Taheri et al., 2019; Tleubayev et al., 2019; Shukla et al., 2015; Taheri et al., 2015a; Costescu et al., 2015; Yun et al., 2016; Chu et al., 2017; Garcia-Sanjuan et al., 2017; David et al., 2018; Sandygulova et al., 2019; Marino et al., 2019; Begum et al., 2015; Conti et al., 2015; Rudovic et al., 2017; Abdollahi et al., 2017; Yu et al., 2015; Wong and Zhong, 2016; Tariq et al., 2016; Zheng et al., 2016; Khosla et al., 2017). This measurement was a very practical, dominant metric during the study of children with ASD. With the development of ICTs, some studies also applied customized software (instead of human effort) to evaluate user's behaviors such as smiles and visual attention (Pino et al., 2020).

2. *Interview.* Interviews were conducted with the primary users (i.e., patients), their caregivers (e.g., parents and other family caregivers) and therapists, to learn about users' opinion and experience, and the performance of the robot-assisted

cognitive training (Darragh et al., 2017; Tleubayev et al., 2019; Paletta et al., 2018; Taheri et al., 2019; Bharatharaj et al., 2017; Sandygulova et al., 2019; Yu et al., 2015). As stated in the book on user experience (UX) lifecycle by (Hartson and Pyla, 2018), user interview is a useful, practical technique to understand users' needs, design solutions and evaluate UX, all of which are basic fundamental activities in UX lifecycle. Specifically, interviews can be applied to extract requirements of people with cognitive disability and/or their caregivers, to create the human-robot interaction design concepts, and to verify and refine human-robot interaction design for cognitive training. For example, in the case studies by (Orejana et al., 2015), older adults with chronic health conditions in a rural community used a healthcare robot (iRobi) in their homes for at least 3 months. Then participants were interviewed to learn personal accounts of participants's experience. Through the interview, the authors found that more familiar games may be easier for older people to relate to and therefore increase users' confidence and that a larger screen would make the functions easier to see and use. The interview also revealed that older people sometimes have less dexterity so making the touchscreen less sensitive to long presses may remove accidental triggering of functions.

3. *Questionnaire.* Most studies utilized questionnaires to evaluate the performance of robot-assisted cognitive training. Researchers adopted questionnaire(s) based on their targeted performance, such as targeted user groups (e.g., patients, caregivers or therapists), targeted cognitive capabilities (e.g., memory or anxiety), and research goals (e.g., users' perception of robot or effectiveness of robot). A few studies designed their own questionnaires according to their study (Lins et al., 2019; Scassellati et al., 2018; Ahn et al., 2017; Bharatharaj et al., 2017; Tokunaga et al., 2019; Abdollahi et al., 2017; Tariq et al., 2016; Khosla et al., 2017; van den Heuvel et al., 2017).

4. *Behavioral measurement.* From a behavioral perspective, researchers measured the number of correct/incorrect responses, response time, and/or time to complete the activity by participants to evaluate the performance of robot-assisted training

(Ioannou et al., 2015; Kajopoulos et al., 2015; Nault et al., 2020; Lins et al., 2019; Costescu et al., 2015; Bozgeyikli et al., 2015; Shukla et al., 2017; Salvador et al., 2016).

5. *Neurophysiological measurement.* The advancement of brain-imaging technologies and deep learning enables researchers to assess the impact of cognitive training on cognitive capabilities from a neurophysiological perspective, using brain-imaging tools such as EEG, fNIRS or functional magnetic resonance imaging (fMRI) (Ansado et al., 2020). Researchers also applied such tools to detect changes in the brain associated with participants' cognitive capability as metrics to evaluate the performance of robots in cognitive training (Kim et al., 2015; Alimardani and Hiraki, 2017).

1.1.3 Robot Products

The development of technologies such as manufacturing and ICTs, has led to the generation of mass-product robots for research, education and therapeutic applications (Wood et al., 2017; Pandey and Gelin, 2018). Particularly in the field of cognitive training/rehabilitation, the developed robots are featured with capabilities such as the aforementioned multimodal perception and multimodal feedback to support the human-robot interaction during cognitive training.

1.1.4 Discussions

Limitations

1. *Sample Size.* Probably, the most common challenge faced by researchers of cognitive training is a small size of participants. This imposes the generalization and reliability of experimental results in question. The limitation of small sample size was caused by the small number of participants or the limited number of available robots for experiments (Kajopoulos et al., 2015; Darragh et al., 2017; Tleubayev et al., 2019; Lins et al., 2019; Shukla et al., 2015; Bharatharaj et al., 2017; Marino

et al., 2019; Zheng et al., 2015; Tariq et al., 2016; Zheng et al., 2015; Lins et al., 2019; Tsardoulis et al., 2017; Garcia-Sanjuan et al., 2017). Typically, a research lab has only a few robots. This would be particularly challenging to experimental studies that require multiple sessions for each individual user. In this case, within the same study period, these studies have to control the number of participants to a small number. The recruitment of participants was influenced by the accessibility to participants during the whole study and sometimes the problems associated with their caregivers (Alemi et al., 2016; Taheri et al., 2019). For example, in the study (Alemi et al., 2016) of exploring effect of utilizing a robot NAO as a therapy-assistive tool to deal with pediatric distress among children with cancer. In terms of the small sample size, researchers mentioned that due to the novelty of their project and scant number of systematical psychological interventions for patients with cancer or other refractory illness in Iranian hospitals, it was difficult to persuade children’s parents to join their study. Also, they mentioned that it was hard for parents to bring their kids to intervention sessions on a regular basis. Moreover, the issue of small sample size also means that the participants in some studies were not general and representative, in terms of factors such as their severity of cognitive disability, their age and gender (Begum et al., 2015; Chu et al., 2017; Yu et al., 2015).

2. *Measurement of Training Effectiveness* Another impeding factor in studies of robot-assisted cognitive training is the evaluation of its training effectiveness, which can relate to choosing tools for specific evaluation metrics, identifying relevant evaluation metrics, or designing experiments to facilitate evaluation. In terms of the evaluation metrics, many studies adopted subjective evaluations, which could be biased and inaccurate. To the authors’ best knowledge, there is no standardized questionnaire to evaluate robot-assisted cognitive training. multiple different questionnaires were applied to evaluate the same target (e.g., robot acceptance), which makes it difficult to compare the performance of robot-assisted cognitive training between different studies (Bharatharaj et al., 2017). Often,

assessment metrics focus on the impact on the specifically trained cognitive capability, ignoring the potential transfer to other cognitive skills (Zheng et al., 2016) and the long-term performance (Richardson et al., 2018). Moreover, evaluations were frequently conducted for the robot-assisted cognitive training in controlled laboratory settings. The real-world environments are usually noisy and dynamic, which brings greater challenges for a reliable, robust user-robot interaction and a good user experience of the robot (Salem et al., 2015; Trovato et al., 2015).

Additionally, the effectiveness of robot-assisted cognitive training may be impacted by users' perceived interaction with the robot. On the one hand, some studies (Pereira et al., 2019; Lopez-Samaniego and Garcia-Zapirain, 2016; Mois et al., 2020) have evaluated the acceptance, satisfaction and perception of robots for cognitive training. On the other hand, many studies (Kim et al., 2015; Demetriadis et al., 2016; Shukla et al., 2015; Pino et al., 2020) have evaluated effectiveness of robot-assisted cognitive training on participant's cognitive capabilities. However, it is rarely addressed in the literature how acceptance and perception of the robot affects the effectiveness of cognitive training. Some studies presented the results of robot-assisted training without comparing to the effectiveness of human-assisted training. For more rigorous evaluation of the effectiveness of a robot-assisted cognitive training approach, it is recommended to compare against human-assisted training and other existing approaches.

3. Uncontrollable Factors. There always exist uncontrollable factors during the study of robot-assisted cognitive training/rehabilitation. The problem is more noteworthy for multiple-session studies since researchers cannot control participants' daily and social activities outside of the laboratory setting. The topic of uncontrollable factors is relatively less studied. In a study on using a social robot to teach music to children with autism, (Taheri et al., 2019) pointed out some improvements observed in music education and/or social skills are attributable to other interventions or education the participants may be receiving. When investigating the influence of robot-assisted training on cortical thickness in the brains of elderly participants, (Kim

et al., 2015) recognized uncontrollable factors due to participants' daily cognitive activity at home such as using computers or reading books.

Challenges and Future Development

1. *Ethical Challenges.* During the development of robots for cognitive training/rehabilitation, there are some ethical issues with respect to human dignity, safety, legality and social factors to be considered. For example, during robot-assisted cognitive training, the interaction between the user and the robot happens at both the cognitive (dominant) and physical level (Villaronga, 2016). There could be the issue of perceived safety, or cognitive harm. For example, the user may perceive the robot unsafe or scary (Salem et al., 2015; Coeckelbergh et al., 2016). In the study (Shim and Arkin, 2016) exploring the influence of robot deceptive behavior on human-robot interaction, a robot NAO deceptively showed positive feedback to participants' incorrect answers in a motor-cognition dual task. The self-report results revealed that the robot's deceptive feedback positively affected a human's frustration level and task engagement. Even though a robot's deceptive action may lead to positive outcome, Shim and Arkin emphasized that the ethical implications of the robot deception, including those regarding motives for deception, should always be discussed and validated prior to its application. Another arising ethical issue is how responsibility can be allocated, or distribution of responsibility (Loh, 2019; Müller, 2020). For example, if a robot acts during cognitive training, will the robot itself, designers or users be responsible, liable or accountable for the robot's actions? We should also pay close attention to ethical issues, such as the affective attachments, dependency on the robot, safety and privacy protection of users' information, and transparency in the use of algorithms in robotic systems (Casey et al., 2016; Fiske et al., 2019; Richardson et al., 2018; Kostavelis et al., 2015). Similarly, designers should accommodate the design of robot to these ethical considerations (Ozcana et al., 2016). To ensure the perceived safety, researchers need to always take end users' perception into account, which can be known through questionnaires and interviews with them (and their

caregivers and therapists if needed), and their behavioral and neurophysiological activities. The tendency for humans to form attachments to anthropomorphized robots should be carefully considered during design (Riek and Howard, 2014; Riek, 2016). Moreover, for fear that the robot could replace human health care from both patients and the professional caregivers, it should be emphasized that the rehabilitation robots are developed with the aim of supplementing human caregivers, rather than replacing them (Doraiswamy et al., 2019).

2. *User-centered Design.* The goal of robotic cognitive rehabilitation is to provide cost-effective cognitive training to vulnerable people with cognitive disabilities, which can supplement their caregivers and/or therapists (Doraiswamy et al., 2019). Therefore, we encourage the idea of user-driven, instead of technology-driven, robot design and development (Rehm et al., 2016). Emphasis should be given to the primary users (i.e., patients) of the robots and other key stakeholders (e.g., caregivers, therapists and doctors) to design and shape this robot, including requirement analysis, robot development and evaluation with different stakeholders (Casey et al., 2016; Rehm et al., 2016; Gerling et al., 2016; Salichs et al., 2016; Barco Martelo and Fosch Villaronga, 2017; Riek, 2017; Leong and Johnston, 2016). It is also important to pay attention to potential technical difficulties for vulnerable populations, such as the elderly and children with ASD (Orejana et al., 2015) and the social and contextual environment that the robot will be applied to (Jones et al., 2015). More standardized, unbiased benchmarks and metrics need to be developed for different stakeholders to evaluate the performance of robots from their perspectives. While it is necessary to start pilot studies with healthy participants, it is crucial to relate the developed systems to patients with cognitive impairment at home settings.

Furthermore, robot development is a multidisciplinary study which requires knowledge from multiples fields, such as social cognitive science, engineering, psychology and health care such as ASD and dementia. Enhanced collaborations

among these fields are needed to improve future technology in robotic rehabilitation.

3. *Reliability, Trust, Transferability and Cost-effectiveness.* The reliability of the robotic system ensures that the robot can consistently work in noisy, dynamic real-world environment. This makes a significant contribution to a user’s confidence and increases positive perception of the robot (Wood et al., 2017). Mistakes made by robots during interaction can cause a loss of trust in human users. More work on human-robot interaction is needed to implement a reliable and robust robot to assist cognitive training. This may cover multimodal sensing technologies, artificial intelligence, and modelling. On the other hand, we need to take into consideration how to effectively restore trust to the robot in case that mistakes are made by the robot during interaction with the user. This may involve how and when the robot apologizes for its mistake for users. (Robinette et al., 2015) found that timing is a key to repair robot trust, suggesting that the robot should wait and address the mistake next time a potential trust decision occurs rather than addressing the mistake immediately.

Currently, most studies focus on specific cognitive training tasks and environments, which means that the robot cannot assist in other cognitive tasks. Here, we encourage the implementation of a transferable mechanism in robots for cognitive training. In other words, we should enable more powerful learning algorithms in the robot so that the robot can learn and adapt to more new cognitive training (Andriella et al., 2019). Researchers should also take cost-effectiveness into account during the design of robot (Wood et al., 2017). From the commercial perspective, cost-effectiveness is considered beyond the purchase, maintenance, and training costs for the system (Riek, 2017). Furthermore, from the perspective of time and effort of users, more work is needed to find out the optimal robot-assisted cognitive training strategy (e.g., the frequency and duration of each cognitive session). Therefore, we encourage future studies clearly state the used training strategies, making it easier

for the community to compare different strategies.

4. *Personalization.* There is no “one-size-fits-all” in health care. To provide a successful cognitive training, the robot needs to be personalized and adaptive in three levels. Firstly, personalization requires the robot to provide appropriate cognitive training and feedback to meet the specific need of groups with different cognitive disabilities (e.g., people with ASD, people with ADRD). Secondly, the robots need to adapt to the diversity existing in the population as well as tailor to each individual user’s severity of cognitive impairment, cultural and gender-dependent difference, personality and preference (Richardson et al., 2018; Sandygulova et al., 2019; Rudovic et al., 2017; Kostavelis et al., 2015; Javed et al., 2016; Riek, 2016; Darragh et al., 2017). For example, children with ASD, have a wide range of behavioral, social, and learning difficulties. And each individual may have a different preference to robot’s gender and modalities of feedback (Sandygulova and O’Hare, 2015; Nault et al., 2020). As a result, we expect that a personalized robot would provide various cognitive training, e.g., a variety of games and adjustable voice, for diverse individual needs and requirements to keep the user engaged and focused over long term (Tleubayev et al., 2019; Scassellati et al., 2018). Furthermore, rehabilitation robots should adapt to individually time-changing characters such as cognitive impairment, task engagement and even personalities (Tsiakas et al., 2018, 2016; Agrigoroaie and Tapus, 2016). For example, the robot should adjust the cognitive training and feedback if the user feels bored, too difficult, or too easy (Lins et al., 2019). Machine learning methods should also take into consideration of personalization. Existing methods such as interactive reinforcement learning (IRL) or incremental learning (Castellini, 2016) provide good examples, where one block module is used to specifically model each user’s information, such as patient’s name, hobbies and personalities related to cognitive training (Salichs et al., 2016). IRL is a variation of reinforcement learning that studies how a human can be included in the agent learning process. Human input play the role of feedback (i.e. reinforcement signal after the selected action) or

guidance (i.e., actions to directly intervene/correct current strategy). IRL can also be utilized to enable adaptation and personalization during robot-assisted cognitive training. For example, (Tsiakas et al., 2016) proposed an adaptive robot assisted cognitive therapy using IRL, where the primary user feedback input (e.g. engagement levels) were considered as a personalization factor and the guidance input from professional therapist were considered as a safety factor. Their simulation results showed that IRL improved the applied policy and led to a faster convergence to optimal policy. (Castellini, 2016) proposed an incremental learning model to enforce a true, endless adaptation of the robot to the subject and environment as well as improve the stability and reliability of robot’s control. Incremental learning enables an adaptive robot system to update its own model whenever it is required, new information is available, or the prediction is deemed no longer reliable.

5. *Human-Robot Collaboration.* Future rehabilitation robots should not only be autonomous but also be collaborative (or co-operative) (Weiss et al., 2017; Huijnen et al., 2016). From the perspective of collaboration between the robot and the primary end users (i.e. people with cognitive disability), there is evidence indicating that a fully autonomous robotic system is not the best option for interaction with the vulnerable population (Peca et al., 2016). Instead, a semi-autonomous robot is a more suitable solution (Wood et al., 2017). With the highest-level goal of enhancing user’s cognitive capabilities, the robot should “care” about the user’s situation, take compensatory reaction as a teammate, engage the user and train/stimulate the user’s cognitive capabilities as best as possible. The capability of collaboration may also help to avoid the user’s feeling of redundancy and increase their feeling of self-autonomy and long-term engagement in cognitive training (Orejana et al., 2015). The robot should have a good perception of the user’s changing situations and an intelligent strategy to engage the user. On the other hand, from the perspective of collaboration among robots, users, and their caregivers (and therapists), more future work is needed to solve the shared control issue. Researchers need to figure out strategies for robots to render the caregivers’ and therapists’ tasks easier as an assistive tool for cognitive

training, instead of totally replacing them (Kostavelis et al., 2015; Coeckelbergh et al., 2016). A distribution between autonomy of robots and teleoperation by caregivers/therapists is needed to support the collaboration of robots for cognitive training.

6. *Social Cognition.* The knowledge gained in human-human interaction can be applied to foster human-robot interaction and to obtain critical insights for optimizing social encounters between humans and robots (Henschel et al., 2020). (Marchesi et al., 2019) conducted a questionnaire study to investigate whether people adopt intentional stance (Dennett, 1989) towards a humanoid robot, iCub. Their results showed that it is possible to sometimes induce adoption of the intentional stance toward humanoid robots. Additionally, non-invasive neuroimaging techniques (e.g., fMRI) in neuroscience enable the possibility of probing social cognitive processing in human brain during interaction with robots. For example, (Rauchbauer et al., 2019) observed that neural markers of mentalizing and social motivation were significantly more activated during human-human interaction than human-robot interaction. (Klapper et al., 2014) showed that human brain activity within the theory-of-mind network (Saxe and Wexler, 2005; Koster-Hale and Saxe, 2013; Price, 2012) was reduced when interacting with agents in a form of low human animacy (i.e. physical appearance) compared to high human animacy. These issues become important when we adopt robots for cognitive training for people with cognitive dysfunction (Frith and Frith, 1999; Chevallier et al., 2012), as they underline the substantial contrast between human-human and human-agent interactions. Additionally, the advanced noninvasive, portable and cost-effective neuroimaging techniques (e.g., EEG and fNIRS) hold the promise of evaluating human-robot interaction from controlled laboratory setting to real-world setting. Herein, we encourage to leverage human neuroscience to facilitate the development of robots for cognitive training, such as understanding the effects of robot-assisted cognitive training and learning the extent and contexts at which it can be beneficial from neurophysiological perspective.

7. *Natural Human-Robot Interaction.* Similar to human-human interaction during cognitive training by human therapists, robots need to be able to interact with users naturally in robotic rehabilitation. This includes having a good understanding of user’s emotions (e.g., happiness, shame, engagement), intentions and personality (Rudovic et al., 2018; Pettinati and Arkin, 2015; Rahbar et al., 2015; Vaufreydaz et al., 2016), being able to provide an emotional response when being shared with personal information (de Graaf et al., 2015; Chumkamon et al., 2016), talking day-by-day more to the user on various topics like hobbies, and dealing with novel events (Dragone et al., 2015; Ozcana et al., 2016; Kostavelis et al., 2015; Adam et al., 2016). These natural user-robot interactions require powerful perception, reasoning, acting and learning modules in robots, or in other words, cognitive and social-emotional capabilities. However, from the perception perspective, understanding users’ intentions and emotions is still a great challenge for robots (Matarić, 2017). Robots need to interpret multimodal signals (e.g., facial expression, gestures, voice and speech) simultaneously to understand users’ covert intentions and emotions. Similarly, more work is needed for the multimodal feedback in the future. To maximize the benefits of physically present robots and facilitate both the short- and long-term human-robot interaction for cognitive training, we need to develop more embodied communication in robots, not limited in verbal communication (Paradedda et al., 2016; Salichs et al., 2016; Matarić, 2017). Haptic sensing and feedback should be strongly considered in future research as part of multimodal perception and feedback (Cangelosi and Invitto, 2017; Arnold and Scheutz, 2017). More specifically, we need to implement the strategy to enable the robot to associate cognitive assistance and exercise with appropriate multimodal feedback, e.g., spoken words, facial expressions, eye gaze and other body movements (Paletta et al., 2018). The embodied communication during human-robot interaction is a challenging research area (Nunez et al., 2015). It is still unclear how and how much the embodied communication from the robot can influence user’s perception of the robot (Dubois et al., 2016). Moreover, previous studies indicated that users’ experience of the

robot could also be influenced by the unexpected behaviors (Lemaignan et al., 2015), synchrony and reciprocity (Lorenz et al., 2016), and even cognitive biases (Biswas and Murray, 2016, 2017) from the robot. A caveat is that there still exist many unknowns for natural human-robot interaction.

In summary, to achieve natural human-robot interaction during cognitive training requires not only multimodal sensing technology and artificial intelligence (e.g., deep learning) (Jing et al., 2015; Lopez-Samaniego and Garcia-Zapirain, 2016; Pierson and Gashler, 2017) but also the development of related fields (Wan et al., 2020), such as cognitive computing (Chen et al., 2018), social-cognitive mechanisms (Wiltshire et al., 2017), and modelling of cognitive architectures (Woo et al., 2017; Kotseruba et al., 2016).

1.1.5 Conclusion

Robots have become a promising tool to assist people with dementia. Many studies have been successfully conducted to evaluate the feasibility, safety, usability and effectiveness of robotic rehabilitation. However, there are still multifaceted challenges in the application of robots to assist people with dementia to provide a better wellbeing. Firstly, ethical issues, such as human safety and violation of social norms, can arise during robot-assisted cognitive training. Secondly, with respect to the design of a robot-assisted function to supplement dementia care, the developers should have a close collaboration with the end-users (e.g., PwDs) and stakeholders from the initial design, implementation, evaluation and improvement. Thirdly, the trust, reliability and the cost-effectiveness should be taken into account. Moreover, the robot should be capable to adapt and personalize to the specific individual PwDs' need, and also learn to collaborate with users in the future. Lastly, the robot should be able to interact with users in a natural way, similar to the PwD-caregiver interaction in daily life.

Noticeably, these challenges are mutually influencing one another. Cross-disciplinary collaboration is necessary to solve these challenges in future.

1.1.6 Summary

A large and increasing number of people around the world experience cognitive disability. Rehabilitation robotics has provided promising training and assistance approaches to mitigate cognitive deficits. In this article, we carried out a systematic review on recent developments in robot-assisted cognitive training. We included 99 articles in this work and described their applications, enabling technologies, experiments, and products. We also conducted a meta analysis on the articles that evaluated robot-assisted cognitive training protocol with primary end users (i.e., people with cognitive disability). We identified major limitations in current robotics rehabilitation for cognitive training, including the small sample size, nonstandard measurement of training and uncontrollable factors. There are still multifaceted challenges in this field, including ethical issues, user-centered (or stakeholder-centered) design, the reliability, trust and cost-effectiveness, personalization of the robot-assisted cognitive training system. Future research shall also take into consideration human-robot collaboration and social cognition to facilitate a natural human-robot interaction.

Chapter 2

Understanding User Acceptance and Needs of Robotic Dementia Care

Using the principle of user-centered design during the development of robot as a complement to care people with ADRD, it is imperative to understand users' requirements before design and implementation of a specific protocol of a robot system (Hartson and Pyla, 2018; Di Nuovo et al., 2018). As found in a literature review of factors affecting the acceptability of social robots among older adults (including people with ADRD and MCI), acceptability is likely to be improved if the robot meets users' emotional, psychological, social, and environmental needs (Whelan et al., 2018). Surveys are a popular, practical approach to learn the acceptability and perceptions of robots and users' needs and requirements. For example, Sancarolo *et al.* (Sancarolo et al., 2016) conducted a multicenter survey in Italy and Ireland about companion robots to understand the needs of caregivers as well as their preferences that would improve their ability in assisting those with ADRD. A majority (64.5%) of caregivers said that the robot MARIO would be useful or moderately useful to improve quality of life, quality of care, safety, and emergency communications. Cavallo *et al.* (Cavallo et al., 2018) conducted a user satisfaction and acceptability study regarding use of the Robot-Era system to provide robotic services to permit older

people to remain in their homes independently. They recruited 45 older users who had normal cognitive functioning and a minimum required autonomy in performing daily activities. Participants' feedback showed that the Robot-Era system has the potential to be developed as a socially acceptable and believable provider of robotic services to facilitate older people to live independently in their homes.

Attitudes towards using robot to assist dementia care can be different across cultures and countries (Coco et al., 2018; Suwa et al., 2020). For example, in a cross-sectional study by Coco et al. (Coco et al., 2018) in Finland and Japan, Japanese care personnel overall showed more positive assessment of the usefulness of robots than their Finnish counterparts, while more Finnish care personnel showed fear related to the introduction of care robots. Currently, most studies on perception and acceptability of social robots for dementia care have been conducted in a few countries including Japan and Australia whereas studies on these questions in other countries are very limited. Moreover, users' experience with technology is also a significant moderating factor for the acceptance of socially assistive robots by older adults (Flandorfer, 2012). As the presence and use of smartphones, computers, and Internet have grown considerably over the past few decades (Ryan, 2018), we would like to know people's recent opinions towards using robots to supplement caring for people with ADRD. Furthermore, feedback from not only from the primary end users (i.e., people with MCI or ADRD) but also from other stakeholders such as family caregivers, paid in-home caregivers, therapists, nurses, and other health care providers will be useful in the design process. In addition, considering that the general public (e.g., young age group) could possibly be the stakeholders in the future, we also took into consideration of their feedback. Therefore, we designed and deployed an online, anonymous survey to collect responses from all these stakeholders.

We developed the survey based on the Almere model (Heerink et al., 2010) and questionnaires adopted from previous relevant studies (Cavallo et al., 2018; Sancarolo et al., 2016). The purpose of this survey study was: 1) to understand public attitudes and acceptance of using a humanoid social robot, Pepper (SoftBank

Robotics) (Pandey and Gelin, 2018), to assist in caring for people with ADRD; 2) to explore users’ needs and requirements for a robot for ADRD care.

2.1 Methods

2.1.1 Participants

The study protocol was approved by the Institutional Review Board (IRB) of the University of Tennessee, Knoxville. Adults over the age of 18 were eligible to participate. There were no specific exclusion criteria. Consent was implied by completing the survey. The survey was distributed via social media (i.e., Facebook, Twitter, LinkedIn, and WeChat), email, and listservs.

2.1.2 Instrument

Using the web survey design tool QuestionPro, we created a structured, anonymous questionnaire written in English (Yuan et al., 2020). At the beginning of the survey, there was an approximately three-minute video (Yuan et al., 2020), where a humanoid social robot Pepper (Pandey and Gelin, 2018), named Tammy Pepper Knox or Tammy, presents potential functions that the robot may perform to help patients with dementia, such as, reminding to take medicine, providing entertainment such as brain games, motivating physical exercise, monitoring safety and health, and keeping them connected to friends and family. After watching the video, participants were asked four questions regarding demographic information, including age, gender, level of education, and familiarity with technology (i.e., smartphones, tablets, computers and robots). A branching question, “Are you currently diagnosed with any of the following conditions?” was used to identify those with MCI and ADRD. Considering the cognitive and physical limitations of people with ADRD, there are only 11 questions/items for those indicating a diagnosis of MCI or ADRD, and 32 questions for other participants. For those participants with ADRD, 11 statements regarding

their opinions of the robot’s appearance, voice, height, and intention to use the robot was provided using Likert-type scale ratings. A second branching question, “Have you ever provided Alzheimer’s care as any of the following types of caregivers?”, was used to identify caregivers, health care professionals, and the general public. Those who identified as caregivers were asked how many hours they provided each week: less than four hours, four to eight hours, or more than eight hours. Caregiver and other participants were asked 32 questions related to acceptability, function, impact, and ethical concerns of using a robot Tammy for ADRD care. Participants could skip any question they did not want to answer. The survey for caregivers and the general public ended with an open-ended question to provide additional comments, suggestions, or concerns regarding the development of a robot to assist in providing ADRD care.

In addition to the aforementioned items, participants’ physical locations (e.g., country and region) were automatically collected and stored by the web survey tool, QuestionPro, through their IP addresses (QuestionPro, 2021a).

2.1.3 Data analysis

For each question, we calculated basic descriptive statistics as appropriate, e.g., mean and standard deviation (SD), frequency and percentage. In the case of missing response to a question, the missing data were excluded. Then, considering that the data are not normally distributed, the Mann-Whitney U test (including p values and effect size (Vargha and Delaney, 2000)) was used to compare the caregiver group versus the other public group and female versus male within the same group. Furthermore, we investigated the relationships of responses among people with ADRD associated with perceptions/acceptability of the robot by calculating the Spearman’s correlation. During computing pairwise correlation of items, the missing data were excluded.

Regarding the open-ended comments, we firstly applied a common text-preprocessing technique, lemmatization (Schütze et al., 2008), to map different forms of a word to its base word, for example, mapping words “patient(s)”, “use(ful)”, “help(ful)”, and “Alzheimer(s)” to “patient”, “use”, and “Alzheimer”, respectively. Then we conducted qualitative analysis using a data visualization tool, word cloud (QuestionPro, 2021b), generated in QuestionPro to gain insight about participants’ interests using word themes. The word cloud tallies up the number of occurrences (denoted as *count*) of a certain word. In addition to key words, we read through all the comments from both groups to have a better understanding of participants’ ideas/meaning.

2.2 Results

From November 1, 2020 to March 13, 2021, a total of 2518 people viewed the survey. Of those, 944 people started the survey and 631 people completed it, with an average time of 11 minutes. The survey was considered completed when a respondent reached the Thank You page, although leaving some questions unanswered (i.e., skipping some questions). Among all the complete responses, 601 (95.25%) were from U.S. and 30 (4.75%) from 12 other countries (e.g., China, Germany, Japan, Australia, and Slovakia). Within the U.S., responses were collected from participants in 32 states. 485 (80.70%) responses were from the state of Tennessee, as shown in Table A.1 (see Appendix for all tables and figures).

2.2.1 Demographic information

Among the 631 complete responses, 80 were from people with MCI or AD/DRD or other dementia, 245 from caregivers, and 306 from the general public. On average, it took those with AD/DRD 10.04 minutes to complete the survey, 17.57 minutes for caregivers, and 16.61 minutes for the general public. The relative number and percentage of

participants in each group in terms of gender, age range, highest level of education, and familiarity with technology are listed in Table A.2.

The disease distribution of those with MCI or ADRD is illustrated in Figure A.1. The majority ($n = 47$) were currently diagnosed with MCI, 10 with mild dementia due to Alzheimer’s disease, 11 with moderate dementia due to Alzheimer’s disease. In addition, 12 participants chose other dementia, including bouts of amnesia (unknown causes), early onset dementia, hardening of arteries, memory loss due to brain hemorrhage, age-related dementia (not diagnosed as Alzheimer’s), either mild or moderate dementia (not sure), Parkinson’s dementia, and vascular dementia.

Participants in the caregiver group provided care as an informal caregiver ($n = 212$), paid in-home caregiver ($n = 13$), nurse ($n = 36$), therapist ($n = 14$), physician ($n = 8$), and psychologist ($n = 36$). The majority (57.55%) of caregivers indicated they provided care for fewer than 4 hours per week, 11.02% provided care for 4–8 hours, and 29.39% for more than 8 hours.

2.2.2 Perceptions of robot among people with MCI or ADRD

With respect to robot height (4 feet tall), the majority of people with ADRD (66 out of 79 response, with 1 participant skipping this question) thought the height was about right, while 11 and 2 participants considered it too short or too tall, respectively. In terms of the level of scare of robot Tammy, 66, 12 and 2 out of 80 of those with MCI or ADRD separately found the robot not scary at all, slightly scary and moderately scary. None reported the robot as very scary. The responses (i.e., frequency, percentage, mean and standard deviation) to other questions associated with perception and acceptability of robot are listed in Table A.3. Except for one item (i.e., "If you use the robot Tammy, would you be afraid to break something of the robot?"), the mean values of responses to items were greater than 3.

Concerning the functions that people with MCI or ADRD hoped the robot could have, participants’ response are presented in Figure A.2.

The top three desired functions in robots were reminders to take medicine, emergency call services, and helping contact medical services. All listed functions, except helping to order food, were desired by more than 50% of people with MCI or ADRD. Additionally, in the "other" option, two participants suggested brain games, two suggested the robot helping with or encouraging to do physical exercise, two suggested the robot helping find continually misplaced items (e.g., glasses, keys, and TV remote), and three suggested the robot offering reminders to pay bills, appointments (e.g., appointment with doctor), the time (e.g., the day of the week and the year), to complete work activities, or how to do something. Other suggested functions included doing laundry, being someone to talk to, explaining why the person entered a third room, bringing things, naming their children to them, warning them if they were experiencing sleep apnea, monitoring for smoke/fire and leading to an exit, video search engine, and interacting with the television.

With respect to ways to control the robot (tablet, speech, or both tablet and speech), there was 1 participant who skipped this question. The majority (50 out of 80) of people with MCI or ADRD would like to control the robot via both tablet and speech, while 29 patients would prefer speech. No participants chose a tablet to control the robot.

The Spearman's correlations between responses to items Q1–Q9 are illustrated in Figure [A.3](#). There was a statistically significant positive relationship between responses to item Q9 (i.e., "Would you like to follow the advice provided by a robot, such as the robot in Tammy in the video?") and responses to other items such as Q1, Q2, Q4, Q5, and Q8. There was a statistically significant negative relationship between responses to item Q7 and responses to items Q1, Q3, Q4, and Q6.

2.2.3 Perception of robot among caregivers and the general public

The descriptive statistics for the responses of caregivers and the general public are reported in Tables [A.4-A.6](#). For both caregivers and the general public, the mean values of their ratings to all the items are greater than 3. Concerning the robot's features, capabilities, and functions (i.e., items in Section B in Table [A.5](#)) to care for people with MCI or ADRD, most mean values of their ratings were greater than 4. Caregivers gave an overall higher rating than the general public for items B1d ($p = 0.0441$, effect size = 0.5468), B1e ($p = 0.0429$, effect size = 0.5433), B1f ($p = 0.0145$, effect size = 0.5524), B2e ($p = 0.0191$, effect size = 0.5437), B2g ($p = 0.0005$, effect size = 0.5740), B2h ($p = 0.0218$, effect size = 0.5391) and B3e ($p = 0.0073$, effect size = 0.5597). With respect to the potential usefulness of robots in caring for people with MCI or ADRD, as shown in the rows associated with Items C1a–C1h of Table [A.6](#), over half of both caregiver and general public participants thought the robot could be extremely useful to ADRD care. Moreover, caregivers overall rated in item C1f (i.e., "Detect when a person is becoming more lonely or isolated"; $p = 0.0091$, effect size = 0.5555) higher than the general public.

2.2.4 Ethical concerns

Regarding the levels of agreement with the three statements related to ethical concerns (i.e., Items C2-C3 in Table [A.6](#)), participants' responses were more scattered especially in terms of the first two statements, whereas the mean value of responses to these three questions were still greater than 3. Caregivers gave higher ratings overall than the general public group for items C3 ($p = 0.0166$, effect size = 0.5605) and C4 ($p = 0.0024$, effect size = 0.5705).

2.2.5 Open-ended questions

Additional comments, suggestions, and concerns that could be meaningful to the development of robot assistance for ADRD care were collected from caregivers and the general public. We received 111 and 110 comments from caregivers and the general public, respectively. To have a better visualization of participants' comments, we removed the words which were highly frequently mentioned by both groups but carried very little useful information, including “also”, “much”, “idea”, “able”, “might”, “even”, “seems”, “good”, “great”, “important”, and “one”. Table A.7 listed the top 10 frequently mentioned words in the open-ended comments by the groups of caregivers and general public.

Comments from caregivers

Overall, caregivers supported the concept of developing a robot to assist in caring for people with MCI or ADRD and showed agreement in the potential application in the real world. The words indicating such positive attitudes, such as “use(ful)” (*count* = 37) and “help(ful)” (*count* = 33), were frequently mentioned by caregivers, as listed in Table A.7. A few people commented that they loved the idea that robots would be used to supplement human care interactions, not replace them, whereas there were several caregivers showing concern that family or other caregivers would be strongly tempted to rely too much on the robot for assistance. A few caregivers expressed that such robots would allow a bit more freedom to caregivers and also provide for the safety and well-being of individuals with cognitive impairment. One caregiver who has cared for many homebound elders with an inadequate support system mentioned that a well-designed robot could allow some seniors to stay at home and do it more safely.

One dominant suggestion from the caregivers was to equip the robot with a menu of more human-like, soothing sounding voices instead of the current machine voice, which would be extremely uncomfortable to someone with ADRD. The word of “voice”

was mentioned 23 times by caregivers, as shown in Table A.7. For example, one caregiver commented that, “Developing a more human sounding voice is needed. The machine/computer voice would be extremely startling to a patient.” It was also suggested that the robot voice should be in regional language. Moreover, regarding the robot voice, one caregiver mentioned, “older people, with and without ADRD, tend to develop difficulties with hearing (especially for higher frequencies) and with rapidly processing of language. These people rely on ‘lip reading’ to enhance cognition. A common request of older people (< 90 years) is, ‘Look at me and speak loudly and slowly.’ Pitch, volume, and cadence controls for the robot voice are each important. Of similar importance, but more challenging, is a display of realistic lip movement while speaking...” Caregivers also provided other suggestions such as the robot might be properly textured and have expressively mobile faces; the robot might be customized by changing its color or adding scent to the robot according to personal preference.

One big concern among caregivers was the cost of the robot. Some caregivers particularly mentioned that the robot for ADRD care should be affordable. One caregiver expressed, “To me, the underserved, under-cared for sector is the lower income sector. Those with little to no family. I believe they would benefit the most from this type of technology.” Also, regarding cost, one caregiver participant asked if the robots are covered by insurance. Caregivers also showed other concerns and doubts such as the robot’s mobility on uneven surfaces or stairs, the size of the robot (e.g., “Not sure about size, not all patients have space for that size.”), and the capability of the robot in understanding and conversing with someone with ADRD (e.g., “Such patients often use the wrong words for things, places and in an inconsistent manner. They use the wrong verbs and refer to people by incorrect names.”). For better acceptability of the robot for ADRD care, caregivers commented that the robot should be introduced very slowly, carefully, and early to ensure that people using it understand its role and purpose. Several caregivers expressed concern that a robot would be a stranger and frightening to someone with ADRD. The robot should also

be easy to use, friendly, and not creepy. For example, one comment of concern about the ease of use of the robot was as follows: “I can’t imagine an Alzheimer’s patient having anywhere near the cognitive or emotional ability to LEARN to use any of the functions, if learning such things is necessary.” One caregiver also thought real-time technical support would be extremely important.

With respect to the capabilities and functions of robot for ADRD care, in addition to what was listed in the survey, caregivers suggested the robot could be used to help patients with staying hydrated, eating on schedule and with adequate nutrition, stress reduction (e.g., through meditation and yoga), and education regarding lifestyle changes (e.g., the importance of diet, water intake, exercise, meditation and sleep). It was also suggested it would be very meaningful if the robot could listen to patients’ repetitive life stories and respond, and provide alerts when someone had gotten up at night or was approaching the stairs.

Comments from the general public

Similar to caregivers, overall the general public showed positive attitudes towards the introduction of a robot for ADRD care, especially for cases where people with MCI or ADRD live alone, their caregivers are not currently available, or the robot can work as a companion. A few participants from the general public also suggested a more humanlike voice (the word “voice” with a count of 17 as listed in Table A.7). One of the obvious differences in comments from the general public and caregivers is that a few participants were afraid of robots replacing human caregivers. For example, one participant commented that “...I am afraid too many families might place a relative with AD or dementia under the long term care of a robot...”. They emphasized that human caregivers are always the most important. Another concern expressed by the general public was the cost of the robot. Participants mentioned that such robots should be available to all socio-economic levels. Associated with the concern of the cost of the robot, people in this group also questioned whether it is meaningful to use such a physically embodied robot (which could be expensive) in ADRD care,

compared virtual agents such as Siri or Alexa. People in this group also shared with some suggestions for better acceptability. For example, the robot may be designed with different colors in terms of its physical appearance and two legs for being more human-like and mobile. There might be potential issues with charging the robot, the robot making a mistake, and patient privacy. Moreover, several participants suggested it would be important to acclimate the person to the robot as early as possible in the course of the disease to lessen the strangeness factor of having a robot around. For example, one participant commented, “Seems as if the robot would need to be in that person’s life at the very early stages of cognitive deterioration so as to allow comfort, trust & acceptance.”

2.3 Discussion

2.3.1 Robot acceptance

People with MCI or ADRD showed an overall positive attitude towards the robot, Tammy, which is developed for ADRD care. As shown in Table A.3, more than 50% of people with MCI or ADRD gave a positive rating (i.e., Probably or Yes) to all the items except item Q7. Correspondingly, the mean values of their ratings to these items were greater than 3. For Item Q7 (i.e., “If you use the robot Tammy in the video, would you be afraid to break something of the robot?”), 53 (66.25%) out of 80 people with MCI or ADRD responded "No" or "Probably not," which indicates potentially low anxiety among these individuals in terms of using the robot (Heerink et al., 2010). As indicated in the Almere model (Heerink et al., 2010), a lower anxiety has a beneficial impact on the user’s positive attitude towards the robot and trust in the system. Noticeably, compared to the robot’s appearance (M=4.56), the robot’s voice (M=3.61) seemed to be less acceptable among people with MCI or ADRD. According to the comments about robot’s voice provided by caregivers and

the general public, we conjecture that the current machine voice in the robot Tammy is not comfortable to some individuals with MCI or ADRD.

Regarding the responses of people with MCI or ADRD to items Q1-Q9, there were statistically significant relationships between some responses as shown in Figure A.3. The responses to Item Q5 were statistically significantly positively related to responses to Item Q6 ($r = 0.26$, $p < 0.05$), Q8 ($r = 0.56$, $p < 0.001$), and Q9 ($r = 0.48$, $p < 0.001$), while the responses to Q8 and Q9 were statistically significant positively related as well (0.62 , $p < 0.001$). Questions Q5, Q6, Q8, and Q9 are closely associated with the construct intention to use (ITU), perceived ease of use (PEOU), social presence (SP) and perceived sociability (PS), and trust, respectively (Whelan et al., 2018). Therefore, to increase the acceptability of using robots to assist ADRD care, robot developers should pay attention to the designs (e.g., user interface) that influence the user’s PEOU, SP, PS, and trust. Regarding Item Q6, responses from people with MCI or ADRD were statistically significantly positively related to responses to items Q1 and Q2 and statistically significantly negatively related to responses to item Q7. At the same time, responses from people with MCI or ADRD to Q9 were statistically significantly positively related to responses to items Q1, Q2, and Q4. Questions Q4 and Q7 are both closely associated with the construct anxiety, which is defined as evoking anxious or emotional reactions when using the robot (Whelan et al., 2018). There is a statistically significant negative relationship between responses to Q4 and Q7. This makes sense considering that a high rating (e.g., 4=Not scary at all) to Q4 represents the robot is not scary at all, while a high rating (e.g., 5=Yes) to Q7 represents the user would be afraid to break something of the robot. The relationship between PEOU (Item Q6) and ITU (Item Q5), the relationship between PEOU (Item Q6) and anxiety (Q7), and the relationship between trust (Item Q9) and SP and PS(Item Q8) we found here agrees with the Almere model, a popular model developed to test the acceptance of assistive social agents by older adult users (Heerink et al., 2010) in terms of the statistically significant positive/negative relationship.

With respect to caregivers and the general public, both groups showed an overall positive attitude towards using robots as a complement to ADRD care. Among the responses to the questions associated with robot’s current appearance (A1), voice (A2), and height (A3), as shown Table A.4, the mean ratings for A2 by both caregivers and the general public were relatively low compared to the mean ratings for A1 and A3. This is plausible considering the negative comments about the robot’s voice provided by both groups in the open-ended question. Regarding the likelihood of using the robot in the example activities (i.e., Items A4a–A4e in Table A.4), both mean ratings from both groups were greater than 4 (4=Somewhat likely) to all items except questions A4b and A4c. The low rating in A4b and A4c could be relevant to robot mobility issues, which was reported in the open-ended question by both groups. The high rating responses to Items C1a–C1h in Table A.6 and the comments by caregivers in the open-ended questions confirmed the potential application of the robot for care of older adults with MCI or ADRD in terms of improving safety, providing companionship, and stimulation for cognitive and physical exercise, as well as reducing burden on the caregiver (Law et al., 2019).

2.3.2 User needs and requirements

Regarding the primary user, people with MCI or ADRD, the top three required functions in robots are reminders to take medicine, emergency call service, and helping contact medical services as shown in Figure A.2. In addition to the functions listed in our survey, participants with MCI or ADRD specifically suggested other functions such as brain games, which was found to be the most popular feature among older adults with dementia (Coşar et al., 2020). Moreover, as indicated in the Subsection 2.2.2, 50 out of 79 participants with MCI or ADRD would like to control the robot through both tablet and speech, while the rest would like to control the robot through speech. It is a little outside of our expectations that none chose a tablet as the only means to control the robot. This encourages us to include the voice control together

with the tablet control to use the robot. There was one participant with dementia who mentioned they were not sure if they had mild or moderate dementia. Considering one advantage of a robot caregiver is wide accessibility, we suggest robot developers take into consideration cognitive assessment as a function of the robot so that the user can use the robot to monitor disease progression.

With respect to the caregivers and the general public, among the list of features (i.e., Items B1a–B1g in Table A.5) that the robot has for ADRD care, the features of the robot being able to be quiet (B1e), taking up no more room than a person while moving about (B1f), and being able to connect to internet (B1g) were rated as the top three highest in terms of the mean value of response. With respect to the listed robot’s capabilities (i.e., Items B2a–B2j in Table A.5) to care for people with ADRD, over 60% of caregivers rated as extremely important and over 50% of the general public rated these as extremely important, with mean values all greater than 4.47 and 4.41, respectively. Thus, all these capabilities should be taken into consideration for implementation in the robot caregiver. In terms of the usefulness of listed functions (i.e., Items B3a–B3j in Table A.5) for a robot caring for people with ADRD, both caregivers and the general public rated with a mean value greater than 4. Based on the mean value and response distribution of these items, the function of monitoring people’s medication to avoid errors in drug use (Item B3c) should be considered in the first position, which is consistent with the top desired functions by those with MCI or ADRD. The functions of monitoring people’s movements at home to reduce risks of falls (i.e., Item B3a) and monitoring the ambient environmental conditions (i.e., Item B3d) should also be put in high priority. Regarding the robot’s function of regulating heating, humidity, lighting and TV channel (Item B3e), the caregiver group (4.48) provided a statistically significantly higher rate than the general public (4.33). This might because the caregivers have the experience of caring for people with ADRD and thus have more insight into patients’ requirements in these daily activities. Moreover, as reported in the rows of items C1a–C1h in Table A.6, approximately 60% of caregivers and the general public thought the robot would be extremely useful for

all eight items. Also, both caregivers and the general public provided the highest mean value, 4.84 and 4.82, respectively, for Item C1d (i.e., carry out emergency communication/alert message for people), which is consistent with the top desired functions by those with MCI or ADRD. Such requirements in robots of managing emergency situations has also been founded in previous relevant studies of the users' needs and requirements (Faucounau et al., 2009; Pigni et al., 2012; Manca et al., 2021; Korchut et al., 2017). Over 93% of caregivers rated the robot as somewhat or extremely useful to patients' quality of life, quality and care, safety, and emergency communications, which has also been found in a multi-center study by Sancarolo *et al.* (Sancarolo et al., 2016). Noticeably, caregivers provided a statistically higher rating response to Item C1f (i.e., Detect when a person is becoming more lonely or isolated) than the general public. We think this might be related to caregivers' experiences of interacting with people with ADRD and their observations of the problem of loneliness among these individuals compared with the general public.

As we presented in the section of open-ended questions, both caregivers and the general public expressed concerns regarding the cost of the robot and that cognitive limitations due to dementia may reduce the acceptability of the robot in ADRD care. These two factors were also found as the two biggest barriers to the use of assistive technology to support people with dementia in the literature review (Kruse et al., 2020).

2.3.3 Ethical concerns

The mean (SD) value of rating regarding item C2 ("Something bad might happen if people with MCI or Alzheimer's depend on robots too much") by caregivers and general public is 3.36 (1.17) and 3.16 (1.19), respectively, as listed in Table A.6. Such not high rating (notice 2=Somewhat agree, 3=Neither agree nor disagree, 4=Somewhat disagree) indicates the concerns of negative impacts of using robots for Alzheimer's care in both groups. Before practically using robots to assist Alzheimer's

care, ethical issues for all stakeholders in this field, such as human dignity, safety and social factors (Yuan et al., 2021b), should be taken into consideration. As a result, cross-disciplinary collaborations and communication are critical to solve these ethical challenges. Regarding item C3 (“People with MCI or Alzheimer’s would feel uneasy if robots really have emotions”), interestingly, the caregiver group (3.32) showed a statistically significantly higher rating than the general public group(3.07). This could be caused by the difference of experience and interactions with people with ADRD between these two groups. However, more research study is required to explain it. The significantly higher rating of item C4 (“Humans would be replaced by a robot in caring for a person with Alzheimer’s disease.”) by caregivers (4.18) compared to the general public (3.91), indicates that the caregivers of people with ADRD are more possible to accept the application of robots to assist Alzheimer’s care than the general public. This higher acceptance might be associated with the huge burden of Alzheimer’s care in caregivers (Brodaty and Donkin, 2009) and caregivers’ personal needs (McCabe et al., 2016) and need of help with this long-duration, time-intense care journey.

2.3.4 Limitations and future work

Some limitations in this survey study need to be taken into consideration in order to put the findings into perspective. First, due to the survey’s online, anonymous nature, we cannot verify the identities of respondents and there is no guarantee that they are people with ADRD and/or caregivers. Since there is no incentive to participate in the study and a participant can skip any question and withdraw from the survey at any time, we believe the participants have no particular motivations to intentionally provide biased responses to distort the results. Second, it is possible that the responses in this study were biased. Because this survey was conducted online, the participants accessed were more likely familiar with technology (e.g., cellphone, computer, and ICT), which may influence users’ acceptance of a robot for dementia

care. This selection bias may lead to the problem in acceptability work that the views of participants who find robots least acceptable may not be captured (Whelan et al., 2018). Also, we used a certain humanoid robot, Pepper, in the video of the survey. Participants’ preference for such a certain humanoid appearance might lead to a potential limitation of the results (Prakash and Rogers, 2015). Third, we used social media but by virtue of the architectural infrastructure the reach of a social media recruitment strategy was limited to a user’s social media community. For this reason, because the researchers reside in Tennessee (TN), USA, our social media recruitment yielded majority (76.9%) responses from TN with fewer responses outside the TN community. Given 76.9% of the respondents were from TN, there may be variations in acceptance and views across different states in US and different countries, and hence the sample representation may be skewed. As a consequent of the small number of responses ($N = 30$) from other countries (i.e., outside U.S.), the cross-country and cross-culture comparison of acceptability and perception are not able to be conducted as expected. Another limitation is that participants’ perceptions of the robot were merely based on watching a video instead of direct interaction with the robot. There might be some changes in their perceptions and attitudes towards robot after interacting with it. In the future, the evaluation of user experience (UX) among people with ADRD or MCI and their caregivers and health care providers will be a key step in the lifecycle of designing a robot for ADRD care (Hartson and Pyla, 2018; Khosla et al., 2017). Additionally, there is a methodological limitation with respect to our qualitative analysis of open-ended comments. Considering the limitation of word cloud which cannot accurately reflect the content/meaning of the texts, we manually summarized participants’ comments, which might result in some subjective bias. The future work will investigate additional tools to analyze these valuable resources of open-ended comments from caregivers and general public.

In the future, we will modify and develop a robot to supplement dementia care according to the user needs and requirements suggested by people with MCI or ADRD, caregivers, and the general public. For example, we will implement a menu of more

human-like robot voices from which individuals can choose at the very beginning of interaction with the robot. In addition, both the caregivers and the general public expressed concerns that the robot would replace human caregiving and human companionship. One caregiver participant provided the following comment: "the video made me sad to think of older adults not having a caregiver to hold their hand." Therefore, we suggest providing the public, especially unpaid and paid caregivers, with sufficient education regarding the advantages of applying social robots to ADRD care in the future. It should be made clear that the introduction of a robot is aimed at supplementing their caregiving instead of totally replacing human caregivers, which is also indicated by the previous study among care personnel (Coco et al., 2018). For example, provided that the robot will be capable of performing routine tasks (e.g., displaying a picture/song during reminiscence therapy), the caregiver will be able to have more emotional, high-quality, personalized interaction with the person with MCI or ADRD, potentially decreasing caregiver burden. The successful application of social robots in ADRD care requires both the acceptance of people with ADRD and their caregivers.

2.4 Summary

In this chapter, we collected and compared the opinions held towards using robots to assist caring for people with ADRD among different groups of people (i.e., people with MCI or ADRD, caregivers, and the general public). All three groups showed overall positive attitudes towards the application of a robot in ADRD care. We also identified users' needs and requirements indicated by people with MCI or ADRD, caregivers, and the general public. Additional comments, suggestions, and concerns from open-ended questions directed toward caregivers and the general public were also discussed. The results of users' requirements and needs, as well as additional suggestions and concerns from the public, will be meaningful to the design and implementation of the social robot protocol for ADRD care.

Chapter 3

Robot-assisted Conversational Engagement

Reminiscence therapy (RT) is a popular psychosocial intervention widely used in dementia care. It involves a discussion of past experiences and events, using tangible prompts (e.g., photographs, music, and videos) to evoke PLWD's memories and stimulate conversation (Woods et al., 2018; O'Philbin et al., 2018). RT has shown positive effects on PLWD's mood, cognition, communication, and quality of life (Woods et al., 2018; O'Philbin et al., 2018). However, RTs are traditionally provided by clinical practitioners or professional facilitators (Van Bogaert et al., 2016; Evans et al., 2019), limiting the accessibility of RT to PLWD. A physically embodied social robot-mediated RT (RMRT), where the robot usually facilitates the RT using attractive physical appearance, expressive gestures and other body language, and/or facial expression (Yuan et al., 2021c) as well as AI-enabled conversation. This approach helps promote social interactions with the PLWD both verbally and non-verbally and may enable more positive user experience and more effective and engaging memory triggers (e.g., recall and recognition) and/or pleasant experiences in reminiscence activity (Bejan et al., 2018; Khan et al., 2022).

Currently, a few studies have been conducted on RMRT (Asprino et al., 2017; Yuan et al., 2021f). For example, during reminiscence work at a care facility in Japan, Yamazaki *et al.* (Yamazaki et al., 2018) introduced a huggable humanly shaped robot, pillow-phone Hugvie, and pilot tested its effect in facilitating RT with PLWD. The results from five PLWD indicated that providing topics related to personal histories through robotic media could positively affect PLWD’s communication. Using a 19.05cm-tall humanoid social robot RoBOHoN, Wu *et al.* (Wu et al., 2019) developed a RMRT, where deep learning techniques were applied to recognize events, objects, and scenes in photographs, and tested the system’s usability with people (aged 22-42) without cognitive impairment in Taiwan. Their results showed that the robot can pose appropriate questions related to personal photographs and had the potential to guide the user to recall the past in an organized way. In another study using a 31.5cm-tall social robot Zenbo Junior, Gamborino *et al.* (Gamborino et al., 2021) developed a robot-assisted photo reminiscence system consisting of two parts, a graphical user interface (GUI) to display photos (i.e., Dynamic and Flexible Interactive PhotoShow) (Vi et al., 2013) and a social robot. This system was designed to autonomously guide an older adult PLWD throughout a reminiscence session, asking questions that were related to the picture that the user chose. The system could automatically extract visual information from the pictures using a pre-trained AI model to detect scenes and events. Gamborino *et al.* tested the system with 10 older adults without cognitive impairment in Taiwan. Most participants found the system responsive, and the questions asked were appropriate for the picture selected, and praised the system. The majority of these studies were conducted with young adults or older adults without cognitive impairments; yet, few studies focused on PLWD. However, to ensure successful adoption of robotic technology among PLWD, it is necessary to evaluate the technology’s acceptability and usability specifically with PLWD (Yuan et al., 2021c; Vollmer Dahlke and Ory, 2020), especially considering that PLWD usually have limited cognitive and physical capacity compared to people with normal cognitive and physical capability and limited experience with technologies (Woods

et al., 2021b). Another limitation existing in the literature is a deficiency of such RMRT studies in the United States. The adoption of robots for dementia care delivery can be different across cultures and countries (Woods et al., 2021b). In addition, during a RMRT, the design of user interface (UI) for PLWD covers the robot’s appearance, voice, and body movement, more than the verbal conversation and/or the GUI to display the reminiscence image. We also noticed that most of the robots in previous RMRT studies lacked a GUI interface for user interaction with the robots, meaning that an additional, separate GUI component (e.g., computer or tablet (Wu et al., 2019; Gamborino et al., 2021)) is needed in support user interaction.

Our long-term goal is to develop a RMRT wherein the social robot can automatically provide engaging, adaptive, and personalized reminiscence activities for people with dementia. Such an RMRT is designed to be easy-to-use and access, personalized cognitive exercise tool by PLWD themselves at home, without the facilitation of professional clinicians. We believe this program will also help increase the accessibility of dementia care, impro

3.1 Development of a Pre-programmed Robot-mediated Reminiscence Activity

We employed the user-centered design principles (Norman, 2013) and guidelines to develop a prototype for a humanoid social robot (Pepper) equipped with a GUI to deliver reminiscence therapy for PLWD (Social care institute for excellence, 2020; Schweitzer and Bruce, 2008; Dementia UK, 2022). For persons with severe dementia, their abilities to verbally communicate are greatly diminished and they may appear unresponsive (Alzheimer’s Association, 2022). In this chapter, therefore, the RMRT is targeted at persons with mild or moderate dementia, excluding those with advanced dementia. Pepper is 1.21-m tall and 0.48-m wide and has 17 joints for graceful and expressive body movements. Pepper can appropriately adjust its body language

(such as gestures and other body movements) as well as voice according to what it is saying. It is equipped with several LEDs in its eyes, ears, and shoulders for color changing to signal and support human-robot communication. Pepper’s size and attractive appearance make it appropriate, acceptable, and enjoyable to users in daily life as well as PLWD (Schüssler et al., 2020; Yuan et al., 2021c,a; Cobo Hurtado et al., 2021; Yuan et al., 2022b). Pepper also has a range of sensors (e.g., cameras and microphones) and uses AI to perceive human interaction and the environment. Pepper can usually make good eye contact with the user during interaction. Pepper is equipped with a 246-175-14.5-mm tablet on its chest, which makes it convenient to display tangible prompts (e.g., photos and videos) to stimulate PLWD’s memories and conversations. The capability of multimodal interaction in Pepper could enable more effective and engaging memory triggers (e.g., recall and recognition) for PLWD in a reminiscence intervention (Bejan et al., 2018).

3.1.1 General Reminiscence Knowledge Base

A multimedia file was created as a source of prompts for memory stimulation for PLWD. The file consists of general music, video clips of movies and TV shows (e.g., the typists from The Carol Burnett Show), and photographs that are familiar to the PLWD, including photos of local popular cultures, holidays (e.g., Christmas), scenes (e.g., Downtown Knoxville), historical buildings, and sports (e.g., the famous football quarterback, Peyton Manning). The use of stimulating concrete prompts such as photographs, music, and videos which are associated with the PLWD’s past experience has been suggested to be most effective for RT (Cuevas et al., 2020). The multimedia prompts for memory stimulation were identified from websites that provide copyright clearance, YouTube, and other websites in the public domain to use for this project. We downloaded the audio clips, video clips, and photographs from the websites and saved them into the reminiscence file. The video clips were designed for approximately 3 minutes, without too negative, complex, or violent information

(Sabal Palms, 2020). We interviewed and discussed with experts in RT these materials to ascertain that all the images, audio, and video clips are appropriate for PLWD. For example, during the discussion, we found that the images including multiple objects (e.g., the first two images on the left of Fig. A.4) could be distracting to PLWD and should be avoided. Eventually, the reminiscence database consists of nine topics, including pets, cars, holidays, hobbies, chores, movies, music, sports, and local scenes.

3.1.2 A Prototype of Robot-Mediated Reminiscence Therapy

Research suggests human users prefer social machines (e.g., chatbots and robots) which convey humanness, increasing acceptance and easing social conversations with humans (Ruijten et al., 2019). Studies finds that female bots are perceived more humanness than male bots and that female bots are preferred over male bots in the context of healthcare (Borau et al., 2021). We also found that majority of adults in Knoxville perceived the Pepper robot as a girl or female. Therefore, we would like to rename Pepper to contextualize its gender as female. We renamed the robot Tammy, one of the most popular girl names in Tennessee. A standalone app, named *Reminiscence*, was implemented in the Tammy, based on common interaction design principles, including visibility, consistency, affordance, feedback, and mapping (Rogers et al., 2011; Norman, 2013; Moon and Park, 2020).. The system will possess a simple and easy-to-use graphical user interface (GUI) that takes into account After tapping the app, a topic selection layer will be displayed on Tammy’s tablet, as shown on the left side of Figure A.5. Each topic was shown together with an image as well as texts in order to facilitate PLWD’s understanding of the content of each topic. The potential user can browse each topic by tapping the topic button. After the user chose a specific topic, Tammy automatically displays an image or video clip closely associated with this topic on its tablet. Considering the primary users of the RMRT, PLWD with short-term memory loss, who might forget what they need to do or why they are there during RMRT, we designed the robot to frequently remind the user

about the next step. That is, at the very beginning of each topic, Tammy robot provides verbal instruction for the next step, i.e., “When you are ready, please click the ‘NEXT’ button or say, ‘Tammy next’”. For each image or video clip, Tammy robot will have 3-4 conversational interactions with PLWD. The conversation is hardcoded using the API, *Topic* and *QiChatbot*. The image or video clip is displayed on the left side of the Tammy robot’s tablet and the conversation on the right side of Tammy’s tablet, as shown on the right side of Figure A.5.

For each conversation round, Tammy starts with some background information about the image or video clip and then comes up with a relatable and engaging question (e.g., “Do you have a favorite memory with a pet?”) to encourage the PLWD to talk. The background information (e.g., “Pets are so adorable. Several months ago, I met a Golden retriever. He was a very kind and smart dog. I got to say hello and play with the dog. It was very exciting!”) is designed to let Tammy share a memory itself, which has been suggested as a good starting point and a good way of leading into asking a question more gently (Social care institute for excellence, 2020; Dementia UK, 2022). Additionally, Tammy would provide a follow-up comment associated with the user’s answer. After all the conversation interactions relating to the image or video clip, Tammy will thank the user for talking about this topic with it and provide a verbal reminder that this is the end of the topic, and the user can go back to the main menu and choose another topic. A flowchart of the robot-mediated reminiscence activity is demonstrated in Figure. A.6.

Under each topic, the user is able to control the robot Tammy by tapping buttons or using voice input. Specifically, the user can move to the next conversation by tapping the NEXT button or saying, “Tammy next”, which on one hand can help the robot know that the user finished their answer and on the other hand, give the user a sense of self-control to skip any question and mitigate potential RT stress (Yuan et al., 2021f; Wilkins, 2017). The user can tap the REPEAT button or say “Tammy repeat” to make the robot repeat what it just said. The user can go back to the topic select layer by tapping the MAIN MENU button whenever they want to go back to

the main menu or stop the current topic. The GUI design for the three buttons (i.e., “NEXT”, “REPEAT”, and “MAIN MENU”) are illustrated on the right side of Figure [A.5](#).

3.2 Usability Study of Robot-mediated Reminiscence Therapy

After the prototype development, we tested it at a dementia specialty clinic with a group of PLWD who used the program and interacted with the robot. We evaluated the acceptability and usability of the program and robot in relation to the robot’s appearance, voice and body language, the GUI on the robot’s tablet, as well as the robot’s conversation in offering reminiscence. This usability study was conducted to answer the following research questions, 1) How do PLWD living in Knoxville, a city in the U.S. state of Tennessee perceive an RMRT program that is facilitated by a humanoid social robot? and 2) How effective is the robot in interacting with PLWD when delivering RT?

3.2.1 Study Design and Participant Recruitment

We conducted a pilot study to assess the acceptance of the robot Tammy through usability testing involving people with dementia, which at the same time contributed to testing feasibility of the RMRT program. We used the survey and observation approaches to conduct the usability testing of Tammy and its GUI tablet. The study protocol was approved by the Institutional Review Board (IRB) of the University of Tennessee, Knoxville. IRB number is UTK IRB-21-06631-XM. We recruited potential participants via emails. To reach more potential participants, we additionally recruited PLWD participants at a local dementia specialty clinic (Genesis Neuroscience Clinic, Knoxville, TN) between 24 January 2022 and 4 February 2022. Inclusion criteria included: 1) aged between 18 and 95, 2) able to understand and

speak English fluently, 3) diagnosed with cognitive impairment or dementia or having experience in caring for people with cognitive impairment or dementia, and 4) no severe hearing or visual impairments that would interfere with the reminiscence process. Exclusion criteria were: 1) having any current significant systematic illness (e.g., brain injury, severe eye or hearing conditions) that could lead to difficulty complying with the experiment, or 2) unstable medical condition. The clinicians at the clinic helped recruit participants by asking a person with dementia if s/he was interested in joining a research study on interacting with a social robot. Participants who were interested and met the eligibility criteria were provided written and verbal information about this study. To ensure that a potential participant was able to provide informed consent, after describing the study to the potential participant, a researcher asked her/him to explain the essential information about the study in their own words, for example, "Can you tell me what this study is about?" The persons who cannot provide an adequate answer to the question were not included in the study. A researcher or a dedicated research nurse who was employed at the Genesis Neuroscience Clinic obtained an informed consent form from participants who agreed to join the study. Data were collected at the Genesis Neuroscience Clinic, Knoxville, TN, with the participants recruited there and the laboratory at the University of Tennessee, Knoxville, TN with the participants recruited from other places. The cognitive status of participants was self-reported via a survey (See Subsection 3.2.3) and cross-checked with the clinician at the Genesis Neuroscience Clinic for verification purposes.

3.2.2 Experimental Procedure

The experimental procedure for this usability study is illustrated in Figure. A.7. After obtaining the consent form from the participant, the researcher distributed a survey questionnaire that collected demographic data from each participant, background experience with technologies, and cognitive status (see 3.2.3). A participant with

cognitive impairment or dementia can participate the study accompanied by their family member. The experiment started with a familiarization session, where the robot welcomed the participant and introduced itself, using a short talk conversation, dance, and/or song. This session can support positive emotional reactions and alleviate PLWD’s possible fears and discomfort while promoting the feeling of safety in being around the robot Tammy. Then the researcher demonstrated how to use the *Reminiscence* app in the robot, for example, tapping buttons and using voice input, and the participant started to try reminiscence activities mediated by Tammy. The participant can try as many reminiscence topics as they wanted. The researcher encouraged the participant to use the reminiscence app by themselves. However, if they had any problems using or interacting with the robot, an interventionist (i.e., trained researcher) would provide help. During the reminiscence process, the researcher observed the human-robot interaction and took field notes. After the reminiscence process, a questionnaire was distributed to gather data about participant’s perception (e.g., usability and acceptability) of the RMRT. See Section [3.2.3](#) for details.

3.2.3 Data Collection

A mixed-method approach, quantitative and qualitative, was employed to collect the data. Quantitative data about demographics and user experience were collected using participant-rated questionnaires. As demonstrated in Figure [A.7](#), a demographic survey was provided before the participant interacted with the robot, and another questionnaire for evaluation was provided after the participant tested the RMRT. Details on the design of the two questionnaires were provided in the following subsections. Qualitative data were collected via the open-ended comments that participants provided, the researcher’s field notes during observation of the robot Tammy’s interaction, and participants’ video-recorded interactions with the robot during the reminiscence therapy. The researcher also noted potential critical problems

in the RMRT, and participants' thoughts, comments, and suggestions for the system. To maximize the number of participants recruited, it is voluntary for participants to be video recorded their interaction with Tammy during RMRT. For participants who agreed to be video-recorded, a GoPro camera, which was put in a corner, was used to record their interactions with Tammy. After the experiment, all the videos were moved to a university-owned laptop for data analysis.

Demographic survey

The survey questionnaire collected the participants' demographic data (age, gender, and education), background experience or familiarity with using technologies (including smartphones, tablets, computers, and robots), and cognitive status (type of cognitive impairment and stage)

Questionnaire for evaluation

After the participant interacted with the RMRT, the participant was asked to complete a 14-item questionnaire (post-test) to evaluate their experience with and perception of the robot Tammy and its tablet's user interface (UI) during RMRT. The survey was adapted from two well-established questionnaires, the Questionnaire for User Interaction Satisfaction (QUIS) (Norman et al., 1998) and the System Usability Scale (SUS) (Brooke, 1996). We also applied Almere's model to gather data about the participants' acceptance of the Tammy (Heerink et al., 2010). QUIS measures the users' overall system satisfaction and user satisfaction on specific interface factors, including screen visibility, terminology and system information, learning factors, and system capabilities (Norman et al., 1998). SUS is a widely used tool for evaluating subjective usability of digital products, services, and designs, providing a holistic view of subjective assessment (user-driven) of system usability including perceived ease of use, effectiveness, efficiency, and satisfaction (Brooke, 1996). The Almere model tests the acceptance of assistive social agents by elderly users that positively

influence elderly users’ intention to use a system over a longer period of time. To minimize the cognitive burden for PLWD in filling out the three questionnaires, we combined these into one 12-item questionnaire (Table A.8). The items generated data on specific constructs that are critical for understanding the participants’ interaction behavior and experience with the robot and the user interface, affective reactions to it, acceptance, trust, and effectiveness. The participants rated each item (Table A.8) on a five-point scale, from 1 = “strongly disagree” to 5 = “strongly agree”.

In addition to the 12 items in Table A.8, we added one item to learn how the PLWD would like to control the robot Tammy (i.e., through the tablet, speech, or both), during the reminiscence activity. Moreover, there is one multi-choice question to learn about the functions of Tammy that people with dementia would like to have in their daily life. Therefore, we added the open-ended question (“Do you have any suggestions or comments?”) to gather additional insights into the participants’ opinions and suggestions about the RMRT. During the study, participants could skip any question they did not want to answer.

3.2.4 Data Analysis

Descriptive statistics including frequency, mean (M), standard deviation (SD), range, and proportions were used to analyze the quantitative data. Considering the small sample size, we manually went through all the comments from open-ended question as well as field notes to develop an understanding of the participants’ experience with the RMRT. As for the recorded videos, we used Simple Video Coder (Barto et al., 2017), free, open-source software for efficiently coding social video data, to code participants’ interaction behaviors during RMRT, including the participants’ emotions (such as laughter/giggle/joy, frown, and confusion) and success or failure in using the RMRT.

3.2.5 Results

Descriptive Statistics

A total of 12 older adults (4 females and 8 males), including 3 informal caregivers, 2 individuals with mild cognitive impairment, and 7 with ADRD, consented to participate in this usability study. Their demographic information is listed in Table A.9. The prototype RMRT has been tested with ten participants at the Genesis Neuroscience Clinic and two participants at the laboratory. There was one participant aged 50-65, three aged 65-75, seven aged 75-85, and one aged above 85. All participants obtained an education of high school graduate or higher. On average, all participants were at least slightly familiar with technologies of smartphones, tablets, and computers. Regarding robots, all participants reported “not at all familiar” with them. Among the seven participants with ADRD, one participant reported early-onset dementia, five with mild dementia due to AD, and one with Frontotemporal dementia. Each participant tried two or more topics for the reminiscence activity. The participants spent 2-3 minutes talking about one topic with the robot. On average, it took 20 minutes to complete both the robot-mediated reminiscence activity and the questionnaires. Three participants agreed to be video recorded for their interaction with the robot.

Evaluation Survey

Participants’ responses, including mean, standard deviation (SD), and range, to 12 items of Table A.8 are shown in Table ???. Overall, except for Item Q7, participants rated each item “somewhat agree” or “strongly agree”. The first three rows in Table ??? lists responses from people with mild cognitive impairment (MCI, $n = 2$), people with ADRD ($n = 7$), and informal caregivers ($n = 3$), respectively. With respect to the robot control method, ten participants (83.33%) indicated that they would like to control the robot using both tablet and voice (speech), while one participant would

like to control the robot only via tablet or speech, separately. Table [A.11](#) counts the number of times robotic functions that participants hoped the robot to have.

Observation, Comments, Field Notes, and Video Coding

During the RMRT, participants shared their stories after the robot came up with a question. However, there were two participants who only gave “yes” or “no” answer or simply skipped answering a question by tapping the “NEXT” button. A few participants verbally provided suggestions in terms of the design and functions of the robot, indicating its use for dementia care. The videos recording participants’ interaction with the robot during RMRT were coded in terms of participants’ behaviors and number of occurrences (N_{occur}) in Table [A.12](#), [A.13](#), and [A.14](#) for participants P1, P2, and P3, respectively. During the first topic in all three tables, participants had difficulty in using the RMRT successfully, for example, failure in tapping NEXT button (Table [A.12](#), [A.13](#), and [A.14](#)) and confusion about what to do at the end of the first topic (Table [A.12](#) and [A.14](#)). After the first session, participants successfully controlled the robot for reminiscence activities most of time. During the RMRT, we also observed that participants laughed, nodded, thought about their own experience, and made eye contact when the robot talked with them (Table [A.12](#) and [A.14](#)). Some participants also sang along with the robot when the robot displayed a song on the Music topic (Table [A.12](#)).

In addition, five (42%) of the 12 participants provided open-ended comments, including “Exciting possibilities!”, “Research was very, very sweet, helpful, and knowledgeable. Great idea”, “I believe this is a wonderful tool for children with problems. Also, it would be great for adults that have problems. I love her (meaning the robot Tammy)!”, “very interesting!”, and “very nice to see”.

3.2.6 Discussion

In this study, we used Tammy, a humanoid social robot (Pandey and Gelin, 2018) to develop a RMRT program for people with dementia. Tammy was able to automate the reminiscence activity for PLWD. A usability study was conducted with 7 individuals with ADRD, 2 with MCI, and 3 informal caregivers to evaluate the user experience and system’s acceptability using usability testing of RMRT at a local clinic and the laboratory. Overall, participants reported a positive user experience with the RMRT and perceived the program as **effective** and easy to use.

User Experience and Usability of RMRT

The findings from this study revealed that although all participants were not familiar with robots, they had an overall positive user experience with the RMRT activity and interaction with the robot, Tammy. As shown in Table ??, on average, participants somewhat or strongly agreed with the statements for all items, except for Item Q7. Items Q1 and Q2 responses showed that Tammy’s appearance was, on average, considered to be pleasing and its voice was clear to participants. In our previous study (Yuan et al., 2022b), we asked caregivers and the general public (people without dementia and without experience in dementia care) their opinion on how likely would people with dementia interact with a video-based robot and how much would they like its sounding voice. The caregivers and the general public rated the voice with a relatively low mean value ($M = 3.17$ and $M = 3.18$, respectively) and provided negative comments about its voice. However, in the present study, participants reported a positive user experience in terms of Tammy’s voice, with a mean (M) rating of 4.33 and a standard deviation (SD) of 1.15. This might be related to the fact that participants interacted with the robot in-person. Item Q3 in Table ?? shows that, overall, the participants rated Tammy’s body movements (e.g., gestures) as high ($M = 4.58$) on a five-point scale. This indicates that delivering reminiscence therapy by a physically embodied social robot can facilitate both verbal and nonverbal social

interaction for PLWD (Bejan et al., 2018; Khan et al., 2022). Additionally, their rating of the tablet’s GUI design (e.g., attractiveness) of the RMRT was $M = 4.42$, suggesting a high potential for adopting our RMRT program by PLWD. Moreover, we found that participants rated nine items (i.e., Q5-Q6 and Q8-Q11) above 4 on a five-point scale (Table ??), suggesting that they would use the RMRT program in the future. This finding means that using a robot like Tammy has promise for successful adoption of RMRT by PLWD.

Regarding Item Q7 (i.e., “I would follow the advice of the robot”), participants provided the lowest rating ($M = 3.73$, $SD = 1.19$). This was due to lack of trust in using robots, which confirms findings from previous studies (Pino et al., 2015). During the experiment, we noticed that participants appeared to be very careful when answering this question, leaving a comment such as “I don’t know.” One participant commented that this is first time for him to use a robot and that he would keep being questionable towards robot’s advice and that given a chance of using the robot for a longer period of time, his response or trust might change. Herein, we conjecture that limited experience with robots as well as exposure to using them for a short-period of time influenced the participants’ ratings. However, it was reported that user trust is a critical factor influencing user’s intention to use of a robot (Whelan et al., 2018; Yuan et al., 2021c). Possible ways to mitigate the issue is to provide literacy and training programs for PLWD about robots and give them opportunities to interaction with robots for a longer period of time (Woods et al., 2021a). It is interesting that people with MCI provided lowest score (Mean = 3.50, $SD = 0.71$) to Item Q7, compared to people with ADRD (Mean = 4.00, $SD = 1.41$) and informal caregivers (Mean = 5.00, $SD = 0$). However, since the sample sizes of three groups are very small, more research is needed to gain insight if there is a significant difference in this item and the underlying reasons. All three groups of participants provided a score of mean 4.50 or greater, meaning that the participants would highly recommend our RMRT to other PLWD. The finding reflects participants’ positive perception of and attitude

towards the robot Pepper and the RMRT program and suggests that the RMRT as well as the robot have a high potential for adoption in the future.

In the video recording the participants' interaction with the robot during RMRT (Table A.12-A.14), we observed that participants sometimes laughed, giggled, made eye contact with the robot, and even tended to shake hands with the robot, when the robot Tammy talked and played body movements. The participants' nonverbal behaviors indicate that a physically embodied social robot can facilitate both verbal and nonverbal social interaction with PLWD during RT, enabling more engaging and positive user experience and thereby increasing beneficial impacts of RT on PLWD's mood. During the RMRT activities, we noticed that some participants sat too close with the robot to clearly see the content on its tablet, which might have reduced the effectiveness of robot's body movements in communication (Beck et al., 2017).

Robot Control Method

Some participants showed interest of controlling the robot Tammy using voice control. However, during the experiments, we found that most of the time it was not successful for participants to control Tammy via voice input, which happened to Participants P1, P2, and P3 (Table A.12-A.14). This may be attributed to the fact that all the participants in this study are older adults, who most of the time had low speaking volumes. Also, due to the COVID-19 pandemic, most participants wore masks when interacting with the robot, which made it more difficult for Tammy to clearly understand their speech. Another hindering factor was a limitation in Tammy's delay in finishing its verbal output and starting to listen to the participant's verbal input. In other words, if the user provided their voice input before Tammy was ready to listen, Tammy would not respond as expected, leading to a negative user experience for PLWD.

Preference for a robot control method depends on each individual user. In this study, one participant (P2, Table A.13) showed a symptom of a shaking hand. This participant planned to tap the "NEXT" button to continue the procedure but,

unfortunately, tapped the “NEXT” button twice within a very short time. In this situation, it might be more convenient for the participant to control the robot through voice input. Thus, we suggest that designers enable the use of both control methods in technologies such as robots, tablets, and computers to support and enhance PLWD’s interaction and experience.

Personalization of RMRT

Through the observation of PLWD-robot interaction and based on the field notes taken during the experiment, we identified three aspects of personalization to incorporate in the current prototype of the RMRT. The first aspect is the design of the UI icons. For example, one female participant verbally mentioned that it would be better if the user’s icon matched the user’s gender. This finding was also confirmed in a previous study (Yuan et al., 2021c). The second aspect is the personal photos and videos. Two participants suggested that topics specifically include photos and videos of individual life events, such as wedding, which people with dementia could be very interested to talk about. In this study, we avoided the use of personal materials to reduce potential privacy concerns. In future work, we will create an additional module for PLWD where they can add their personal photos and/or videos of interest to them and also be able to talk with Tammy about their life stories, experiences, and memories to improve potential effectiveness of RT for PLWD (Cuevas et al., 2020). During the experiments, when the robot Tammy asked a simple question such as “do you have a favorite memory with a pet?”, two participants only provided a “yes” or “no” answer or directly skipped answering the question by tapping the “NEXT” button, while other participants shared their stories. Considering that PLWD might feel stressed because of the inability to answer difficult, open-ended questions, we hardcoded Tammy to ask easy, closed-ended questions most of the time. However, this turned out to lead to less conversation from the participants. Therefore, another potential aspect of personalization should be that Tammy adaptively asks relatable, engaging, and appropriate questions for reminiscence. For example, when a user

is cognitively able to answer a more difficult question, Tammy may ask different questions such as “what is your favorite memory with a pet?”. Conversely, if a user is cognitively unable to answer a difficult question, Tammy should adaptively ask easy questions such as “do you have a favorite memory with a pet?”. Such personalization can stimulate PLWD to converse as much as possible while promoting a sense of comfort and well-being. This personalization might be enabled by using advanced AI techniques, such as deep learning (Carós et al., 2020) and reinforcement learning (Yuan et al., 2021f).

Robot Functions Desired by PLWD

With respect to the functions that the participants would like Tammy to do to support dementia care, the top four required functions found in the present usability study of RMRT were, helping call family and friends, helping contact medical services, setting reminders to take medicine, and providing emergency call service; while the top four functions found in our previous study (Yuan et al., 2022b) included, setting reminders to take medicine, emergency call service, helping contact medical services, and setting reminders to turn off the stovetop, which excluded “helping call family and friends”. One possible reason for this difference is that participants in the current study interacted with the robot in-person, obtaining an impression that Tammy may not be appropriate for calling family and friends, whereas, in the previous study, the participants watched a video of the robot and did not have a sense of its live presence. Additional studies are needed using a large sample to identify the most important functions PLWD desire in a robot. As for Tammy playing music, one participant had a hobby of playing music and instruments. When answering this multi-choice question, he particularly wrote down “play music” under *Other* in the survey. This finding suggests that the personalization of the robot Tammy for PLWD varies based on each individual PLWD’s hobbies (such as listening to music, reading books, or watching a movie) (Wu et al., 2021). Individualized personalization could facilitate

a more successful long-term adoption of social robots by PLWD for dementia care (Yuan et al., 2021c).

Accessible Technology-Enabled RT

Two family caregivers shared their opinion about the RMRT as well as technology-enabled dementia care. One participant’s caregiver expressed appreciation for our RMRT. She mentioned that her loved one with dementia was very knowledgeable and could still talk a lot about his knowledge. This RMRT was a good idea because it could stimulate and engage her loved one to talk. This caregiver provided insights into users’ needs from a family caregiver perspective, indicating that more access to reminiscence therapy and other dementia care is still a challenge for PLWD and their caregivers. We suggest leveraging the advanced digital health technology, such as mobile devices, social robots, and AI, to support dementia care delivery, which will in turn support aging in place (Yuan et al., 2021c; Khan et al., 2022; Astell et al., 2019). An early introduction of digital health, for example, in stages of mild to moderate dementia, may lead to a better user acceptability of the technology and enable the technology to assist more in dementia care (Yuan et al., 2022b; Sousa, 2021).

When testing the RMRT with a participant with early-onset (or young-onset) dementia, his family caregiver mentioned that there was a critical shortage of supportive care resources for people with early-onset dementia, compared to other types of dementia, and hoped we could work more to assist caring for this group. One reason for this comparative shortage might be that early-onset dementia is less common (Knopman, 2021; Bannon et al., 2022). We encourage cross-disciplinary collaboration (such as policy and political decision-makers, clinicians, researchers, and ethicists) (Berridge et al., 2021) to increase the use of dementia-care technologies for people with early-onset dementia and their caregivers to address their needs. In fact, dementia-care technologies can be provided in different forms, such as computers, tablets, smartphones, and social robots. Of note, dementia care that is assisted by physically embodied social robots can be more engaging and efficient and can lead

to a more positive user experience. However, the cost may be an issue. As the cost of humanoid robots decreases, we expect that the use of robots in RT and other dementia care increases. We suggest that researchers, professionals in healthcare, and robot manufacturers focus on making robots and dementia care affordable and accessible to all PLWD and caregivers.

Limitations and Future Work

In this study, we identified several limitations regarding the design of RMRT, PLWD-robot interaction during the reminiscence process, as well as the research design. Tammy was very limited in hearing participants' verbal input. Verbal conversation is an essential interaction modality during RT. Therefore, our next step is to integrate a wearable, wireless Bluetooth into Tammy to enable the robot to better capture PLWD's verbal input. Additionally, sitting close to the robot to see the content on its tablet interfered with its body movements. This limitation concerns the design of physically embodied social robots. On one hand, the tablet attached to its tablet contributes to delivering an integrated robot-based system for reminiscence therapy. On the other hand, the tablet should be large enough for PLWD to enable seeing the content on the screen easily.

Another limitation resides in the small sample size (12 participants). Nonetheless, this sample should be sufficient for identifying critical usability problems and improve interactive design (Alroobaea and Mayhew, 2014). It is a common challenge to recruit PLWD to participate in research studies, especially those that involve technologies such as robots. During the design and development of the current prototype of RMRT, experts in RT were concerned that the GUI design of PLWD-robot conversation (with the conversation displayed on the right side of the robot's tablet, Figure A.5) might be distracting to people with moderate dementia. In future work, we will make a prototype of RMRT suitable for people with moderate dementia and test it to evaluate its usability and feasibility. If needed, we will adapt the GUI design of the current prototype for people who cannot follow directions. Another limitation lie in

potential bias in the results of this usability study. Due to voluntary participation, it could be that the participants were more interested in using the robot as it was a novel tool for them, which may have influenced the assessment of the participants' interaction and experience with the RMRT program. Lack of personalization affected the participants' interaction with Tammy. This feature will be addressed in future prototypes.

There are two potential limitations of the data collection methods employed in this study. The questionnaire we used to evaluate the participants' experience did not include items on efficiency and user satisfaction, which are core factors in evaluating system usability. Another limitation is that the qualitative data were collected by using one open-ended question in the survey questionnaire. In future work, we will use individual interviews to collect additional insights into participants' experiences.

3.2.7 Summary

In this section, we implemented a robot-mediated reminiscence therapy (RMRT) program using a humanoid social robot which we named Tammy. Tammy was able to provide multimedia reminiscence therapy for PLWD and persons with mild cognitive impairment. We evaluated the acceptability and user experience of RMRT with PLWD through usability testing of Tammy and its GUI tablet. PLWD reported a positive experience with the program, had an overall positive emotional reaction to it, and were willing to use the program in the future. PLWD sang along with Tammy and/or laughed during reminiscence. The findings from the usability study suggest that RMRT has the potential as an engaging, effective, and accessible home-based cognitive exercise for people with dementia. This usability study also identified several limitations in the current RMRT program, including improving the auditory sensing capability of Tammy and adding personalization capabilities in Tammy. These will be addressed in the next prototype. This endeavor should facilitate a more effective long-term adoption of RMRT for PLWD.

3.3 Adaptive Robot-Assisted Reminiscence Therapy

To train a robot to automate RT for PwDs, many types of learning algorithms have been proposed, including supervised learning, unsupervised learning, and reinforcement learning (RL). Caros *et al.* (Carós *et al.*, 2020) applied deep learning technique to develop a smartphone-based conversational agent which automated RT by showing a picture, asking questions about the pictures, and giving comments on users' answers. However, PwDs may have different dementia degrees, and an individual PwD may show time-varying behaviors, emotions, personalities, and cognitive capabilities (Cerejeira *et al.*, 2012; Kobayashi *et al.*, 2019). It is very challenging for supervised or unsupervised learning to achieve a learning agent with sufficient adaptivity to different individual PwDs. We herein target the robot training using RL, which allows the robot to constantly learn from interacting with the PwD and end up with an optimal conversation strategy for the target PwD (Hemminahaus and Kopp, 2017). There are several existing works that investigated PwD-robot dialogue management using RL. For instance, Magyar *et al.* (Magyar *et al.*, 2019) employed Q-learning (QL) to learn a robotic conversation strategy to promote the PwD's response with considering the PwD's interested topics and emotions. Yuan *et al.* (Yuan *et al.*, 2021d) developed a robotic dialogue strategy via QL to handle the repetitive questioning behaviors from the PwDs. However, a pervasively applicable patient model is still lacking in the existing literature which can *i*) integrate a comprehensive list of the major factors impacting the PwD's behaviors during RT, and *ii*) accurately characterize the probabilistic transitions between the PwD's mental states under different robotic actions. Such a model will provide valuable guidance to more targetedly design the clinical experiments and collect the data, and serve as a customizable interface between the clinical data and the robotic RT strategy design.

To this end, we aim to build a pervasive simulation model for PwDs to characterize their probabilistic behaviors during RT and develop a RL-based conversation strategy for robot-assisted RT. Specifically, our contributions are three-fold. Firstly, we

design a parameterized pervasive PwD model which incorporates the PwD’s response relevance, emotion levels and confusion conditions as the mental states, and depicts the probabilistic behaviors of PwDs during RT as probabilistic transitions between different mental states. Secondly, we define a Markov Decision Process (MDP) model for the robot-assisted RT and design a Q-learning (QL) algorithm to achieve the optimal conversation strategy for the robot. The strategy is sensitive to the PwD’s mental states and promotes the PwD’s talking by duly adjusting the difficulty level of the prompts, repeating or explaining the prompts to clear confusion, and comforting to help the PwD out of the bad moods. In case that bad moods continue, the strategy offers the PwD the initiative to continue or change the topic, or stop the conversation so that the stress of RT is mitigated. The impacts of the PwD’s choices are also considered during the learning towards the optimal strategy. Finally, simulations are conducted to demonstrate the learning convergence and validate the efficacy of the achieved strategy in promoting conversation.

The remainder of this section is organized as follows. Section 3.3.1 describes the simulation model of PwD in the context of RT. Section 3.3.2 elaborates the design of the robotic conversation strategy, including the definition of MDP and the revised QL algorithm based on the proposed PwD model. The experimental results are presented and discussed in Section 3.3.3 with suggested future work.

3.3.1 Simulation Model for a Person with Dementia (PwD)

In the robot-assisted RT, the robot provides memory triggers (e.g., photographs, music, or video clips) and stimulates the PwD to talk about relevant past memory and experiences. During the conversation, the PwD with limited cognitive capacity may provide relevant, irrelevant, or even no response to the robot. In addition, the PwD may show different emotions, such as joy and discomfort, as a reaction to different memory triggers and the robot’s actions. Moreover, the PwD may become confused about a question or memory trigger provided by the robot. Thus, in the context of

robot-assisted RT, we represent the current state of a PwD by their response relevance, emotion levels, and confusion conditions. In this model, a PwD's response relevance can be relevant response (*RR*), irrelevant response (*IR*), or no response (*NR*). A PwD's emotional level is categorized as negative (*Neg*), neutral (*Neu*), and positive (*Pos*). A PwD's confusion condition is classified as confused (*Yes*) and unconfused (*No*). All these PwD's states can be recognized using the technology of artificial intelligence (e.g., deep learning), such as affective computing (Picard, 2000) and the OpenAI CLIP (Radford et al., 2021).

Depending on the robot's actions during RT, the PwD's state may switch from one to another. We consider the following robot actions. On one hand, to stimulate the conversation during RT, the robot can provide appropriate prompts (e.g., questions) about the current memory trigger (Dijkstra et al., 2004; Small and Ann Perry, 2012). The difficulty level of the prompt can be adjusted, i.e., easy prompt (a_1 , e.g., yes-no question), moderately difficult prompt (a_2), and difficult prompt (a_3 , e.g., open-ended question). On the other hand, when the PwD gets confused or in a negative emotion, conditions known as "harmful" or "bad" moments (Hofer et al., 2017), the robot may take actions to help the PwD out of these bad moments. Inspired by previous relevant studies (Hofer et al., 2017; Smith et al., 2011), the robot will repeat (a_4) or explain (a_5) the prompt when the PwD feel confused (Dijkstra et al., 2004; Small and Ann Perry, 2012), and comfort (a_6) the PwD to alleviate their fears or discomfort (Woods et al., 2012) during RT.

The probabilistic behaviors of the PwD is modelled with the transition probabilities (go to the next url: https://drive.google.com/drive/folders/1FmhNsXJnG_WUUKtEpBBflig3ipks1qTb?usp=sharing) among different PwD states given each robot action. Basically, as the difficulty level of the prompt from the robot increases (e.g., a_3 vs. a_1), the probabilities of the PwD responding relevantly and showing positive emotion will decrease, and the probabilities of getting confused will increase. When the PwD is in negative emotion or confused, the probabilities of relevant response will be smaller. If the PwD gets confused and the robot chooses to repeat

or explain on the prompt, the probabilities of the PwD responding and showing non-negative emotion will increase, with the confusion condition possibly changed. If the robot chooses to comfort when the PwD is in bad moment, the probabilities of relevant response will be increased, with the emotion levels possibly changed better.

Moreover, our designed RT strategy will give the PwD initiative to control the conversation tendency when the bad moments continue. This will give the PwD a sense of control, thus mitigating the RT stress (Wilkins, 2017). If the PwD shows confusion or negative emotion continuously twice, the PwD will be provided with the choice of stopping the RT, continuing to talk about the current memory trigger, or changing to another memory trigger. If the PwD chooses to stop, the current RT session will terminate. If the PwD chooses to continue, the PwD’s next state will remain unchanged. If the PwD chooses to change the memory trigger, the PwD’s next state is considered to be no response (*NR*), with neutral emotion (*Neu*), and no confusion. We define the robot’s action of providing choices as a_7 .

Note that the state transition probabilities of different memory triggers are set to be identical in our simulations, but can be set different according to personal preferences (Gowans et al., 2004) in the future.

3.3.2 Adaptive Robot-Assisted Reminiscence Therapy

In this section, we apply the technique of reinforcement learning (RL) to learn a conversation strategy for the robot to deliver reminiscence therapy. The goal is to maintain the RT for a target number of conversation rounds, stimulate the PwD to express as much as possible, and keep the PwD’s state as positive as possible. A revised Q-learning (QL) algorithm is used to achieve the best conversation strategy personalized to the PwD modelled in Section 3.3.1.

Definition of Markov Decision Process

In order to learn the optimal policy, we firstly formulate the problem of robot-assisted RT for PwD as the following MDP model (Sutton and Barto, 2018):

State Space S . A state s in this problem is defined as the collection of the PwD’s response relevance to the prompt from the robot, the emotion level, and the confusion condition. Based on the designed simulation model of PwD in Section 3.3.1, the state space S has a cardinality of $3 \times 3 \times 2 = 18$.

Action Space A . During RT, there are seven actions possibly taken by the robot, i.e., providing easy prompt (a_1), providing moderately difficult prompt (a_2), providing difficult prompt (a_3), repeating the prompt (a_4), briefly explaining the prompt (a_5), comforting the PwD (a_6), and giving the PwD choices (a_7). Note that even the PwD responds to a prompt incorrectly, the robot will NOT correct the PwD (RT is not aimed to correct PwDs). However, the response relevance will be considered by the RL agent in the reward function. Moreover, as mentioned previously, the robot will take action a_7 as long as the PwD shows confusion or negative emotion twice in a row. In other words, the condition of taking action a_7 is determinant, therefore, the actual action space for the RL only includes actions $a_1 - a_6$. Although the Q values of taking action a_7 is not learned during the training, the impacts of taking a_7 is deliberately integrated into the Q-value update of other actions, which will be detailed in section 3.3.2.

Reward Function R . The design of the reward function aligns with the objectives of the robot-assisted RT, i.e., stimulating the PwD to talk while keeping the PwD in a generally positive mood. Thus, the reward function is a function of the PwD’s response relevance, emotion level and confusion condition. Specifically, the robot should always try to prevent the PwD from getting trapped in the bad moments, i.e., being in negative mood or confused, as bad moments will hamper the conversation and lead to a higher chance of terminating the current session. Accordingly, the reward component of PwD’s emotion level being negative, neutral, and positive is set

to -3 , $+1$, and $+2$, respectively. The reward component of the confusion condition is set to -2.5 and $+2$, respectively, for being confused and unconfused. As to the difficulty level of the prompt, it should be properly adjusted according to the PwD’s cognitive capability and mental state so that the PwD is more engaged and interested, thus stimulating their memory and conversation to the most extent (Tapus et al., 2009). In other words, optimal tradeoff needs to be learnt between taking an easy prompt for higher chance of being in positive state and taking a more difficult prompt (e.g., an open question) to encourage the PwD to talk more. Correspondingly, we provide two reward settings (as listed in Table A.15) for prompts as a function of the difficulty level and resultant response relevance for later experimental study.

Learning Algorithm Design and Training

Although the RL agent only learns the optimal policy for taking actions $a_1 - a_6$, the previously taken actions have decisive impact on the probability of taking action a_7 . For example, if the robot always takes action a_3 (providing difficult prompt) and ignores PwD’s bad moments, there will be a very high chance of the PwD choosing to stop. Therefore, we revise the standard QL algorithm and deliberately integrate the negative impact of taking a_7 in the Q-value updates of other actions to avoid over-aggressive policies, as summarized in Algorithm 1.

The RL agent is trained for 1500 epochs, each with 30 episodes. The learning rate and discount factor are set to be 0.05 and 0.95, respectively. At the beginning of each episode, the environment is reset to an initial state, $[NR, Neu, No]$. In each iteration, the ϵ -greedy approach ($\epsilon = 0.1$) is used to select actions. An episode is terminated if the PwD chooses to stop, the maximum 50 rounds are reached, or the number of memory triggers having been discussed reaches 15.

Algorithm 1 Revised Q-learning for robot-assisted RT

```
1: Initialize  $Q(s, a) \leftarrow 0$ , for all  $s \in S$ ,  $a \in A$ 
2: function LOOP FOR EACH EPISODE
3:   Initialize  $s_0 = [NR, Neu, NO]$ ,  $Done = False$ 
4:   while not  $Done$  do
5:     Choose  $a_t$  from  $s_t$  using policy derived from  $Q$  ( $\epsilon$ -greedy)
6:     Take action  $a_t$ , observe  $r_t$ ,  $s_{t+1}$ 
7:     if  $a == a_6$  then
8:        $Q(s_{t-1}, a_{t-1}) \leftarrow Q(s_{t-1}, a_{t-1}) + \alpha[r_t + \gamma \max_a Q(s_{t+1}, a) - Q(s_{t-1}, a_{t-1})]$ 
9:     else
10:       $Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha[r_t + \gamma \max_a Q(s_{t+1}, a) - Q(s_t, a_t)]$ 
11:    end if
12:     $s_{t-1}, a_{t-1}, s_t \leftarrow s_t, a_t, s_{t+1}$ 
13:  end while
14: end function
```

Evaluation Metrics

To evaluate the performance, we compare the average return per epoch obtained by the revised QL (denoted as ϵ -greedy QL) to that obtained by a random policy (denoted as *Random action*) as well as that obtained by a policy of always providing easy prompt (denoted as *Always action a_1*). Also, we extract the temporal policy π' suggested at the 10th Episode of each epoch, apply it to run 40 experiments, and calculate the average return (denoted as *Greedy QL*). Moreover, we monitor the averaged sum of Q-table per epoch (i.e., Q-value sum) as well as its relative change (i.e., Q-value update) to evaluate the convergence performance. Additionally, all the optimal policies suggested in the last 600 episodes are recorded. We use the top five policies mostly suggested to run 1000 experiments and choose the policy that obtains the maximum return as the final policy, denoted as π'_* . Finally, we conduct 20 experiments with π'_* and observe the dynamics of state-action transition in each experiment.

3.3.3 Results and Discussion

The learning process of our revised QL (i.e., ϵ -greedy QL) with reward function R_1 is shown in Fig. A.8. As shown on the left of Fig. A.8, the average return per epoch obtained by ϵ -greedy QL (blue curve) was much greater than the random action selection policy (black curve) and the policy of always providing easy prompt (green curve), which validated the efficacy of applying the RL approach for the robot to automate RT. The average return per epoch obtained by greedy QL was greater than ϵ -greedy QL. This makes sense because the greedy QL always took optimal policy due to greedy action selection provided the achieved strategy is optimal, while the ϵ -greedy QL selected random action for exploration. With respect to the convergence, the curve of average return per epoch (blue curve in left figure of Fig. A.8) indicated the RL agent was able to converge within 200 epochs, whereas the Q-values sum and Q-values update (the middle and right figure in Fig. A.8) converged within in 800 epochs. Additionally, we observe that the optimal policy suggested by the RL agent in the last 600 episodes is still changeable, which might be due to the design of reward function and the model of simulated PwD. In Table A.16, we listed the dynamics (e.g., state-action transition) of one experiment using the most nearly optimal action policy, π'_* , learned by Q-learning with reward R_1 .

Compared to reward function R_1 , Q-learning with reward function R_2 showed similar performance, i.e., curve of average return per epoch, converging Q-values sum, and changeable optimal policy during the last 600 episodes. We present the most nearly optimal policy learned by QL using the two types of reward function, R_1 (the blue square) and R_2 (the red circle) in Fig. A.9.

The scatter plots demonstrates that the robot is able to comfort the PwD when they feel negative emotion. For example, the optimal actions suggested for state $s = [NR, Neg, No]$ with R_1 and R_2 were both a_6 , comforting. When the PwD feel confused (e.g., $s = [NR, Pos, Yes]$), the RL agent with R_1 and R_2 both suggested to take action, a_4 , repeating the prompt to the PwD. There were 3 states, $s = [NR,$

Neu, Yes], [*RR, Neu, No*], and [*RR, Pos, No*], where the RL agent suggested different actions regarding R_1 and R_2 . The RL agent with R_1 suggested to take action a_0 and a_1 when the PwD in a state of $s=[RR, Neu, No]$ and [*NR, Pos, No*], respectively. Comparatively, the RL agent with R_2 would take action a_2 when the PwD in state $s=[RR, Neu, No]$ or [*NR, Pos, No*]. Such difference make sense because the two types of reward function R_1 and R_2 (in Table. A.15) indicated how much we value PwD’s response relevance and the level of PwD’s conversation being stimulated. The reward function R_2 was more aggressive compared to R_1 , that is, the memory and conversation being stimulated was much more valued by R_2 than the condition of emotion and confusion. On the other hand, this scatter plot also indicates that our RL approach was able to learn to adjust the difficulty level of prompt adaptive to PwD’s conditions.

In this section, we employed a revised QL to learn a conversation strategy for the robot to stimulate a PwD to talk as much as possible while keeping the PwD in a generally positive mood during RT. The PwD was modelled as the transition probabilities among different conditions consisting of the response relevance, emotion levels and confusion status. Our experimental results showed that the strategy learned by QL was capable to adjust the difficulty level of prompt (e.g., yes-no vs. open-ended question) according to the PwD’s states, take actions such as repeating/explaining the prompt or comforting to help the PwD out of bad moments (Smith et al., 2011; Hofer et al., 2017), and allow the PwD to mitigate potential conversation stress during RT. To the best of our knowledge, this is the first time for technology-enabled RT to learn adaptive strategy, while taking into consideration of complicated PwDs’ mental states and communication strategies suggested in the traditional healthcare field. This might offer a promising solution for automatic, person-centered RT for PwD living alone.

However, there are still some limitations in this study. The patient model, the matrix of state-action transition probabilities, was created based on previous qualitative studies. As we discussed earlier, the nature underlying our PwD’s model

might result in the optimal policy was still changing during the last 600 episodes. For better learning of RL for RT as well as the real-world application of robot-assisted RT, a patient model based on real-world data should be developed, which is our next step. Additionally, we designed two types of reward function to test the feasibility of RL approach. However, the design of reward function might be associated with a PwD’s own personality and needs (e.g., psychological needs vs cognitive stimulation). From this perspective, in future work, we will closely collaborate with professional facilitators in this field and PwDs to adjust the reward function, to ensure an effective, person-centered RT using RL.

3.4 Causal Structural Learning of Conversational Engagement for Socially Isolated Older Adults

Social isolation, marked by a small social network and lack of social contact as well as loneliness characterized by dissatisfaction with the frequency and quality of social communication negatively affect the quality of life. Older adults are at increased risk of social isolation (Maharani et al., 2022). Social isolation is a risk factor for mild cognitive impairment (MCI) and dementia (Ishikawa et al., 2022). As a public health priority, it is essential to address social isolation among older adults, especially those with cognitive impairment who may struggle with social interactions. The COVID-19 pandemic has further intensified the negative impact of social isolation (Smith and Lim, 2020). Coping strategies must be developed to increase social contact with older adults with cognitive impairment and to prevent/mitigate relevant cognitive decline (Sabbagh et al., 2022). Maintaining an active social life can boost cognitive reserve, providing a buffer against age-related cognitive decline and dementia. A body of evidence demonstrates that fostering social connections can help slow ge-associated cognitive decline and delay the onset of dementia symptoms (Roth, 2022).

Conversational chatbots, which can be embodied in smartphones, computers, or social robots (Motger et al., 2022; Goodman-Casanova et al., 2020), may become a rational cost-effective approach to provide quality social connectedness for socially isolated elderly (Hwang et al., 2022). During the conversation AI-based psychotherapy, it is vital for the chatbot to possess the ability to engage and empathize with the user, that is, recognize user’s emotional state, thoughts, and situation, and express congruent emotions accordingly in order to elicit older adults’ positive perceptions and improve their cognitive and mental states (Park and Whang, 2022; Li et al., 2021; Woods et al., 2021b; Yuan et al., 2021b, 2022b). The data-efficiency, safety, and trust of conversation AI have been received attention (Miner et al., 2019). However, in order to enable robots, we need to learn from human experts. Previous research uncovered causal relationships between certain emotions and dialogue acts (DAs) in interpersonal conversations and suggested a more universally applicable method for developing dialogue systems that utilize abstract, global features rather than low-level word embeddings (Cao et al., 2021). In this section, we would like to explore the conversation strategies for the chatbot to interact with socially isolated older adults using causal inference approach. More specifically, given the professional moderator-participant interaction during the semi-structured conversational engagement trial, we would like to investigate the moderator’s conversational strategy to engage the participant in the conversation and the causal effects of the strategy during this conversational context on participants’ engagement.

3.4.1 Materials and methods

Data and Participants

We have access to 123 manual transcriptions based on the audio and video recordings from a completed randomized controlled clinical trial, Internet-based conversational engagement clinical trial (I-CONNECT; ClinicalTrials.gov: NCT02871921) (Yu et al.,

2021). I-CONNECT is a multi-site, assessor-blind, randomized controlled behavioral intervention trial. There are 155 participants in the experimental group who chatted with trained conversational staff (i.e., moderator) using internet/webcams. The conversation used in I-CONNECT is semi-structured with pre-specified topics with crafted questions to promote natural conversations. Each 30-minute conversation session had a predefined theme (defined based on the image cue shown to the participant), but the participant responses (e.g., word choice, topics of interest, etc.) were allowed to vary in order to provide natural conversational settings.

The participants were socially isolated adults 75+ years old, with normal cognition or mild cognitive impairment (MCI), excluding dementia. The social isolation is defined by at least one of the following: (1) score $\leq$ on the 6-item Lubben Social Network Scale (LSNS-6) (18), (2) engages in conversations lasting 30 minutes or longer no more than twice per week, per subject self-report, (3) answers “often” to at least one question on the 3-item UCLA Loneliness Scale. Participants received 30min video chats with trained conversational staff 4 time/week for 6 months (high dose) followed by 2 times/week for an additional 6 months (maintenance dose) and weekly check-in calls that monitored their social activities and adverse health events (Yu et al., 2021).

Preprocessing and Feature Extraction

In each conversational session, the moderator-participant communication was pre-processed per moderator-participant turn t . Each session was started by a moderator asking, “I will show you a picture. Please describe the image to me.” After the participant provided the description, the moderator followed up with comments and questions to continue the conversation. In this work, we would like to format this semi-structured conversation as following: given the participant response X_t at t , the moderator followed up with comments and questions, denoted as Z_t , and the participant responded (denoted as Y_t) to the moderator’s comments and/or questions.

Moderator’s Utterance Features Based on the moderator’s utterance in each turn, features regarding the moderator’s DAs were extracted based on Dialogue Act Markup in Several Layers (DAMSL) tag set (Bothe et al., 2019). DAs provides an intention and performative function in an utterance of the dialogue. For example, it can infer a user’s intention by distinguishing Question, Answer, Request, Agree/Reject, etc. and performative functions such as Acknowledgement, Conversational-opening or -closing, Thanking, etc. According to DAMSL, each DA has a backward-looking function (e.g., Accept, Reject, Answer, and acknowledgement) and a forward-looking function (such as Statement, Info-request, Question, and Thanking). A model *distilbert-base-uncased* (Sanh et al., 2019), a distilled version of BERT based model, was used to extract the DA features from moderators. A python library, DialogTag, was imported for this task. The DialogTag can classify an utterance into 38 DA tags.

Participant’s Response Features With respect to the participants’ response during the conversation, their emotions and length of utterance (T) were extracted. Emotion recognition in conversation (ERC) is a crucial component in affective dialogue systems, which helps a conversational partner to understand another speaker’s emotions and generate empathetic responses (Bothe et al., 2019). The transition of speakers’ emotions is a crucial factor and indicator of engaging, empathetic conversation. We extracted the emotional features using the model, *Emoberta* (Kim and Vossen, 2021). Participants’ emotions were classified into 7 emotion categories, including joy (J), neutral (N), sad (Sa), surprise (Su), anger (A), fear (F), and disgust (D), whose value indicated the probability of the emotions.

Structural Learning and Estimation of Causal Effects

We employed the causal discovery method, PC algorithm, to explore the causal relations and causal effects between the participant’s response features and the moderator’s features. The implementation of PC algorithm used the *pcalg* package (Kalisch et al., 2021) in R. The participant’s response (denoted as X_t) at conversation

turn t may have potential causal effects on the dialogue action (denoted as Z_t) taken by the moderator. Furthermore, both the participant’s response and the moderator’s action at t may have causal effects on the participant’s response (denoted as Y_t) at following conversation turn, $t+1$. In this section, we learned the causal graph between the variables of X_t , Z_t , and Y_t and estimated the causal effects of X_t and Z_t on Y_t .

Based on the transcription manually coded from I-CONNECT study, we extracted features of interest in and converted each conversational session into a .csv file, where the rows represented the conversation turns and the columns represented X_t , Z_t , and Y_t . The structural learning algorithm from (Kalisch et al., 2021) was used to estimate the undirected causal structure (denoted as *CPDAG*), with the argument of *fixedGaps* to ensure that there is no causal relations within the elements of X_t , within the elements of Z_t , and within the elements of Y_t . Then, the background knowledge on the orientation (e.g., $X_t \rightarrow Z_t$, $X_t \rightarrow Y_t$, and $Z_t \rightarrow Y_t$) of the undirected edges was added using *addBgKnowledge()*, resulting in *PDAG*. Finally, we computed the causal effect using the function *ida()*.

3.4.2 Results

Manually generated transcriptions from 123 chat sessions (i.e. semi-structured conversational interactions) between participants and trained moderators from the I-CONNECT study were analyzed in this paper. The chat sessions were recorded from 92 participants, including older adults and older adults with mild cognitive impairment. All the transcriptions of chats included 13,913 participant-moderator conversation turns. On average, there was approximately 113 conversational turns per session, with a maximum of 235 turns and a minimum of 20 turns.

We analyzed the moderators’ utterance features. The DialogTag can classify an utterance into 38 DA tags. However, some of the tags are very sparse or never appeared in the I-CONNECT semi-structured conversational dataset. Therefore, as shown in Fig. A.10 and Fig. A.11, we consider 21 tags, which include 15 DAs with

backward-looking function and 6 DAs with forward-looking function. The backward-looking DA tags are Statement-non-opinion (denoted as *StaNo*), Acknowledge (Backchannel) (*Ack*), Statement-opinion (*Sta*), Agree/Accept (*Agr*), Appreciation (*App*), Conventional-closing (*ConC*), Hedge (*H*), Other (*Oth*), Quotation (*Quo*), Action-directive (*AcD*), Collaborative Completion (*CoC*), Repeat-phrase (*Rep*), Offers, Options Commits (*Off*), Self-talk (*Sel*), and Apology (*Apo*). The forward-looking DA tags are Yes-No-Question (*YNQ*), Wh-Question (*WhQ*), Declarative Yes-No-Question (*DYNQ*), Open-Question (*OpQ*), Or-Clause (*OrC*), and Conventional-opening (*CoO*). Additionally, participants' response features were extracted from aspect of ERC and utterance length. Table A.17 reports summary statistics like mean, SD, range, median about the emotions and utterance.

We calculated the causal relationships in conversation turn level using the structural learning and causal inference approach. A causal graph was found in 74 experiments. Fig. A.12-A.14 presented three examples of causal graphs learned from three conversational sessions from three different participants. The nodes in green, orange, pink, and yellow color represent the variables of X_t at conversational turn t , backward-looking dialogue action Z_{tb} taken by the human moderator, forward-looking dialogue action Z_{tf} taken by the moderator, and the outcome variables of Y_t , correspondingly. The text in each vertex is the aforementioned short name of participant's and moderator's utterance. In total, 176 different causal relationships were found between X_t and Z_{tb} , between X_t and Z_{tf} , between X_t and Y_t , and between Z_{tb} and Y_t , and between Z_{tf} and Y_t . Table A.18 -A.22 listed the causal relationships identified for more than 5 times. For example, as shown in Table A.20, the causal effects of current emotional status on following emotion status have been indicated for more than 5 time, for example, ' $Anger_t \rightarrow Anger_{t+1}$ ', ' $Joy_t \rightarrow Joy_{t+1}$ ', and ' $Sadness_t \rightarrow Sadness_{t+1}$ '. This makes sense in real-world context, where human's emotion are continuous.

3.4.3 Discussion and Summary

In order to infer strategies to promote social interaction, we analyzed 123 transcriptions of conversational engagement between facilitators and participants, which were previously collected in a clinical trial study based on semi-structured conversations, named I-CONNECT (Yu et al., 2021). We used ERC and dialogue act modelling to process the discourse record to produce a time series of state X_t , intervention Z_t , and outcome Y_t , respectively. Here, state X_t is a vector representing the participant’s emotions (including joy, neutral, sad, surprise, anger, fear, and disgust) and length of utterance at conversational turn t . Intervention Z_t implied the conversational strategy used by the moderator to engage the participant in the semi-structured conversation. Z_t includes the backward-looking dialogue act (Z_{tb}) and forward-looking dialogue act (Z_{tf}) taken by the moderator. And the outcome Y_t is measured as the participant’s following emotions and length of utterance, which is the same to X_{t+1} in this work.

We created a causal graph to identify causal relations between X_t , Z_{tb} , Z_{tf} , and Y_t . The causal relationships implied that the trained moderators adjusted their dialogue strategy (Z_{tb} and Z_{tf}) according to the participants’ emotions and utterance. The estimated causal effects presented in Tables A.18-A.22, whether positive or negative, represent the magnitude by which an increase in the value of a potential cause would correspondingly increase or decrease the value of a possible outcome. For example, the edge *Disgust* $\rightarrow$ *Agree/Accept* in Table A.18 implies that when the participant expressed disgust or unpleasant feeling, the moderator showed agreement and acceptance to show understanding an/or empathy during the conversation. In addition, the causal relationships infer that the dialogue acts, Z_{tb} and Z_{tf} , taken by the moderator influence the participant’s following emotions and engagement in the conversation. For example, the strategy of asking why-questions (Table A.22) have causal positive effects on the participants’ length of utterance.

The causal relationships inferred in this work makes sense in real-world human-human conversation. Our next step is to explore how to leverage the causal relationship learned from these human-human conversation to improve the conversational chatbot in smartphones, computer, and the robots to communicate with older adults with healthy cognition and cognitive impairment in a more engaging way. This might be integrated with reinforcement learning (RL) approach (Seitzer et al., 2021). On one hand, conversational strategies suggested by causal graphs can serve as a good and efficient starting point for training RL-based chatbots. On the other hand, RL agents equipped with knowledge of potential causal effects of their actions can make more informed decisions and better select their actions, resulting in reduced exploration and a faster learning process (Méndez-Molina et al., 2022). There still exists some limitations in current study. For example, there might be other crucial features from the participant and the moderator which might influence the dynamics of participants' status during the conversation, for example, the participant's engagement level (Karimah and Hasegawa, 2021) and their cognitive capacity. Moreover, the dialogue coherence (Xu et al., 2018), which relates to both the participant and the moderator, can influence the efficacy of the conversation engagement intervention. Therefore, in the future, we would like to take these factors into our causality learning.

Chapter 4

Robotic Assistance for Activities of Daily living

A successful application of SAR to assist a PLWD in ADLs requires the empowerment of a powerful, reliable, and trustworthy AI, which would enable SAR to identify forgetful moments and to provide appropriate, effective assistance at the right time and place to the PLWD ([HealthinAging.org, 2022](#); [Shi et al., 2023b](#); [Tian et al., 2023](#); [Liu et al., 2023](#)). The robot would learn to provide minimal but effective assistance (e.g., reminders, guidance, coaching) to help PLWDs out of forgetful moments and to ensure safety and improve autonomy in ADLs. The strategy of providing minimal assistance aims to maximize engagement in PLWDs, augmenting their autonomy, and potentially slowing down disease progression.

Although the vision of building a powerful and autonomous SAR capable of adaptively providing minimal but effective assistance is compelling, the reality is that the current state of robotics technology and AI is far from achieving this capability outside of very narrowly constrained contexts. Compared to robotic applications in therapy or engagement contexts, the use of robot assistants in ADLs has received relatively limited attention ([Ghafurian et al., 2021](#)). Wang et al. ([Wang et al., 2017](#)) used a tele-operated robot to provide stepwise prompting for PLWDs to complete

activities of hand-washing and preparing a cup of coffee, exploring perspectives of both PLWDs and their caregivers on the robot. This study provided evidence of the effectiveness of social robots, especially in assisting caregivers. Other studies have examined a meal-time assistant robot that provided prompts related to eating a meal, showing success in engaging older users with positive reported attitudes (McColl and Nejat, 2013; Derek et al., 2012). Adding to this challenge is the current absence of a publicly accessible dataset of PLWDs performing ADLs, which significantly hinders the development of a powerful, reliable, trustworthy, and adaptive AI and SAR.

In this context, we propose using teleoperation scalable to different ADLs as a strategic approach to bridge this gap. Robotic teleoperation involves a human teleoperator who controls a robot over a communication channel, collects information about the remote environment, provides commands related to task completion, and the robot executes these tasks based on the control and feedback from the teleoperator (Moniruzzaman et al., 2022). This nuanced control is crucial when assisting PLWDs, especially given the complexity of tasks and behaviors that may be too challenging for an autonomous robotic system.

By employing teleoperation, we aim to collect a rich, multimodal dataset of PLWDs’ behaviors and performance in the context of different ADLs. This effort will lay the groundwork for future SAR systems that are both adaptive and sensitive to the complexities of assisting PLWDs. This step is crucial before fully autonomous solutions can be reliably implemented. Through this approach, we anticipate the development of more sophisticated AI (Wang et al., 2022; Zhao and Lv, 2023; Qi et al., 2021) and SAR capabilities that can reason, communicate, and assist PLWDs in completing ADLs more effectively.

In the present work, we aimed to develop a robotic platform that can effectively administer Performance of Self-care Skills (PASS) tasks (Chisholm et al., 2014) for human participants and meanwhile collect multimodal data from participants. The study in this work will set up the stage for future development of AI and SAR to effectively aid PLWDs in ADLs. PASS is a performance-based, criterion-referenced,

observational tool widely used by occupational therapists to evaluate individual’s capacity to perform ADLs and live independently and safely in the community for people with mild cognitive impairment and AD/ADRD (Rodakowski et al., 2014; Dham et al., 2020; Keleman et al., 2021). PASS consists of core tasks categorized into four domains: functional mobility (FM), basic ADLs (BADL), instrumental ADLs with a physical emphasis (IADL-P), and instrumental ADLs with a cognitive emphasis (IADL-C) (Chisholm et al., 2014). Ten PASS tasks were adapted into a social robot to be administered for participants. These tasks will allow researchers to comprehensively evaluate occupational performance of ADLs and identify which daily tasks are compromised among PLWDs and the point of their task breakdown, i.e., lost moment. Multimodal sensors were deployed to collect behavioral, audio, and physiological signals in participants while performing ADLs. Additionally, we conducted a preliminary usability study with healthy adults to evaluate the acceptability, feasibility, and efficacy of the platform. The main contribution of the present work is the development of a robotic platform to instruct an individual to perform ADLs and collect multimodal data from the user. The development of our teleoperated robotic platform marks a significant advancement in supporting PLWDs through SAR. This approach not only navigates the current limitations of robotic systems in complex environments but also initiates a new paradigm for personalized, adaptive assistance for PLWDs. It offers a robust starting point for researchers, facilitating the nuanced interaction necessary for effectively assisting PLWDs with ADLs. Our work lays the foundational steps towards more sophisticated SAR systems, promising a future where robots can offer more autonomous, tailored support. This progression holds the potential to significantly enhance the quality of life for PLWDs and alleviate the caregiving burden, marking a pivotal contribution to the field and a leap forward in dementia care technology.

The remainder of the paper is organized as follows. Section 4.1 elaborates the development of the robotic platform to administer PASS for a human. Section 4.2 describes a preliminary usability study conducted with young adults without cognitive

impairment to assess acceptability, user experience, and feasibility of the robotic platform in administering PASS tasks. The results of usability study are presented and discussed in Section 4.2.4 with suggested future work.

4.1 A Platform of Robot-guided PASS at Smart Home

A humanoid social robot, Pepper (Pandey and Gelin, 2018), was adopted to be developed to administer the PASS tasks for a person. To make the Pepper robot more friendly, approachable to users, we renamed it Tammy, one of the most popular girl names in Tennessee. The Pepper robot stands at 1.21-m tall and features 17 joints for graceful and expressive body movements. It can adjust its body language (such as gestures and other body movements) as well as voice to match its communication. It is equipped with several LEDs in its eyes, ears, and shoulders to facilitate color-based signaling and support human-robot interaction. Pepper’s size and attractive appearance render it suitable for use in daily life and research settings (Schüssler et al., 2020; Yuan et al., 2021c,a; Cobo Hurtado et al., 2021; Yuan et al., 2022b). Pepper incorporates a range of sensors (e.g., cameras and microphones), enabling it to record the user’s behaviors and the environment from its perspective and utilize AI to perceive the user and environment. It maintains good eye contact with the user during interaction. A 246-175-14.5-mm tablet is mounted on the robot’s chest, facilitating the display of important two-dimensional information (e.g., text) to the user. Using an Android Studio plug-in, QiSDK (SoftBank Robotics, 2021), the robot was programmed for control to deliver instructions for PASS tasks to the user using multimodal interaction, including verbal language, body movements (e.g., gestures), as well as GUI information on its tablet. The platform of robot-assisted PASS was built in the Smart Home in the Health Innovation Technology and Simulation Lab at the University of Tennessee, Knoxville. This Smart Home simulates a fully equipped,

one-bed room and one-bathroom apartment, providing a comfortable setting for users to perform PASS tasks and aiding in training AI and SAR to assist users in their ADLs. The Smart Home also features remote video monitoring, permitting researchers to discreetly observe users performing PASS without imposing undue stress.

4.1.1 Ten PASS tasks

The PASS tool encompasses a total of 26 tasks, spanning four domains of FM, BADL, IADL-P, and IADL-C. Acknowledging the potential limitations in physical and cognitive capacity of our future participants, PLWDs, we selected ten PASS tasks from the four domains for implementation in the Pepper robot. These ten PASS tasks include bed mobility, changing bed linen, checking home safety, telephone use, medication management, obtaining critical information from the radio, obtaining critical information from a poster, cleaning teeth, sweeping, and meal preparation. To prioritize safety in PLWDs, we modified the meal preparation task to making a sandwich with at least two toppings.

4.1.2 Teleoperation

Due to the current limited capabilities of the Pepper robot in administering the complex PASS tasks, we employed teleoperation to guide the robot in providing instructions to the user. The teleoperation system utilizes a Python interface that interacts with the Pepper robot through a database hosted on Firebase, Firebase Realtime Database. This database stores data in JSON trees. Our interface operates by updating different flags on the database that Pepper monitors. When a flag reaches a desired condition, it activates a corresponding event on the Pepper robot. To optimize performance, the database employs a many-to-many relationship, enabling distinct data points to be stored in separate branches, as opposed to a many-to-one

relationship. Figure A.15 illustrates part of this database structure, showcasing data corresponding to the robot functions of “Video Recording”, “Rotation”, and “Speak”.

4.1.3 Experimenter Interface

Considering the complexity involved in operating the Pepper robot for administering PASS tasks—such as leading a participant to different rooms for tasks, administering various tasks, and providing step-by-step instructions within a PASS task—we designed a graphical user interface (GUI) for the experimenter. This interface simplifies teleoperation of the robot for PASS tasks and thus reduces the experimenter’s workload. As shown in Figure A.16, an interface programmed in Python was built to control and communicate with the robot. The experimenter can use the interface to control the robot from a different room outside the Smart Home. We developed the experimenter GUI using a Python library, PyQt6, and used a python wrapper library, Pyrebase, to communicate the GUI with the Firebase Realtime Database. The experimenter interface, presented on the left side of Figure A.16, features a form (including details like date, starting time of the experiment, and participant ID) for the experimenter to fill out for each new participant, a task list selector, movement and rotation buttons, and a reset button to initiate a new experimental session for another participant. The experimenter interface at startup presents on the left of Figure A.16. The interface features a form (including information of date, starting time of the experiment, and participant ID) for the experimenter to complete for each new participant, a task list selector, movement and rotation buttons, and a reset button to start a new experimental session for another participant.

The form on the interface allows the experimenter to easily keep track of the participant of each recording. During the experiment, the Pepper’s application checks the most recent information to name the video recording file, thereby organizing all gathered data efficiently. The naming format for the recording follows "*date_startTime_patientID_PASStaskId*." Upon submission of this form,

the recording is uploaded with this naming convention. Clicking the reset button automatically updates the form on the GUI.

The interface features a drop down menu which contains the names of each PASS task to select from, e.g., PASS 1 (bed mobility), PASS 2 (changing bed linen), and PASS 3 (checking home safety). Upon choosing a PASS task, the interface displays a list of commands (step-by-step instruction) for the experimenter to conduct the session from, as is shown on the right of Figure A.16. Each "Play" button sends the corresponding command to the Firebase Realtime Database, and the Android app receives the command for Pepper to read. The play buttons allow the experimenter to reiterate commands if the subject does not understand them. The interface also changes the color of the "Play" button after the corresponding command is read. This makes it less likely for the experimenter to forget what command was read last and reduce the number of mistakes made throughout the experiment. Lastly, the play buttons are able to be pressed out of order, which allows the experimenter better control in case the participant is confused about the robot's instructions. The experimenter is able to restart the activity or go back a few steps in order to keep the subject engaged with the activity.

The movement buttons ("Up-1m", "Up", "Down", "Left", and "Right" enable the experimenter to adjust Pepper's position in the room, while the rotation buttons ("Rotate Left" and "Rotate Right") alter the direction Pepper faces. By pressing one of the movement buttons, Pepper will move a short distance in that direction, which is 100cm if the button of "Up-1m" is pressed and otherwise, 20 cm. The rotation buttons will rotate Pepper by 30°.

4.1.4 Tammy Agent

To ensure the instructions are as comprehensible as possible for the participant, we have enabled the robot to display its verbal instructions on its tablet. This is particularly beneficial for participants who may have hearing or memory impairments.

This feature is crucial for participants (PLWDs) in future studies. Hence, we implemented an app, named Tammy Agent, on Pepper’s tablet. This app displays a cartoon representation of Pepper’s face along with the text of the task Pepper is describing, as demonstrated in Figure A.17. Throughout the experiment, the app receives commands from the experimenter interface (Figure A.16). To retrieve these commands from the Firebase Realtime Database, the app utilizes Google’s Firebase API for Android Studio. Specifically, it employs *ValueEventListeners* to detect changes in the database and respond accordingly. These event listeners operate on separate threads from the main UI thread on the device and interrupt the main thread upon receiving new information.

4.1.5 Multimodal Data Collection During PASS

During the robot-assisted PASS tasks, multimodal sensors, including a wearable E4 wristband, cameras equipped at Smart Home as well as the camera equipped on the Pepper robot’s tablet, will be utilized to collect physiological signals, behaviors, and human-robot interaction data from the participant. Figure A.18 illustrates the platform of robot-assisted PASS using teleoperation and the process of multimodal data collection. During the experiment, the participant will wear the E4 to collect their heart rate, skin conductance, skin temperature, and acceleration. The E4 is equipped with a PPG sensor, EDA Sensor (GSR Sensor), accelerometer, and infrared thermopile. The recorded physiological signals include data from the temperature sensor expressed in degrees on the Celsius scale, data from the electrodermal activity sensor expressed as microsiemens (μS), data from the photoplethysmograph, data from the 3-axis accelerometer sensor, inter-beat interval (IBI) extracted from the BVP signal, average heart rate extracted from the BVP signal, and event mark times (corresponding to different PASS tasks). All data collected will be saved as a zipped csv file.

A multi-camera capture system is equipped at Smart Home and SimCapture Cloud is used for data storage and access. There are in total 8 cameras at Smart Home, including one rotating camera in the dining room, one rotating camera in the living room, two cameras (one rotating camera and one static camera) in the kitchen, two cameras (one rotating camera and one static camera) in the bedroom, and two cameras (one rotating camera and one static camera) in the bathroom. The rotating cameras allow the experimenter to adjust camera angles and zoom in/out. The experimenter can choose to capture and stream up to 4 camera angles in one or several simulation rooms at the same time. The data will be automatically uploaded to the SimCapture Cloud and can be downloaded within the building of Smart Home.

For the long-term development of a powerful integrated robot-based system to assist ADLs for PLWDs, the camera embodied in the Pepper robot is used to record audio and video during each PASS task. The recording is achieved specifically through the camera on the robot’s tablet, as access to the microphones and cameras on its head is not available for recording. The audio and video are recorded using the CameraX library for Kotlin, which provides a simple way to manage camera devices to record both audio and video.

4.1.6 Prototype Verification and Refinement

The prototype of robot-assisted PASS was developed in the laboratory. Despite our best effort, the prototype design could be flawed, particularly in a new environment of Smart Home. To address this, we invited two participants (young adults, 1 female and 1 male) to test the prototype at the Smart Home of University of Tennessee, Knoxville, to identify potential critical problems which might not be realized before, but could negatively influence the robot’s functions and usability. Overall, the robot was able to successfully administer the PASS tasks for participants. However, we discovered several problems that occurred during testing at Smart Home. First, during the first task of bed mobility, participants were required to lay on the bed and turn from their

stomach to their back. The robot was required to remind participants with glasses to put their glasses on the bedside table first before turning over. Second, at the end of each PASS task the robot directly continued onto the next PASS task without any indication of the end or beginning of a task. This approach might not be optimal for human-robot interaction. Future iterations should explicitly indicate task completion and the start of a new task. Third, particularly in the Smart Home environment, there are some blind zones in the robot’s vision. The robot identified obstacles based on cameras and laser sensors located on its head and wheel. However, the height of the kitchen island at the Smart Home was approximately the same as the robot’s height. As a result, the robot could not detect it. The first two problems were addressed by including corresponding instructions. Regarding the third problem, the experimenter who controlled the robot using teleoperation had to be more aware of the physical environment to avoid the robot colliding with objects in the environment.

4.2 Usability Study of Robot-guided PASS Platform

With careful consideration of ethical implications and practicality, we initially focused on a cohort of young, cognitively normal adults to test the usability of our robotic platform. Engaging a young and cognitively healthy population first allowed us to refine our system in a lower-risk environment. The purpose of this study was to provide preliminary results before using the platform of robot-assisted PASS with PLWDs, a vulnerable population with cognitive and/or physical impairment. Such a preliminary study on healthy subjects is essential prior to the recruitment of people with dementia to minimize any confusion on the users’ part and to identify any problems with the robot administering the PASS which might negatively impact user experience and system performance (Smith et al., 2015). However, we acknowledge the significant differences between this initial study group and our targeted end-users, namely PLWDs. The cognitive and physical disparities between these groups are not

overlooked, and it is recognized that the findings from this preliminary group may not fully extrapolate to the target population.

The experimental study of robot-assisted PASS was approved by the IRB (IRB number is UTK IRB-21-06514-FB). Inclusion criteria included: 1) aged between 18 and 95, 2) English-speaking, and (3) able to stand and walk for a while without assistance. Exclusion criteria included: any current significant systematic illness (e.g., brain injury, eye or hearing conditions, physical disability) or unstable medical condition that could lead to difficulty complying with the PASS protocol (Chisholm et al., 2014). Five young adults (2 females and 3 males), aged 22 ± 2.28 , without brain injury or severe eye/hearing conditions, were recruited from the University of Tennessee for this usability study. The participants were with an educational background of some college (3), college graduate (1), and post-graduate (1). All participants reported very familiar or extremely familiar with technologies, including smartphones, tablets, computers, and robots. The usability study was conducted at the Smart Home of University of Tennessee, Knoxville.

4.2.1 Experimental Procedure

Before the experimental study, a researcher provided each participant with an informed consent form. To build the publicly accessible dataset, we included four statements regarding permissions for the use of identified audio and video data at the end of the consent form. These permissions related to the storage and sharing of audio/video recordings for future research. Participants were given the option to agree or disagree with any of the four statements voluntarily.

After obtaining the consent form from the participant, the researcher distributed a survey questionnaire that collected demographic data from the participant, including age, gender, education, race and ethnicity, and background experience with technologies. Then the experimenter helped the participant wear the E4 wristband. Later the experimenter went to the control room and the participant stayed at

living room, as illustrated in Figure A.19. During the PASS experimental study, the experimenter controlled the robot movements and communication in the control room according to the remote video monitoring system equipped at Smart Home. The robot would lead the participant to the appropriate room (the shaded area in Figure A.19) for each PASS task, e.g., bedroom for tasks of bed mobility and changing the bed linen, living room for tasks of using the telephone and obtaining information from the radio and a poster, bathroom for the task of cleaning teeth, and kitchen for meal preparation.

Then the robot provided the participant with corresponding guidance to perform the task, for example, in the task of bed mobility, the robot provided instructions verbally and via tablet as shown in Figure A.17. In each PASS task, the robot commenced with a verbal instruction, "please press the button on your smartwatch", to signify the start of a PASS task. It concluded with the verbal instruction, "This is the end of the task. Thank you", to indicate the completion of the task to the participant."

4.2.2 Evaluation of Acceptability and User Experience

After participants completed the PASS tasks following the robot's instructions, a 13-item self-reported questionnaire was administered to evaluate their experience, satisfaction, and perception of the robotic platform. The survey was adapted from three well-established questionnaires, the Questionnaire for User Interaction Satisfaction (QUIS) (Norman et al., 1998), System Usability Scale (SUS) (Brooke, 1996), and Computer System Usability Questionnaire (CSUQ) (Lewis, 1995). QUIS measures users' overall system satisfaction and user satisfaction on specific interface factors, including screen visibility, terminology and system information, learning factors, and system capabilities (Norman et al., 1998). SUS is a simple, widely-used tool to evaluate subjective usability of a digital product and service, including users' perceived ease of use, effectiveness, efficiency, and satisfaction (Brooke, 1996).

The CSUQ assesses users’ satisfaction with system usability, measuring system characteristics such as ease of use, ease of learning, simplicity, effectiveness, information, and the user interface (Lewis, 1995). We combined the three questionnaires into one questionnaire, removed redundant questions, and adapted into an efficient, 13-item survey (Table A.23) for the participants. The items generated data on specific constructs that are critical for understanding the participants’ usability experience with the robot and user GUI, affective reactions to it, acceptance, trust, satisfaction and effectiveness. The participants rated each item on a five-point scale, from *strongly disagree*, *somewhat disagree*, *neither agree nor disagree*, *somewhat agree*, and *strongly agree*. Additionally, we included an open-ended question (“Do you have any additional comments, suggestions, or concerns you would like to share, in order to develop the robot to assist people with dementia in their daily activities?”) to gather any in-depth insights into the participants’ opinions and suggestions about the platform of robot-assisted PASS.

4.2.3 Privacy Protection

The physiological data collected via E4 are de-identified and cannot be linked to participants. Audio and video recordings are securely stored on cloud storage services, namely SimCapture Cloud and Firebase Cloud Storage, both of which are password-protected. Following each experiment session, the audio and video data are transferred to a password-protected computer owned by the University of Tennessee.

All participants’ identifiable information and data are treated with strict confidentiality. Participants are informed about their privacy rights, as outlined in the study consent form. This form includes information on Health Insurance Portability and Accountability Act (HIPAA) regulations, approved by the IRB at UTK. A HIPAA-compliant secure server is utilized for all collected data, which will be retained for three years post-study completion. Access to this data is restricted to IRB-approved researchers. Additionally, participants and, if applicable, their legally authorized

representatives, have the option to consent or opt-out of having their video and audio recordings stored and used for future research.

4.2.4 Results and Discussion

In the preliminary study, the robot demonstrated effective communication and successfully administered PASS tasks, and the participants had a pleasant experience with the robot. During the experiments, using teleoperation, the experimenter moved the robot forward, backward, left or right in different rooms of the Smart Home and controlled the robot to provide step-by-step instructions for each PASS task. The participants generally knew what to do after the robot provided instructions for a PASS task in most instances. Examples of participants' behaviors and human-robot interaction during PASS observed by the cameras equipped at the Smart Home are shown in Figure A.20. Similarly, examples of participants' behaviors during PASS observed by the camera mounted on the Pepper robot's tablet are shown in Figure A.21.

Additionally, our study highlights the tele-operated robotic platform's flexibility and scalability for use in various environments, extending beyond the smart home setting. This adaptability is crucial for tasks that require minimal setup, such as using a telephone or managing medication, where only basic furnishings like a table and a chair are necessary. However, it is important to recognize that specific activities, particularly those involving bed mobility and changing bedlinen, do require a bed. This distinction underscores the platform's broad adaptability, while also acknowledging the inherent environmental prerequisites for certain tasks. Furthermore, the design of our tele-operated robotic platform facilitates easy adaptation to a wide range of tasks and settings, from smart homes to more traditional living environments, without extensive modifications. Its modular nature allows for the integration of additional sensors or components to accommodate new activities, making it a versatile tool for various care scenarios. This scalability not only broadens

the platform’s application spectrum but also highlights its potential to cater to a diverse PLWD population with varying needs.

4.2.5 User Acceptance and Experience

The participants’ responses to Items Q1-Q13 (Table A.23) are presented in Table A.24. Two participants provided additional comments. Overall, participants reported a positive user experience and a high user satisfaction (Item Q12, Mean = 4.60, SD = 0.80) with the robot-assisted PASS platform. The mean values of responses to all items, except Item Q3, were greater than 4 (4 = Somewhat agree), indicating a promising potential for the successful adoption of the platform among PLWD. The platform was perceived as easy to use (Item Q10, Mean = 4.40, SD = 1.20). The robot’s appearance was pleasing and its voice was clear to participants. The robot’s instructions, on-screen messages, and body language were clear (Item Q5, Mean = 4.20, SD = 1.17), effective (Item Q6, Mean = 4.40, SD = 0.80), and easy-to-understand (Item Q9, Mean = 4.40, SD = 1.20) to participants, suggesting that the information provided by the Pepper robot was good-quality for participants to perform PASS tasks. The participants felt relaxed to use the robot-assisted PASS platform (Item Q7, Mean = 4.20, SD = 0.98; and Item Q8, Mean = 4.40, SD = 0.80), demonstrating the feasibility of using the Pepper robot to administer PASS tasks for PLWD.

Compared to responses to other items, participants provided a relative low rating to Item Q3 (Mean = 3.60, SD = 0.80). Through participants’ feedback after the experiment, we conjecture two potential reasons underlying participants’ perception of the robot’s gestures and other body movements. First, this might be caused by the slow motion of the Pepper robot across different rooms. During the experiment, the experimenter controlled the robot to move forward, backward, left, or right based on the remote monitoring system. It was challenging to move the robot in real-world simply according to the position of the robot at Smart Home from cameras’ view.

The default setting of the Pepper robot keeping its focus on the human user (i.e., making eye contact with a user (SoftBank Robotics, 2022)) made it more difficult for the experimenter to tele-operate the robot to move in the Smart Home. As a result, sometimes Pepper moved very slowly or kept staring at the participant without moving. To fix this problem, our next step is to implement the capability of navigation in the Pepper robot, enabling the robot to map the environment of Smart Home and navigate between points of interest (PoIs) in the Smart Home. Second, in some PASS tasks the robot provided instructions behind the participant. One participant mentioned that he had to turn around to interact with the robot, making him feel uncomfortable. Regarding this issue, we think the robotic function of navigation, which allows to create PoIs, may be able to mitigate this problem. We will also test this in our next step. Additionally, in the rows for Item Q2, Q3, Q9, and Q10 of Table A.24, there was one response of 2 (2 = Somewhat disagree), all rated by one participant. This participant also commented that instructions in some PASS tasks such as changing the bed linen and managing medication were unclear to him. The instructions in the robot-assisted PASS platform were translated from the protocol of clinician-administered PASS (University of Pittsburgh, Department of Occupational Therapy, 2021). However, it seems that the same instructions delivered by the robot might not be clear to users, which might be caused by limited verbal and nonverbal communication capability in the robot, e.g., tone and gestures. In the future, we will rephrase the instructions of these PASS tasks, making it more clear to the participants.

4.2.6 Limitation and Future Work

In this study, we identified several challenges in using a social robot to administer the PASS tasks for an individual. Our usability study, while providing valuable insights into the acceptability, usability, and user experience of the robotic platform with a young, healthy demographic, revealed a key limitation: its applicability to our

target population of older adults with dementia (PLWDs). To initiate exploration in this area, we conducted preliminary interactions with PLWDs in a small-scale case study (n=3) (Yuan et al., 2022c). These initial interactions, focusing primarily on collecting multimodal data while participants interacted with the robot, offered insights into the potential challenges and necessary adaptations for working with PLWDs. Despite observing that the robot’s multimodal interactions, such as verbal communication, eye contact, and gestures, facilitated PLWDs’ adoption and use of SARs, and that PLWDs attributed human-like qualities to the robot during the PASS tasks, the case study revealed significant challenges in user interaction and experience. PLWDs reported that the robot’s speech pace was too rapid, unlike findings from the study with young adults. Additionally, some PLWDs expressed confusion when the robot failed to provide affirmation after completing a subtask or task (Yuan et al., 2022c). However, this case study did not conduct an in-depth analysis of acceptability and user experience, as our primary aim was to observe the basic interaction dynamics between PLWDs and our robotic platform. In the future, we plan to undertake a comprehensive study involving a larger cohort of PLWDs. This forthcoming study will involve detailed observations of PLWDs’ interactions with the robotic platform, supplemented by extensive surveys and interviews to assess user experience and acceptability. This research will provide essential data for evaluating the validity, effectiveness, and generalizability of our platform for aiding individuals with dementia in their daily activities. By incorporating feedback from the targeted population, PLWDs, we aim to refine our platform to better meet the unique needs of our end-users.

Another challenge identified in the usability study was the robot’s camera, integrated into its tablet, occasionally failing to capture participants’ behaviors and faces. The camera, positioned at a height of approximately 85cm, struggled to adequately capture facial expressions and body movements. An optimized design of Points of Interaction (PoIs) for the robot and participants for each PASS task may mitigate this issue. Future work will also explore supplementing the robot’s video

data with other modalities, such as participants’ physiological signals and additional video data from cameras installed in a Smart Home environment or through innovative sensing technologies (Shi et al., 2023a), to capture moments, emotions, and behaviors not detected by the robot’s camera.

Moreover, it is crucial to acknowledge and address potential biases in participants’ interactions with the robot during the PASS tasks, such as social desirability bias (Grimm, 2010), where participants may offer socially desirable responses instead of their genuine feelings. Furthermore, user perceptions and attitudes towards the robot might be influenced by its novelty (Woods et al., 2021b), considering the current study’s short-term engagement. To effectively counter these biases, future research should include long-term studies to observe and analyze participants’ reactions over extended periods. This approach will offer a more comprehensive understanding of the authentic and evolving dynamics of user-robot interaction, beyond the initial biases of novelty and social desirability.

Considering that the PASS tasks and daily living activities closely involve key stakeholders in dementia care - PLWDs, their caregivers, and professionals like occupational therapists - our future work will incorporate these stakeholders’ perspectives in the robotic development lifecycle. We plan to engage them in co-design sessions, collaboratively designing and prototyping robotic functions and interactions tailored to ADLs. This approach ensures that the robotic designs are informed by the stakeholders’ expertise and insights. Moreover, we will invite them to participate actively in the evaluation process, refining the robotic system based on real-world feedback and scenarios. This stakeholders-in-the-loop approach aims to align the robotic system’s functionalities with the actual needs and preferences of PLWDs. By involving these key stakeholders in the design, development, and evaluation phases, we seek to enhance the robot’s functionality and interactivity and improve our methodology, contributing to a more effective, engaging, and robust robotic solution for assisting PLWDs in their daily activities.

As part of our ongoing development, we acknowledge the current limitations in the bidirectional interaction capabilities of our tele-operated robotic platform with PLWDs. While our system facilitated a degree of responsive interaction by observing participants’ verbal and non-verbal reactions to adapt its follow-up actions, the scope of this mechanism was inherently limited. Participants had the opportunity to verbally interact with the robot, and the robot sought feedback on their understanding and readiness to proceed with tasks. Nonetheless, the depth and breadth of these interactions were not as extensive as we envision for optimal user support. Looking forward, we are committed to significantly enhancing these bidirectional communication capabilities. Our planned enhancements include improving interactions both during task performance and upon task completion, aiming to more accurately determine whether difficulties or failures encountered by PLWDs are attributable to the robot’s interface or to the inherent challenges faced by PLWDs themselves. We intend to explore a variety of technologies and methodologies, such as advanced natural language processing, video recognition, and multimodal perception, to facilitate these improvements. Our goal is to provide a more interactive and supportive experience for PLWDs, thereby enriching their engagement and autonomy in daily activities.

4.2.7 Summary

In this section, we presented the development and application of the tele-operated socially assistive robot, Pepper, to administer ten PASS tasks for human users. The results of our usability study showed that participants had overall positive user experience and satisfaction with the platform. This platform facilitated the collection of multimodal data, including physiological signals, audio, behavioral, and users’ interactions with the robot, during PASS tasks. We identified several critical challenges in current robot-assisted PASS platform. Our next step involves refining the robotic functions to address these issues, such as integrating navigation

capabilities into the robot, and evaluating its usability with persons with dementia. Subsequently, we aim to engage a large cohort of PLWDs in the PASS experimental study using this refined platform, with the goal of generating a comprehensive dataset.

4.3 Portable Robot-assisted PASS Platform

While currently SAR has been applied to different contexts, such as therapy, social activities, and companionship, the application in the context of activities of daily living (ADLs) receives relatively limited attention (Ghafurian et al., 2021). This might be caused by a list of reasons: First, compared to other contexts, the ADLs are more complex and have a lot of variations, which needs some requirements for the environment. From interaction perspective, to perform ADLs, PLWDs need to perform the tasks physically, verbally, mentally, cognitively, and even socially. This multi-dimensional interaction and task performance introduces the task complexity. Additionally, due to cognitive deficits, each individual PLWD may show various performance breakdown, which introducing another dimension of complexity. As a result, a SAR needs to be capable of handling these complexity. Another challenges existing in robot-assisted dementia care is that it is very challenging to recruit PLWDs in the robotic studies. All these complexity has hindered the development, investigation, and application of SAR for PLWDs during ADLs.

Acknowledging these challenges, we have developed a portable robotic platform which can guide and assist PLWDs in performing 8 advanced activities of daily living. All these 8 tasks are table-based, with a cognitive emphasis. There are three main contributions of this portable robotic platform: 1) The whole platform is standardized, portable, and easy to transfer to any place and location, such as clinic centers, dementia memory care center, and even PLWD’s homes. 2) All the tasks are table-based. Therefore, the whole platform can be used in most environment whose space is large enough for a table, chair and the robot. 3) During performing the task, the robot can not only provide guidance and instructions regarding the task, the robot can

also provide appropriate level of assistance to PLWDs. Therefore, this platform will allow us to not only observe and collect data of PLWD’s performance breakdown, but also observe and learn PLWD’s reactions to robotic assistance (e.g., remind/support, redirect, chat). Both dataset will greatly benefit the robotic perception of PLWD’s status (particularly the moments of performance breakdown) and robotic learning and decision-making of assistive strategy for PLWDs during daily routine activities. 4) Since all the tasks which the robot will guide and assist PLWDs to perform are with a cognitive emphasis, it will allow researchers to more efficiently collect the performance breakdown due to cognitive deficits. 5) In addition to the robotic technologies, we have also designed the biomedical experimental protocol, so that other researchers who are interested in PLWD-robot interaction can easily use our protocol.

4.3.1 Robotic Assistance

In addition to guidance, we have designed and developed different levels of assistance, with different intention and purposes, as illustrated in Fig. A.22, A.23, and A.24. Regarding the cognitive deficits, for example, being unable to correctly recognize grocery items, process information, and/or recall information, the robot will be controlled to provide verbal assistance to remind and/or support PLWDs. Considering the potential situations where PLWDs might struggle with a task for a while, the robot is able to provide verbal assistance to direct PLWDs from the struggling situation. Moreover, inspired by the previous finding about PLWD-robot interaction that PLWD may initiate the conversation with the robot (Yuan et al., 2022c) , the robot is developed with the chatting capability, to build the bond with the user with dementia and provide companionship.

4.3.2 Experimental Design of Portable Robot-assisted PASS

In addition to the design of the portable tele-operated robotic platform for PLWDs to perform advanced daily life tasks, with collaborations with occupational therapists

and clinicians, we have designed the experiment protocol so that the researchers can use the platform and conduct the robotic experimental study with people with dementia in a standardized way, and furthermore, have a better understanding of PLWD's behaviors during the experiments. The experimental protocol is illustrated in Fig. [A.25](#). The details for each procedure are presented in the following paragraphs.

Eligibility Screening

The procedure of eligibility screening and consent interview can be conducted before the experiment, which can allow more time flexibility of for participants and thus make the whole experimental study more efficiently. An electronic eligibility screening questionnaire is distributed using a HIPAA-secured Qualtrics survey platform, which would take no more than 5 minutes to complete. This eligibility screening questionnaire can allow researchers to quickly learn a person's eligibility of participate in the robotic study. Those participants who screen eligible for the study will provide their names, phone numbers, email addresses and/or mail addresses in the online form so that a member of the study team may contact them to schedule a time to review the informed consent documents. This review will take place either via Zoom or telephone.

Consent Interview

During the scheduled Zoom or telephone call, a member of the study team will review the informed consent documents with a potential participant. A member of the study team will thoroughly describe the study to the potential participant, determine eligibility, and review the IRB-approved informed consent forms. The study team member will answer any questions about the study. Also, the study team member will tell the potential participant that they can be accompanied by one family member or one friend to participate in the experiment in a place they preferred. To make sure a potential participant can make the decision to consent

for themselves, when reviewing the consent form, the researcher will administer the Decision-Making Capacity Assessment Tool to the potential study participants. For potential participants who are unable to make decision to consent for themselves, their legally authorized representative will be invited to walk through the eight portable table-based ADL tasks, to ensure that the participant feels comfortable and definitely safe. No research data will be collected from the legally authorized representative.

Finally, if the potential participant is willing to participate in the study, they will choose a preferred experimental location from the reserved spaces that have given us consent to host our study. The researcher and the participant will schedule a time to conduct the experiment at the experimental location chosen by the participant. Since all the tasks can be performed on a table by the participant, it will be flexible to choose an experimental location. Our previous experience with seniors and seniors with dementia has shown that these population would prefer to participate in the study in the clinic and senior centers, instead of the campus. Moreover, due to our previous experiences with participants (older adults) and clinicians, we were told that it is very challenging for seniors and seniors with dementia to drive a specific location (for example, the campus) to participate in the experiment. Therefore, we would conduct the portable table-based daily routine tasks in a location that have given us consent to use and are comfortable and convenient to potential participants

Experimental Procedure

Each participant can invite their legally authorized representative, or one family member, or one friend to walk through their ADL tasks at the experimental location chosen by the participant.

During each experiment, there will be two experimenters staying in the same room with the participant: 1) *On-site facilitator*, who stays closely with the participant, provide necessary nonverbal assistance (that the robot cannot provide currently), and handle unexpected situations to ensure the participant’s safety; 2) *Teleoperator*, who

will stay in the same room but with some distance from the participant and the on-site facilitator, and will control the robot's speech so that the robot can appropriately guide and assist the participant to complete the 8 table-based ADL tasks. The experiment consists of pre-test surveys (about 20 minutes), an orientation phase (about 10 minutes), a table-based ADLs phase (about 90 minutes), and post-test survey (about 10 minutes).

Pre-test Surveys The participant will complete two surveys in paper format: the demographic survey and the Montreal Cognitive Assessment (MoCA) survey. The demographic survey is distributed to learn participants' information such as age, gender, disease stage, familiarity with technology, as well as capability and performance of ADLs. The MoCA survey assesses different cognitive functions (e.g., attention and concentration, memory, calculations, and orientation) for a person. The participant's MoCA score is not for screening, but merely help researchers understand their performance in the later ADL tasks. To protect the confidentiality of participants' information, the researcher will not include the participant's personal information but assigns a unique subject ID for each participant.

Familiarity with Robot After the administration of surveys, there will be an orientation during which the participant can freely interact with the robot and explore the experimental location. The orientation is designed to allow the participants to become more familiar with the robot and the experimental location. The participant will freely talk with the robot, enjoy dancing and songs from the robot, as well as play some fun games such as animal bingo on the robot's tablet. During orientation, the experimenter, on-site facilitator, will be with the participant to demonstrate how to use the robot (if needed) and answer any questions from the participant.

Task of Interest Selection While a total of 8 tasks were implemented in the robotic platform, to make the PLWD feel more comfortable with and controllable of the experiments, we let the participant to choose which task(s) they would like to participate in during the experiments. This can further increase the chance of successful participant recruitment.

Table-based ADL tasks After the orientation, the on-site facilitator, will help the participant wear the E4 wristband. Then the robot will provide instruction to the participant to perform the the tasks of interest which they selected previously. Meanwhile, the on-site facilitator will always stay closely with the participant to make sure everything is going well. All these eight tasks are table-based, that is, during the whole experiment, the participant will just need to be seated at a table. Also, we will prepare all the materials (e.g., printed checks, pen, and pill boxes) for these tasks.

Post-test survey After the completion of the task, a post-test survey will be administered by the on-site facilitator for the participant to learn the acceptance and feasibility of the robot. This survey will be evaluating the participants' personal experience of using and interacting with the robot. Additional questions will be asked to learn the user's perceptions and opinions on the robotic interface design. The data collected by the post-test survey will be useful to refine the designs and development of the robot to assist PLWDs in their daily routine tasks.

4.4 Evaluation Framework for PLWD-robot Interaction

To build an intelligent SAR which can automatically assist people with dementia during their daily life activities, it is critical for the robot to understand when the PLWD need assistance (i.e., the moment of PLWD showing performance breakdown) and what the performance breakdown is specifically from the PLWD. Moreover, the robot need to understand how the PLWD perceive the robotic assistance, i.e., feedback for the robot. From the perspective of PLWD, they need to perform ADL tasks physically, verbally, mentally, cognitively, and even socially. This multi-dimensional nature underlying ADLs introduces the complexity and variation in PLWD-task-environment transactions. Additionally, due to cognitive deficits, each individual PLWD may show various performance breakdown, which introducing

another dimension of complexity. All these complexity has hindered the robot and AI to understand the PLWD’s status during ADLs, which is the same to the robotic developers.

Acknowledging this challenge, in this section, we come up with a comprehensive framework for robotic researcher to design, observe, and evaluation PLWDs’ interaction with the SAR. The main contributions of this work are: 1) Taking into consideration both robotic developers and occupational therapists, our framework is evaluating the PwD-robot interaction from both patients (clinical, nursing) perspective and the robotic technology perspective; 2) We have tested our evaluation framework through both human experts in dementia care, through which our framework has demonstrated generability and reliability of use in difference cases. 3) The proposed framework can used as a standard or benchmark, for both stakeholders in clinical and robotics. With these standards, robotic researchers can not only evaluate the performance of the robot, but also understand the PLWDs’ response and interaction from a clinical perspective, which can be further used to facilitate the robot’s understanding of PLWDs’ status.

4.4.1 Development of Holistic Framework for PLWD-robot Interaction

From a high level, a robot-assisted daily activity, can be regarded as PLWD-robot collaboration to complete the task together. In other words, if the task is not completed successfully, then it can be caused by the PLWD, the robot, and/or the environment. Therefore, we design and develop this framework to assess the performance breakdown from these three dimensions. Table [A.25](#) lists the main components taken into consideration by our framework. In addition, due to the complexity of daily routine activities, when performing the task, the dynamics and interplay between the PLWD with the task, the robot, and the environment can be manifested as different dimensions, including cognitive, social, behavioral, verbal,

and visual, etc. Therefore, regarding the performance breakdown from the PLWD, we have categorized it into three perspectives, including an individual’s cognitive function, physical function, and psychosocial status. Such a multi-dimensional description will allow the robot to have a understanding of PLWD’s cognitive capability, physical capability, and psycho-social status, through which, thus, further to help the robot to provide more effective, targeted assistance.

Noticeably, as listed in Table A.25, our framework also covers the scoring mechanism used by the PASS protocol (Chisholm et al., 2014). This allows our framework bridges the knowledge of robotics, nursing, and occupational therapy. The components in cognitive domain is referring to the criteria given by the Diagnostic and Statistical Manual of Mental Disorders (DSM-5) (?). Regarding the psychosocial status, we have considered it from multiple dimensions, adopting from the Engagement of a Person with Dementia Scale (EPWDS) (?), which is manifested in 5 different dimensions: 1) *Negative affect*, for example, frustration, apathy, anger, anxiety, fear, or sadness (e.g., disinterest, distressed, restlessness, repetitive rubbing of limbs or torso, repeated movement, frowning, crying, moaning, and/or yelling); 2) *Visual disengagement* or *visually avoidant*, appearing inattentive, having an unfocused stare, or turning head/eyes away from the activity, materials used, or the person’s involved. 3) *Verbal disengagement* or *verbally avoidant*, refusing to participate in the activity or in a conversation related to the activity by verbalizing e.g., “no,” “stop,” etc. OR verbalizing negative comment, complaint, and sound (e.g., groaning, or cursing, or swearing) in response to the activity, or the materials used, or the person/s involved. 4) *Behavioral disengagement* or *behaviorally avoidant*, responding to the activity by avoiding, shoving away, pulling back from, hitting, or mishandling the activity, the materials used, or the person/s involved. 5) *Social disengagement* or *socially disruptive*, distracting or disrupting others (e.g., staff/facilitator and other residents), in response to the activity.

4.4.2 Results

Examples of coding results are presented in Table [A.26](#). As presented in the table, for one moment (e.g., 1:07:30), the PLWD kept the hand on his/her face, looking confused. This performance breakdown is related to their cognitive capability, but also manifests as a psychosocial aspect of breakdown.

4.4.3 Discussion

In this section, we come up with a framework which captures the PLWD-robot-task-environment transaction, i.e., the complex and dynamic interplay between the PLWD, the task they perform, the robot designed to assist PLWD during the task, and the environment in which these tasks occur. With this framework, an evaluator (or a robot in the future), can understand and analyze how a PLWD’s capabilities and needs interact with the activities they undertake (the task) within the constraints and supports provided by the environment and the robot, physically and mentally. With this understanding, the robot can be able to provide appropriate assistance that are holistic and personalized, considering not just the individual’s capabilities (physical, mental, and cognitive) but also how they interact with their surroundings and the tasks they need or wish to perform. As a role of standards and criterion, this evaluation framework may contribute to the PLWD-centered, adaptive dementia care, which at the same time enhance the fit between the PLWD’s capabilities and their environment to support independence and quality of life.

4.5 Reinforcement Learning for Adaptive Robotic Assistance of PLWDs During Activities of Daily Living

With the feature of physical embodiment and the capacity of multimodal interactions (e.g., voice, gestures, and graphical user interface), socially assistive robotics has shown the advantages of engaging older adults and PLWDs in social activities and therapies (Ghafurian et al., 2021; Yuan et al., 2021c). Previous studies have demonstrated public enthusiasm for such innovations in dementia care, and highlighted the importance of safety features, voice communication, and personalization in AI robots for assisting individuals with ADRD (Yuan et al., 2022b). However, the use of SAR in aiding with activities of daily living has received relatively limited attention and the majority of existing studies have predominantly used tele-operated robots (Ghafurian et al., 2021). For instance, Wang et al. (Wang et al., 2017) used a tele-operated robot to provide stepwise prompting for PLWDs to complete activities of hand-washing and preparing a cup of coffee, exploring perspectives of both PLWDs and their caregivers. While these studies underscore the effectiveness of social robots in assisting caregivers and engaging older users, they rely on tele-operation, which requires human intervention and does not fully exploit the potential for autonomy in robotic assistance. Another fundamental challenge hindering the transition from tele-operated to fully autonomous robotic systems in dementia care is the scarcity of datasets for training. Without access to comprehensive, realistic data reflecting the wide range of cognitive and affective statuses of PLWDs during daily activities, developing robots capable of autonomous, context-aware decision-making remains a formidable challenge.

Acknowledging these challenges, our work introduces a breakthrough in the form of a simulator designed to mimic the cognitive and affective statuses of PLWDs during daily routine activities, with or without assistance, aiming to explore and enhance

autonomous robotic decision-making for dementia care. Our simulator models not only the patients’ statuses during tasks but also their responses to various levels of assistance, providing an invaluable open-source tool for reinforcement learning (RL) research. The simulator aims to facilitate the development of robotic decision-making in dementia care, improving the independence, safety, and well-being of PLWDs.

Building upon our simulator, we have developed an RL framework that offers a novel and adaptable simulation environment tailored for RL research to explore and enhance robotic decision-making and assistive mechanisms for PLWDs. This framework provides a customizable and scalable platform compatible with existing RL algorithms. While its initial setup is straightforward, our framework represents a unique research tool, paving new avenues for experimentation and study in AI. It showcases the capabilities of our simulator and promotes collaborative development and iterative improvement within the RL community, setting a innovative approach toward autonomous, intelligent, and adaptive SAR solutions for dementia care.

4.5.1 SIMULATOR OF A PERSON WITH DEMENTIA

In response to the lack of datasets for persons with dementia performing daily activities, we have built a simulator to mimic the performance breakdown in persons with dementia during performing activities of daily living, with and without external assistance. The performance breakdown is particularly manifested as PLWD’s cognitive and affective statuses, including forgetfulness, confusion, anger, and disengagement, which are affected by AD/DRD such as cognitive deficits. All these four statuses might hinder PLWDs’ success, safety, independence, and adequacy in performing the daily tasks. In other words, all these moments could be moments when the socially assistive robot assists PLWDs in task completion. In this work, we will mainly focus on persons with early- or moderate-stage dementia, the population who typically shows performance breakdown from a cognitive perspective.

Context of Simulation

To live independently, safely, and adequately, a person needs to perform a list of daily routine tasks, such as bed mobility, shopping, and meal preparation (Chisholm et al., 2014). Considering our target population, people with early- and moderate-stage dementia, our current simulator will focus on the advanced activities of daily living with a cognitive emphasis. For the convenience of discussion, we are introducing concepts of scenarios, tasks, subtasks, trials, and timesteps in the simulator. Their definitions and examples are listed in Table A.27.

External Assistance

The potential external assistance is designed by adopting the hierarchy of assistive levels for PLWDs from the performance-based, criterion-referenced, observational tool, Performance of Self-care Skills (PASS) (Chisholm et al., 2014). PASS has been widely used by occupational therapists to evaluate individuals' capacity to perform ADLs and live independently and safely in the community for people with AD/ADRD (Dham et al., 2020; Keleman et al., 2021; Yuan et al., 2022b). In PASS protocol, there are 10 different levels of assistance that could be provided to PLWDs to help them successfully complete their daily routine tasks. Considering that our current target population includes people with mild or moderate dementia, this paper focuses on assistance from the cognitive and affective perspectives; therefore, the assistance includes 'No Assistance', 'Verbal Supportive Assistance' (encouragement), 'Verbal Non-directive Assistance' (cue to alert), and 'Verbal Directive Assistance' (instruction). Their definitions and examples are given in Table A.28.

Probabilistic Model of PLWD

Given the terms in Table A.27 and four types of assistance in Table A.28, the dynamics of PLWD's cognitive and affective statuses when performing the tasks is simulated. The PLWD's dynamic statuses could be influenced by their cognitive deficits, the

task and subtask, and external factors (i.e., assistance). For simplification, we use Markov Chain to simulate the dynamics of PLWD’s four cognitive and affective statuses, taking into consideration their current cognitive and affective statuses as well as external assistance. Fig. A.26 illustrates the mechanisms of PLWD’s dynamic probabilistic transitions.

Noticeably, our current probabilistic PLWD model only considers general situations, instead of the varieties in dementia population. Here are the four assumptions to simulate PLWD’s cognitive and affective statuses. The four statuses, *Forgetfulness*, *Confusion*, *Angry*, and *Disengagement*, are modelled as binary (Yes = 1, No = 0). Each status is assumed to have a base probability of transitioning from No to Yes, and from Yes to No, in the absence of the other three statuses and external assistance. At the same time, the dynamics of each status will be influenced by the presence of other three statuses and external assistance (if applicable). Without external assistance, there is a very small or even 0 probability of transition from Yes to No, which represents a process where dementia patients could become better by themselves. In other words, there is almost a probability of 1 of transition from Yes to Yes, without external assistance.

Without external assistance Based on the aforementioned assumptions and the previous qualitative understanding and observations of PLWD’s cognitive and affective behaviors (Chisholm et al., 2014; Yuan et al., 2022c), we have simulated the dynamics of PLWD’s four statuses using the probabilities listed in Table A.29. These probabilistic model considers both the fluidity (changeable) and continuousness (consistent) of cognitive and emotional states in PLWDs, influenced by individual cognition, mood, task nature, and coping mechanisms. However, it is crucial to note that these probabilities are simplifications of the complex and highly individualized nature of dementia. They serve as a framework for understanding general trends rather than definitive predictions of patient behavior.

For example, for the status of *Forgetfulness*, the influence of *Angry* and *Disengagement* indicates the immediate impact of cognitive-emotional stressors on

memory functions. Acknowledging that *Angry* can be a very negative emotion and can more significantly disrupt memory process and other cognitive functions, *Angry* is designed to contribute a relatively increase to the other three statuses. Our model reflects a stronger connection between cognitive impairments (forgetfulness and confusion) and emotional responses (anger), acknowledging that cognitive challenges often precede and exacerbate emotional distress. The model also accounts for that PLWD’s cognitive and emotional statuses (i.e., *Forgetfulness*, *Confusion*, and *Angry*) can also contribute to withdrawal or lack of engagement. Moreover, the statuses of confusion, anger and disengagement can exacerbate forgetfulness. Anger, being a more intense emotional state, having a larger influence than disengagement aligns with clinical observations where emotional distress can significantly impact cognitive functions like memory.

With external assistance The transition probabilities of four cognitive and affective status will be influenced by the presence of external assistance in Table A.28. More specifically, in the presence of verbal supportive assistance, if PLWD current status *Anger* (*Disengagement*) is Yes, the following status of *Anger* (*Disengagement*) being Yes is 5%; Otherwise, it will be 0. For the other two statuses, *Forgetfulness* and *Confusion*, their dynamics will follow the rules in Table A.29. In the presence of verbal non-directive assistance or verbal directive assistance, these two types of assistance will not influence the dynamics of emotional states, *Angry* and *Disengagement*, whose dynamics will follow the rules in Table A.29. Regarding the statuses *Forgetfulness* and *Confusion*, if their current status is No, the probability of following status being Yes will be 0% and 0%, correspondingly. Comparatively, if their current status is Yes, the probability of following status being Yes will be 40% and 60%, correspondingly, given verbal non-directive assistance, and 5% and 5%, correspondingly, given verbal directive assistance.

Subtask skipping In each subtask, if PLWD successfully finish the current subtask within *MaxTrial*, with or without assistance from the caregiver, PLWD will move to next subtask. On the other hand, if PLWD cannot finish the current

subtask within *MaxTrial*, PLWD will skip current subtask and move to next subtask. If PLWD skips the current subtask and moves to next subtask, PLWD’s state will transit to a *skipped state*. Acknowledging the complexity of PLWDs’ cognitive and affective responses, skipping a task might alleviate some negative emotions but does not guarantee an immediate cognitive and/or emotional reset. Therefore, the transition probability of skipped states follows the following rules: For *Forgetfulness* (*Confusion*), the probability of persistence after skipping a subtask is set at 0.5 if the PLWD is already forgetful and confused, and 0.2 if forgetful (confused) but not confused (forgetful), reflecting the impact of emotional stress on memory retention. For the statuses *Anger* and *Disengagement*, a probability of 0.5 has been assigned for their persistence after subtask skipping, recognizing the potential for these emotions to either continue or abate.

4.5.2 Reinforcement Learning Framework

In this section, we have explored reinforcement learning (RL) based on the simulator built in Section 4.5.1. The goal is to teach the RL agent (robotic caregiver) to learn the optimal assistance strategy to help a person with dementia to complete the activities of daily living. In each episode, the RL agent needs to assist PLWD to complete a scenario, consisting of a sequence of tasks and subtasks.

State Space

A state is defined based on PLWD’s four cognitive and affective statuses, that is, a state s includes four components, including *Forgetfulness* (denoted as s_{for}), *Confusion* (denoted as s_{con}), *Angry* (denoted as s_{ang}), and *Disengagement* (denoted as s_{dis}). The values of these four components can be Yes (1) or No (0). Therefore, the size of the state space is $2 \times 2 \times 2 \times 2 = 16$. For each episode, the state will be reset to the *starting state*, S_0 ($[0, 0, 0, 0]$), where PLWD is not in a state of forgetfulness, frustration, angry, or disengagement, and ends in the *terminal state*. The terminal state is reached when

the PLWD successfully finishes all the tasks and subtasks of the scenario, or when PLWD finishes all the tasks and subtasks with skipping subtask(s).

4.5.3 Action Space

The action space includes ‘No Assistance’ (a_0), ‘Verbal Supportive Assistance’ (a_1), ‘Verbal Non-directive Assistance’ (a_2), and ‘Verbal Directive Assistance’ (a_3), as given in Table A.28. In addition, considering the possibility that many failures might negatively influence PLWD’s status, for each subtask, if the PLWD has tried *MaxTrial* times with actions taken by the RL agent but still cannot finish the subtask successfully, the RL agent will take the action ‘Skip current task’ to move to the next subtask. Here we set *MaxTrial* as 5.

Immediate Reward

The immediate reward function is designed such that the robotic assistant can help PLWDs following two rules: 1) keeping PLWDs in a positive affective mood; and 2) helping PLWD out of performance breakdown (e.g., forgetful, confused, and/or angry) and thus complete the task by providing minimum but effective assistance. The strategy of providing minimal assistance aims to maximize engagement in PLWDs, augmenting their autonomy, and potentially slowing down disease progression. As a result, the immediate reward function takes into consideration of PLWD’s cognitive and affective status, total timesteps, number of trials, subtask completion, and task completion, as represented in Equation 1. Inspired by this, we have specified the

immediate reward function r_t as Equation 2.

$$\begin{aligned}
r_t = & f(\text{Forgetfulness}) + f(\text{Confusion}) \\
& + f(\text{Anger}) + f(\text{Disengagement}) \\
& + f(\text{Increased trial}) \\
& + f(\text{Subtask completion, Assistance level}) \text{ if applicable} \\
& + f(\text{Skipping subtask}) \text{ if applicable} \\
& + f(\text{Timestep}) \\
& + f(\text{Task completion}) \text{ if applicable}
\end{aligned} \tag{1}$$

$$\begin{aligned}
r_t = & w_{forget} \times s_{for} + w_{confuse} \times s_{con} \\
& + w_{anger} \times s_{ang} + w_{disengaged} \times s_{dis} \\
& + w_{increasedTrial} \times \Delta N_{trial} \\
& + (w_{subtaskCompleet} + w_{assist}) \times Flag_{subtaskCompleet} \\
& + w_{subtaskSkip} \times Flag_{subtaskSkip} \\
& + w_{increasedTimestep} \times \Delta N_{timestep} \\
& + w_{taskCompleet} \times Flag_{taskCompleet}
\end{aligned} \tag{2}$$

The variable $Flag_{subtaskCompleet}$ will be true (with a value of 1) when the PLWD has already started performing the subtask and all of the four state components are 0. The variable $Flag_{subtaskSkip}$ will be true if the number of trials for a subtask, N_{trial} , reaches $MaxTrial$ and there is at least one state component that is 1. Based on the reward function 2, we have designed the reward component for each component by considering their positive or negative contribution and relative significance to the PLWD during performing the task. The detailed design of the immediate reward function is presented in Table A.30. As shown in this table, the RL agent will be

assigned with a negative reward component, -5, due to PLWD being in a negative affective status. Compared to the other three statuses, forgetfulness, confusion, and disengagement, the status of anger can be a very negative situation, which the RL agent (i.e., the robot assistant) should intervene in first.

Additionally, to teach and encourage the RL agent to provide useful but minimal assistance, a relatively large negative reward will be assigned when the PLWD complete the subtask with the highest assistance level (i.e., verbal direction assistance). Comparatively, a relatively smaller negative reward is assigned for less intrusive forms of assistance, promoting a balance between support and independence for the PLWD.

Learning Algorithm Design and Training

Epsilon greedy Q-learning is used by the RL agent to learn the assistive strategy. The learning rate and discount factor are set to be 0.05 and 0.95, respectively. The RL agent is trained for 6000 epochs, each with 30 episodes. To explore the potential influence of exploration and exploitation, two types of epsilon-greedy approaches are used: one with a constant epsilon ($\varepsilon = 0.1$) and the other with an exponentially decaying epsilon. The exponential decaying expression is shown in Equation 3, where $\epsilon_{\min} = 0.03$, $\epsilon_{\max} = 1$, and t is the current epoch. The decay rate λ is adjusted such that $\varepsilon = 0.8$ at $t = 300$ epochs, starting from $\epsilon_{\max} = 1$.

$$\epsilon(t) = \epsilon_{\min} + (\epsilon_{\max} - \epsilon_{\min}) \cdot e^{-\lambda t} \quad (3)$$

Evaluation Metrics

To evaluate the performance, we extract the temporal optimal policy π' suggested at the 10th episode of each epoch, apply it to run 40 experiments, and calculate the average return, compared to the performance of random action selection strategy. Additionally, we record all the optimal policies suggested in the last 100 episodes and use the top five policies most frequently suggested to run 10000 experiments and

choose the policy which enables the maximum return as the final policy, denoted as π'_* .

4.5.4 Results

The learning process of the three agents, constant-epsilon greedy RL, decaying-epsilon greedy RL, and the agent with a random action selection strategy, is shown in Fig. A.27. As plotted in Fig. A.27, after converging, the average return obtained by the constant-epsilon greedy RL and decaying-epsilon greedy RL is approximately the same, around 140. From this perspective, the performances of our RL agents are better than the agent with a random action selection strategy, whose average return is around 70.

The optimal policies learned by the two RL agents are plotted in Fig. A.28. We can see that the optimal actions suggested by the two RL agents are the same for all states, except for the first one. Three policies were suggested by the the constant epsilon RL agent during the last 100 episode, and two policies were suggested by the decaying epsilon greedy RL agent. We evaluated the three unique policies by running 1000 experiments. The policy which suggests taking action a_3 , verbal directive assistance, in state $s = [0, 0, 0, 0]$ obtained an average return 139.2, while the policy suggesting to take action a_2 and a_1 obtained an average return of 144.3 and 133.5, respectively. Therefore, the final optimal policy, π'_* , is the policy suggesting taking action a_2 , verbal non-directive assistance, in state $s = [0, 0, 0, 0]$.

4.5.5 Discussion and Summary

In this paper, we have presented a novel approach that integrates a simulated environment and reinforcement learning to enable adaptive robotic assistance for persons living with Alzheimer’s disease and related dementias (PLWDs) during activities of daily living (ADLs). Our simulator models the typical cognitive and affective states of PLWDs during daily tasks, capturing the complex dynamics and

performance breakdowns commonly observed in this population. The design of the simulator was informed by clinical tools and theoretical understanding of dementia, providing a realistic testbed for developing intelligent assistive technologies.

Building upon the simulator, we have developed a reinforcement learning framework that allows robotic agents to learn optimal assistive strategies tailored to the individual needs of PLWDs. The reward function was carefully crafted to encourage the agent to provide minimal but effective assistance while prioritizing the emotional well-being of the PLWD. Our initial exploration using Q-learning demonstrated the potential of this approach in enabling adaptive and personalized robotic assistance.

The integrated simulation and learning approach presented in this work offers several key contributions and implications for the field of socially assistive robotics and dementia care. First, it addresses the critical lack of datasets on PLWDs performing ADLs, which has hindered the development of intelligent assistive technologies. By providing a realistic simulated environment, our approach enables researchers and developers to train and evaluate robotic systems in a safe and controlled manner, without the need for extensive real-world data collection.

Second, our reinforcement learning framework provides a flexible and scalable platform for developing adaptive robotic assistance strategies. While we focused on Q-learning in this work, the framework is compatible with a wide range of RL algorithms, allowing for future explorations and comparisons of different learning approaches. This opens up exciting possibilities for developing more sophisticated and effective assistive strategies that can adapt to the unique needs and preferences of individual PLWDs.

Third, our approach takes a step towards addressing the growing need for advanced technological solutions in dementia care. As the global population ages and the prevalence of dementia continues to rise, there is an urgent need for innovative tools and technologies that can support PLWDs and their caregivers. By enabling adaptive and personalized robotic assistance, our work has the potential to improve the quality

of life for PLWDs, enhance their independence and autonomy, and alleviate the burden on caregivers.

However, it is important to acknowledge the limitations of our current work and identify avenues for future research. The simulator, while informed by clinical knowledge, relies on simplifications and assumptions that may not fully capture the complexity and variability of real-world dementia behaviors. Future work should aim to refine the simulator based on empirical data and incorporate more advanced probabilistic models to better represent the nuances of PLWD behaviors.

Moreover, the reinforcement learning framework presented here is a proof-of-concept and requires further validation and testing. Future studies should explore the performance of different RL algorithms, investigate the scalability of the approach to more complex ADL scenarios, and assess the effectiveness of the learned assistive strategies in real-world settings. It is also crucial to engage stakeholders, including PLWDs, caregivers, and healthcare professionals, in the design and evaluation process to ensure the developed solutions are effective, acceptable, and aligned with their needs and values.

In conclusion, our work presents a promising approach for developing intelligent and adaptive robotic assistance for PLWDs during ADLs. By leveraging simulated environments and reinforcement learning, we have taken a step towards addressing the challenges and opportunities in this important domain. However, much work remains to be done to realize the full potential of socially assistive robotics in dementia care. We hope our contributions will inspire further research and development efforts in this direction, ultimately leading to innovative solutions that can improve the lives of PLWDs and their caregivers.

Chapter 5

Robot-assisted Psycho-Education for Dementia Caregivers

5.1 Background

In 2021, more than 11 million Americans acted as an informal caregiver (e.g., family, friend, and other unpaid caregiver) for someone with ADRD, providing an estimated 16 billion hours of unpaid care ([Alzheimer’s Association, 2022](#)). This high level of burden associated with dementia caregiving negatively impact caregivers’ mental and physical health, increasing their risk for depression and poor health ([Brodaty and Donkin, 2009](#)). Spousal caregivers of people with ADRD have a six times greater risk of developing dementia ([Wennberg et al., 2015](#); [Larson and Stroud, 2021](#)). In addition, family caregivers often feel unprepared for their roles and responsibilities, uninformed about care options, and unsupported by professionals in their decision-making ([Xie et al., 2018](#)).

The Resources for Enhancing Caregiver Health (REACH), REACH II, REACH OUT (Offering Useful Treatments) as well as other caregiver intervention programs ([Elliott et al., 2010](#); [Czaja et al., 2018](#); [Wisniewski et al., 2003](#); [Gitlin et al., 2015](#); [Burgio et al., 2009](#)) have demonstrated significant benefits by addressing the complex

impact of caregiving on caregivers' emotional and physical health. These evidence-based REACH programs have been shown to lessen caregiver stress, improve mental health and quality of life, and increase satisfaction with caregiving across racial and ethnic groups (Elliott et al., 2010). However, equipping clinicians with the tools and skills to administer REACH programs is resource intensive and presents challenges in maintaining the integrity of their evidence-based design in real-world settings (Larson and Stroud, 2021; Gitlin et al., 2015; Burgio and Wynn, 2021). To address implementation barriers, additional studies, such as the REACH OUT caregiver support program, were designed to engage caregivers through home visits and phone calls over a 4-month period (Burgio et al., 2009). As a result, the translation of these REACH program into practice has been slow.

Recent advancements in artificial intelligence (AI) and AI empowered robotics technology demonstrate the potential to support humans in a variety of healthcare environments (Kyrarini et al., 2021; Yuan et al., 2021c). Employment of AI- and robot-assisted healthcare technologies could increase fidelity of intervention implementation (Yuan et al., 2021a). Currently older adults have not received the full benefit of these technologies when compared with their younger counterparts (Hargittai et al., 2019; Knowles and Hanson, 2018). While older adults may be eager and willing to adopt new technology, they are often hindered by a lack of support to learn about them and by a lack of access to these technologies (Wang et al., 2019).

Our long-term goal is to leverage AI and social robotics technology to speed up the translation of REACH OUT into practice, thereby allowing more caregivers access to the much needed support. In this article, we discussed our aim to develop a social robot-assisted psycho-educational program adapted from the REACH OUT program to support caregivers of people with ADRD in an engaging and interactive way. A usability study was conducted with dementia caregivers to evaluate user experience and satisfaction with our program.

5.2 Development of a Social Robot-assisted Psycho-educational Program

A humanoid social robot, Pepper (Pandey and Gelin, 2018), was adopted to implement a prototype of a psycho-educational support program for caregivers of people with dementia. The psycho-educational materials were created based on the contents recommended in REACH OUT (Burgio and Wynn, 2021). The Pepper robot is 1.2-m tall and 0.48-m wide and equipped with a 246-175-14.5-mm tablet in its chest. The robot has 17 joints for graceful and expressive gestures and other body language. It can appropriately adjust its body language (such as negative-emotion associated animation and questioning-related animation) as well as voice according to what it is saying. The Pepper robot is equipped with several LEDs in its eyes, ears and shoulders for color changing to signal and support human-robot communication. Pepper’s size and attractive appearance make it appropriate, acceptable, and enjoyable to users in daily life as well as research participants (Schüssler et al., 2020; Yuan et al., 2021c,a; Cobo Hurtado et al., 2021; Yuan et al., 2022b). Pepper can usually make good eye contact with the user during interaction. The tablet embodied in the robot makes it convenient to display the psycho-educational materials for caregivers. The capability of multimodal interaction in the Pepper robot has been suggested to enable more effective and engaging interaction for users during human-robot interaction (Bejan et al., 2018).

5.2.1 Psycho-educational Materials for Dementia Caregivers

The psycho-educational support program consisted of five modules, including *Alzheimer’s disease and caregiving* (Module 1), *safety* (Module 2), *healthy lifestyle* (Module 3), *stress and relaxation* (Module 4), as well as *caregiving challenges* (Module 5). All these modules were developed according to the clinician guide given by the skills training program in the REACH OUT (Burgio and Wynn, 2021). The modules were

further enriched with relevant materials provided by authorized reports and websites, such as Alzheimer's Association, American Association of Retired Persons (AARP), Family Caregiver Alliance, Strategies for Well-Being, and Dementia.org ([Alzheimer's Association, 2019](#); [Mayo Clinic, 2011](#); [Carbo, 2022, 2019](#); [Family Caregiver Alliance, 2022b,a](#)). The first module provided an introduction to ADRD (such as neurological perspective of ADRD, its early signs, and symptoms along the disease trajectory) and caregiving to help caregivers understand the disease, their role in caregiving as well as disease detection. The second module addressed home safety, presenting tips to make a safer environment for people with dementia, including bathroom, kitchen, bedroom, living room, laundry room, garage, shed and basement, outdoor, cooking, smoking, wandering, and others ([Mayo Clinic, 2011](#); [Carbo, 2022, 2019](#)). The third module focused on caregiver health and provided guidance on a healthy lifestyle, covering caregiver exercise, nutrition, sleep, and taking breaks. It has been reported that the long-duration, time-intensive dementia caregiving negatively impacts caregivers' mental and physical health, increasing their risk for depression and poor health ([Wennberg et al., 2015](#)). Therefore, the third module was included to help caregivers identify strategies to take care of themselves. The fourth module presented some simple but practical approaches to reduce stress and anxiety, aimed at assisting dementia caregivers in better managing their daily stress during the caregiving journey. This module first emphasized that because caregiving itself is tough, it is almost inevitable for a caregiver to feel stressed and anxious. This module also listed activities for caregiver breaks, such as practicing signal breath, walking, meditation, playing music, and respite services. The fifth module of caregiving challenges presented caregivers with potential challenging situations during the caregiving journey and provided guidance on managing them. It mentioned that ADRD can cause a person to act in different, unpredictable, or even violent ways, e.g., wandering and becoming lost, repetition, aggression, suspicions, and delusions ([Alzheimer's Association, 2019](#)). In addition, to make the program more empathetic, a story of caregiver isolation and loneliness was included in this module ([Family](#)

Caregiver Alliance, 2022a). Notably, the materials in this program were not aimed to replace any human professional or caregiver support program. Instead, we would like this program to be a basic but useful tool to support dementia caregivers. Information to encourage caregivers to ask for help from friends, relevant organizations, and professionals were included in all five modules. There is a sixth module, called national and local resources, in the REACH OUT (Burgio and Wynn, 2021). Due to expected changes in the needs a person with dementia and the caregiver has over the course of their illness, we believe the sixth module is better served as a printed tool which caregivers can keep and refer to. The sixth module will be included a future effectiveness study.

5.2.2 Prototype of a Social Robot-assisted Psycho-educational Program

A standalone app, named *FAIR REACH* (Friendly AI- and Robotics-based REACH), was developed in a Pepper robot to provide the psycho-educational intervention to dementia caregivers. To make the Pepper robot more intimate to caregivers, we renamed the robot as Tammy, one of the most popular girl names in Tennessee, during the interaction (The terms of “Pepper” and “Tammy” are used interchangeably in the rest of the manuscript). Using an Android Studio plug-in, QiSDK (SoftBank Robotics, 2021), the robot was programmed to provide the intervention to a user using multimodal interaction, including verbal language, body movements (e.g., gestures), as well as user-friendly graphical user interface (GUI) on its tablet. After clicking the app, a module selection layer was displayed in Pepper’s tablet, as shown in left figure of Figure A.30. At the same time, the robot provided a verbal instruction to facilitate the intervention, “Please click on the button in my tablet. There will be five modules about caregiving. Please choose one you would like to see”. After the user chose the specific module they were interested in, the robot Tammy provided a brief introduction to the module and the knowledge blocks (i.e., blocks of detailed

information). In addition, interactive approaches were designed and developed to enable the robot to deliver the program to the user in an engaging, interactive, and efficacious manner, as shown in Figure A.31. In a module, after presenting a knowledge block, the robot automatically asked the user one question relevant to the content. After the user responded to the robot’s question, Pepper would provide follow-up feedback/comments to the user. All the questions and feedback were hardcoded. Table A.31 lists several examples of follow-up questions and feedback by the robot in FAIR REACH app. Here, we designed and included the step of follow-up questions and feedbacks in our robot-assisted support program to help engage caregivers and encourage them to think about their own situation.

To maximize the utility of the program for caregivers, we included as much content as possible. Determining the specific content for each module was challenging given the wide array of behaviors or symptoms a person with ADRD may experience. Our goal was to include enough content to cover any topic a caregiver may want more information on. To accomplish this, we included a topic-selection layer in the GUI design and divided the content into simple topics. For example, Module *Safety* was divided into 11 topics, including bathroom, kitchen, bedroom, living room, laundry room, garage, shed and basement, outdoor, cooking, smoking, wandering, and others, with respect to the application environment of safety tips as illustrated in the right figure of Figure A.30. To make the program more user-friendly, the robot was designed to provide additional verbal instruction (e.g., “Please select the topics that you would like to hear more about in this presentation.”) for the next step in the topic-selection layer. A user can learn more information about their interested topic(s) by clicking the corresponding button(s).

Once the user clicks the button of interested topic, the robot automatically presents more information about this topic via speaking, gestures, and other body language as well as images and texts on its tablets. Figure A.32 shows two screenshots of the GUI on the robot’s tablet from the presentation of psycho-educational materials. As shown in these screenshots, when the robot displayed a presentation,

there were three buttons on its tablet, including “RETURN TO MENU”, “REPLAY”, and “CONTINUE”, which can be clicked by the user to go back to the previous layer (i.e., topic-selection layer or module-selection layer), replay the current materials, or skip current materials, respectively. These buttons can give users a sense of control of the program and make the intervention more informative and efficacious to them, while allowing them to skip the materials irrelevant or already known.

5.2.3 Prototype Verification and Refinement

In spite of our best effort, the early design of our robot-assisted psycho-educational program could be flawed. Before evaluating the program with a large number of caregivers, we invited one dementia caregiver (female, aged 65 – 75) to test the prototype to identify potential critical problems which might negatively influence user experience. This participant previously worked as a paid in-home caregiver, caring for her neighbor with dementia 4-8 hours per week. She believed the program would be useful to caregivers of people with dementia and reported a positive user experience with the user interface designs of the program. The program was easy to use for her. Additionally, she provided some suggestions on robot’s functions. She mentioned that the robot spoke too fast in Module 5, *Caregiving challenges*. On the basis of her own caregiving experience, the participant suggested the robot should display an image of medical ID such as a bracelet when presenting about the topic of wandering in Module *Safety*. Regarding the techniques of stress management and relaxation, the participant emphasized that if the music would not irritate their loved one with dementia, a caregiver can still play music for relaxation, even if the patient cannot follow the music. We modified the robot to speak more slowly in Module 5 and included this participant’s suggestions of dementia caregiving in the program according to this participant’s feedback.

5.3 Usability Study

5.3.1 Study Design and Participants

A pilot study was conducted to assess the acceptance, usability, and feasibility of this robot-assisted psycho-educational program with caregivers who provided care for people with dementia. User survey and observation approaches were applied for assessment. The study protocol was approved by the Institutional Review Board (IRB) (IRB number is UTK IRB-21-06631-XM). We recruited potential participants via emails. To reach more potential participants, we additionally recruited participants at a local senior center, O'Connor Senior Center, Knoxville, TN. Eligible participants included adults 1) aged between 18-95; 2) able to understand and speak English; 3) no severe hearing or visual impairments that would interfere with interactions with the robot; and 4) having experience in caring for a person with dementia. Participants who were interested and met the eligibility criteria were provided written and verbal information about this study. Data were collected at the O'Connor Senior Center, Knoxville, TN and the laboratory at the University of Tennessee, Knoxville, TN.

5.3.2 Experimental Procedure

The experimental procedure for this usability study is illustrated in Figure. [A.33](#). After obtaining written consent from the participant, the researcher provided a demographic survey to the participant to collect their descriptive information. The experiment started with an orientation or familiarization session, where the robot welcomed the participant and introduced itself, using a short talk conversation, dance, and/or song. This session can help participants become familiar with the robot and facilitate positive user experience and interactions with the robot. Then the participant used the psycho-educational program assisted by the robot. The participant could try as many modules as they wanted. During the experiment, the

researcher observed the human-robot interaction and made field notes for important experimental details. After the robot-assisted psycho-educational intervention, a post-test evaluation was conducted to learn the participant's perception (e.g., usability and acceptability) of the robot mediated intervention.

5.3.3 Data Collection

Quantitative data were collected using participant-rated questionnaires. Qualitative data were collected via the open-ended comments and field notes during the intervention.

Descriptive Measures

Data collected for the characteristics of participants consisted of demographic information (age, gender, education, and race/ethnicity), familiarity with technologies (including smartphones, tablets, computers, and robots), as well as dementia caregiving experience (including their relationship to care recipient, types of caregivers, and hours of caregiving per week).

Outcome Measures

A mixed-method approach, including observation, field notes, and participant-rated questionnaire, was used to evaluate the user experience (e.g., acceptance and usability) of the robot-assisted psycho-educational intervention among caregivers of people with dementia. During the experiment, the researcher observed participants' verbal and nonverbal (e.g., smiling, nodding, or frowning) interaction with the robot. The researcher also recorded potential critical problems in the program which resulted in negative user experience, and participants' thoughts, comments, and suggestions for the system.

After the intervention, a user questionnaire (post-test) was used to quantitatively assess user experience, satisfaction, and perceptions towards the robot-assisted psycho-educational program. The survey was adapted from the following questionnaires: the Questionnaire for User Interaction Satisfaction (QUIS) (Norman et al., 1998), System Usability Scale (SUS) (Brooke, 1996), Almere model (Heerink et al., 2010), and Computer System Usability Questionnaire (CSUQ) (Lewis, 1995). QUIS measures the users’ overall system satisfaction and user satisfaction on specific interface factors, including screen visibility, terminology, and system information, learning factors, and system capabilities (Norman et al., 1998). The administrator can adapt the items to analyze the sections that are of interest to the study. SUS is a simple tool providing a global view of subjective assessment of system usability (Brooke, 1996). The Almere model tests the acceptance of assistive social agents by elderly users that positively influence elderly users’ intention to use a system over a longer period. The CSUQ assesses users’ satisfaction with system usability, measuring system characteristics such as ease of use, ease of learning, simplicity, effectiveness, information, and the user interface (Lewis, 1995). To minimize the cognitive burden for participants, we adapted the four survey tools into one 13-item questionnaire, as shown in Table A.32. The items were selected based on our comprehensive content regarding the main constituents of usability in the robot-assisted psycho-educational program. The 13-item questionnaire assessed system characteristics including interface quality, information, system usefulness, system ease-of-use, and willingness to recommend. All these 13 sub items can be rated from *strongly disagree*, *somewhat disagree*, *neither agree nor disagree*, *somewhat agree*, to *strongly agree*. Finally, an open-ended question (i.e., “Please share your thoughts, experience, and comments about the FAIR-REACH program. Please provide any suggestions for improving the FAIR-REACH program.”) was included to gain more details and insights of how people think about this robot-assisted psycho-educational intervention. During the study, participants could skip any question they did not want to answer.

Data Analysis

Quantitative data were analyzed in terms of frequency, mean, standard deviation (SD), and proportions. Qualitative data consisting of participants' responses to open-ended question and researchers' observations of participant robot interaction were summarized

5.4 Results

Nine older adults (5 female and 4 male) were recruited to participate in this usability study. Seven participants tested the prototype FAIR REACH at a local senior center and two participants at the laboratory. Participants' demographic information is listed in Table A.33. Participants aged above 50, i.e., one participant aged 50 – 65, three aged 65 – 75, four aged 75 – 85, and one aged above 85. All participants reported an education of some college or higher. Seven out of nine participants reported themselves as informal caregivers, two reported as doctors and one reported as not a caregiver. One participant was a relative of person(s) with ADRD, two were a senior companion, and two were doctors for people with ADRD. Two participants provided caregiving under 4 hours per week, two provided caregiving 4-8 hours per week, and two participants provided care above 8 hours per week. With regard to familiarity with technologies, most participants were moderately or very familiar with the technologies of smartphones, tablets, and computers. Comparatively, five out of 6 participants (3 participants skipped this question) reported “not at all familiar” with robots and one reported “slightly familiar”.

Each participant tried at least two modules in the robot-assisted psycho-educational program. During the intervention, participants nodded or provided comments such as “That’s true” or “I didn’t realize this”. However, several participants skipped answering the robot’s questions by clicking the “NEXT” button. Participants’ responses (mean and standard deviation) to 13-item survey were plotted

in Figure A.34. Each bar corresponds to an item in Table A.32. The height of the bar represents the mean of participants' response to that item and the error bar represents the standard deviation of the responses. On average, participants provided a rating of above 4 for most items, except for Item Q5 and Q11. In addition, seven participants provided open-ended comments, as listed in Table A.34.

5.5 Discussion

In this study, we developed a robot-assisted psycho-educational program to support caregivers of people with dementia using a Pepper robot (Pandey and Gelin, 2018). The intervention consisted of five modules, including Alzheimer's disease and caregiving, safety information, healthy lifestyle guide, stress and relaxation, as well as caregiving challenges, aimed to help caregivers prepare themselves for their caregiving journey and provide guidance to enhance their physical and mental well-being. Nine older adults, who had experience of caring for people with dementia, were recruited to evaluate the system usability of the program. Participants were relative, senior companion, or doctors of people with dementia, or suggesting group work for people with dementia. We observed user-robot interaction during the intervention and used a post-intervention questionnaire to evaluate user experience and satisfaction. Overall, participants reported a positive user experience and satisfaction with our robot-assisted psycho-educational program. The program was rated as useful to dementia caregivers and perceived as easy to use.

5.5.1 User Experience and Satisfaction

Participants reported a high-quality user interface in our developed robot-assisted psycho-educational program. The robot's appearance (Item Q1, Mean = 4.63, SD = 0.74 in Figure A.34) was pleasing to participants. During the intervention, the robot's voice (Item Q2, Mean = 4.50, SD = 0.76) was clear to users and the robot's

body language (Item Q3, Mean = 4.50, SD = 0.76) was appropriate to them. Based on the bar plot for Item Q4 (Mean = 4.38, SD = 0.74), the GUI design such as the module-selection layout, topic-selection layout, and buttons in Figure A.30 and A.32 on robot’s tablet were attractive to participants. In Figure A.34, participants provided a low rating (Mean = 2.25, SD = 1.39) to Item Q5 (i.e., “It is hard to understand the robot’s instruction and know what to do”), indicating that the robot’s instructions were clear and understandable to users during the intervention. The participants’ high rating to Item 12 (Mean = 4.38, SD = 0.74) also demonstrated that our robot-assisted psycho-educational program was easy to use to them, although that majority of participants aged above 65. As for the psycho-educational materials in five modules presented by the robot, the modules were perceived useful, all with an average rating of 4.38 or greater (4 = *somewhat agree*), as shown in Figure A.34. Eight out of nine participants somewhat or strongly agreed that the modules were useful. Most participants expressed willingness to recommend our robot-assisted psycho-educational program to others, with a high rating to Item Q13 (Mean = 4.38, SD = 0.74) as shown in Figure A.34.

Another overall evaluation for our program is Item 11, i.e., “The program meets my expectation”. Compared to other items, participants provided a comparatively low response to this item, i.e., Mean = 3.63, SD = 1.77. Majority of participants somewhat or strongly agreed the statement of Item 11, while two participants strongly disagreed the statement. Both participants provided positive responses to the rest of the items, which suggests that they had positive user experience and high user satisfaction with the program. Both participants provided additional open-ended comment, “Will you continue to improve. Tammy’s vital information!” and “I have many thoughts on ‘when the human touch is needed’”. Herein we conjecture that there might be two potential reasons underlying their unmet expectation. First, the robot was still very limited in interaction capability or psycho-educational materials on dementia caregiving. Second, the robot Tammy cannot provide human touch. The need of touch was out of our expectation. However, such an interaction modality will

be taken into account in the future, considering that touch can buffer stress and have a calming effect on caregivers (Eckstein et al., 2020).

5.5.2 Open-ended Comments from caregivers

Seven participants provided additional comments in their survey. Comments such as “This program would be very useful” (P1), “All around great program” (P5), and “I think the program is very interesting and should help a lot” (P6) in Table A.34 reflected positive user experience and attitudes towards the robot-assisted psycho-educational intervention, which is consistent to the results in Figure A.34. Participant P1 indicated one potential benefit of using social robot, instead of computers, to deliver the intervention. The intervention delivered by the physically embodied social robot might be more engaging and effective and enable more positive user experience (Bejan et al., 2018; Yuan et al., 2021c). On the other hand, Participant P2 expressed doubts about using a social robot to deliver the intervention for dementia caregivers, who were presumably with normal cognitive capability, as listed in Table A.34. It might not be cost-effective to use the robot to simply deliver such psychoeducation to caregivers. However, considering the potential application of robotics in healthcare field over long term, the study here would be meaningful to dementia caregivers. Also, Participant P1 suggested to improve the robot’s capability of verbal communication when asking follow-up questions or providing follow-up comments during the intervention, which will be our next step.

5.5.3 Limitations and Future Work

Several limitations were identified in the usability study for the robot-assisted psycho-education. One limitation resides in the small sample size (9 participants), though this sample should be sufficient for identifying critical usability problems and improve interactive design (Alroobaea and Mayhew, 2014). It is a common challenge to recruit older adults to participate in research studies, especially those that involve

technologies such as robots. Additionally, the information (Section 5.2.1) included in current robot-assisted psycho-educational program can continue to be expanded and curated to better inform the users. Moreover, in the current prototype, all the follow-up questions and follow-up comments were hard coded in the robot, limiting the verbal communication between the caregiver and the robot. Our next step is to integrate advanced AI technology (such as OpenAI) in our robot-assisted program to improve its conversational capability and make the program more interactive and engaging. Another limitation in our robot-assisted intervention is lack of touch. One possible solution is to include a human facilitator into the program so that the robot and the facilitator would work collaboratively to deliver the intervention for caregivers. That is, the robot would present the materials and the facilitator would provide emotional support, e.g., hugging or touching caregivers. Another possibility is to develop the robot to touch or hug caregivers under appropriate conditions, which can also have a calming effect on users (Eckstein et al., 2020).

5.6 Summary

In this chapter, we discussed the design and development of a psycho-educational intervention using a humanoid social robot for caregivers of people with dementia. The results of the usability study demonstrated the feasibility of our program to support caregivers and to enhance their physical and mental well-being. Our next step is to integrate advanced AI to increase the interactive capabilities of the robot during the intervention and test the program effectiveness with a large number of dementia caregivers.

Chapter 6

Conclusion

My PhD research focused on developing socially assistive robotics (SAR) to enhance the cognitive, social, emotional, and physical well-being of persons living with Alzheimer’s Disease and Related Dementias (PLWDs) and their family caregivers. Utilizing the state-of-the-art humanoid robot, Pepper, we designed and developed several robotic prototypes for cognitive exercises, assistance, and dementia care education. These were extensively tested in clinics, assisted living facilities, and senior centers, providing critical insights into the practical challenges and opportunities within this domain.

Rooted in real-world experiences with PLWDs and their caregivers, my work consistently aimed to advance SAR and human-centered AI for dementia care. My interdisciplinary approach—integrating insights from nursing, occupational therapy, computer science, and human-computer interaction—ensured that our developments were holistic, addressing not only the physical but also emotional, social, and cognitive needs of PLWDs. Throughout this process, the primary focus was on PLWDs and their caregivers, prioritizing their needs to develop user-centered SAR solutions that bridge the gap between theoretical AI and robotic applications and practical dementia care.

To better understand the needs and attitudes of stakeholders towards the humanoid SAR, we employed multifaceted research methods, including online surveys. Gathering diverse perspectives was crucial in shaping our robotic solutions to meet end-user requirements effectively and ensure they were designed with the user at the forefront. From these insights, we developed and assessed robotic functionalities aimed at assisting PLWDs with daily living activities, psychosocial interventions, and dementia care education. Both semi-controlled lab environments and real-world settings were used for preliminary studies, providing affirmative results and valuable feedback for further enhancement.

Moreover, I explored various human-robot interaction (HRI) techniques such as teleoperation, causal inference, and reinforcement learning. These techniques were aimed at improving interactions by enhancing both verbal and non-verbal communication skills of the robot, such as its graphical user interface design, gestures, and eye movements. This research contributed significantly to developing adaptive and personalized robotic interactions.

Recognizing the lack of adequate evaluation tools in the field, I collaborated with cross-disciplinary experts to address the complex behaviors of PLWDs during interactions with robots. We developed a robust suite of evaluation strategies that intricately assess the dynamics of PLWD-robot interactions, capturing a wide range of cognitive, psychological, and physical states of PLWDs, alongside the operational status of the robots. These strategies provide a strong foundation for future developments, aiming to design more adaptive and personalized robotic interactions for dementia care.

While my studies have demonstrated the potential of SAR in enhancing dementia care from various perspectives, substantial work remains to improve their interactive and assistive capabilities. The goal is to evolve SAR into more intelligent, effective, adaptive, and personalized tools for real-world applications. Many PLWDs struggle to articulate their needs, both verbally and non-verbally. To bridge this communication gap, I plan to leverage AI-powered SAR with advanced multimodal sensing,

perception, and feedback capabilities. Although SARs are proficient in text-based interactions, their performance often diminishes with PLWDs due to their limited capacity to process verbal cues. Another significant challenge is the vast amount of data required to effectively train the robotic system for personalized dementia care. My proposed solution involves using generative AI to build synthetic datasets that augment real-world data, thus enhancing the training of embodied AI systems. Additionally, I will explore and integrate causal AI that mirrors human dementia care expertise into robot-PLWD interactions. These innovations will not only improve the efficiency of data utilization but also the robustness and explainability of AI-driven robots. Furthermore, maintaining the active involvement of PLWDs and other stakeholders will continue to be a crucial aspect of my research. This ensures that the practical applications of these robotic innovations are consistently tested and refined in real-world scenarios.

Bibliography

- Ab Aziz, A., Ahmad, F., Yusof, N., Ahmad, F. K., and Yusof, S. A. M. (2015). Designing a robot-assisted therapy for individuals with anxiety traits and states. In *2015 International Symposium on Agents, Multi-Agent Systems and Robotics (ISAMSR)*, pages 98–103. IEEE. [3](#), [7](#), [8](#), [10](#)
- Abdollahi, H., Mollahosseini, A., Lane, J. T., and Mahoor, M. H. (2017). A pilot study on using an intelligent life-like robot as a companion for elderly individuals with dementia and depression. In *2017 IEEE-RAS 17th International Conference on Humanoid Robotics (Humanoids)*, pages 541–546. IEEE. [13](#), [14](#)
- Adam, C., Johal, W., Pellier, D., Fiorino, H., and Pesty, S. (2016). Social human-robot interaction: A new cognitive and affective interaction-oriented architecture. In *International conference on social robotics*, pages 253–263. Springer. [24](#)
- Agrigoroaie, R. M. and Tapus, A. (2016). Developing a healthcare robot with personalized behaviors and social skills for the elderly. In *2016 11th ACM/IEEE International Conference on Human-Robot Interaction (HRI)*, pages 589–590. IEEE. [21](#)
- Ahn, H. S., Lee, M. H., Broadbent, E., and MacDonald, B. A. (2017). Is entertainment services of a healthcare service robot for older people useful to young people? In *2017 First IEEE International Conference on Robotic Computing (IRC)*, pages 330–335. IEEE. [6](#), [7](#), [9](#), [14](#)

- Alemi, M., Ghanbarzadeh, A., Meghdari, A., and Moghadam, L. J. (2016). Clinical application of a humanoid robot in pediatric cancer interventions. *International Journal of Social Robotics*, 8(5):743–759. [12](#), [16](#)
- Ali, S., Mehmood, F., Dancey, D., Ayaz, Y., Khan, M. J., Naseer, N., Amadeu, R. D. C., Sadia, H., and Nawaz, R. (2019). An adaptive multi-robot therapy for improving joint attention and imitation of asd children. *IEEE Access*, 7:81808–81825. [6](#)
- Alimardani, M. and Hiraki, K. (2017). Development of a real-time brain-computer interface for interactive robot therapy: an exploration of eeg and emg features during hypnosis. *International Journal of Computer and Information Engineering*, 11(2):187–195. [6](#), [15](#)
- Alroobaea, R. and Mayhew, P. J. (2014). How many participants are really enough for usability studies? In *2014 Science and Information Conference*, pages 48–56. IEEE. [65](#), [137](#)
- Alzheimer’s Association (2019). Behaviors: How to respond when dementia causes unpredictable behaviors. [Accessed January 8, 2022]. [127](#)
- Alzheimer’s Association (2022). 2022 alzheimer’s disease facts and figures. *Alzheimer’s & Association*, 18. [1](#), [48](#), [124](#)
- Aminuddin, R., Sharkey, A., and Levita, L. (2016). Interaction with the paro robot may reduce psychophysiological stress responses. In *2016 11th ACM/IEEE International Conference on Human-Robot Interaction (HRI)*, pages 593–594. IEEE. [3](#)
- Andriella, A., Suárez-Hernández, A., Segovia-Aguas, J., Torras, C., and Alenyà, G. (2019). Natural teaching of robot-assisted rearranging exercises for cognitive training. In *International Conference on Social Robotics*, pages 611–621. Springer. [20](#)

- Andruseac, G. G., Adochiei, R. I., Păsărică, A., Adochiei, F.-C., Corciovă, C., and Costin, H. (2015). Training program for dyslexic children using educational robotics. In *2015 E-Health and Bioengineering Conference (EHB)*, pages 1–4. IEEE. [3](#)
- Ansado, J., Chasen, C., Bouchard, S., Iakimova, G., and Northoff, G. (2020). How brain imaging provides predictive biomarkers for therapeutic success in the context of virtual reality cognitive training. *Neuroscience & Biobehavioral Reviews*. [15](#)
- Arnold, T. and Scheutz, M. (2017). The tactile ethics of soft robotics: Designing wisely for human–robot interaction. *Soft robotics*, 4(2):81–87. [24](#)
- Asprino, L., Gangemi, A., Nuzzolese, A. G., Presutti, V., and Russo, A. (2017). Knowledge-driven support for reminiscence on companion robots. In *AnSWeR@ESWC*, pages 51–55. [47](#)
- Astell, A. J., Bouranis, N., Hoey, J., Lindauer, A., Mihailidis, A., Nugent, C., Robillard, J. M., et al. (2019). Technology and dementia: The future is now. *Dementia and geriatric cognitive disorders*, 47(3):131–139. [64](#)
- Bannon, S. M., Reichman, M. R., Wang, K., Uppal, S., Grunberg, V. A., and Vranceanu, A.-M. (2022). A qualitative meta-synthesis of common and unique preferences for supportive services among persons with young onset dementia and their caregivers. *Dementia*, 21(2):519–539. [64](#)
- Barco Martelo, A. and Fosch Villaronga, E. (2017). Child-robot interaction studies: From lessons learned to guidelines. In *3rd Workshop on Child-Robot Interaction, CRI 2017*. [3](#), [19](#)
- Barto, D., Bird, C. W., Hamilton, D. A., and Fink, B. C. (2017). The simple video coder: A free tool for efficiently coding social video data. *Behavior research methods*, 49(4):1563–1568. [56](#)

- Beck, A., Yumak, Z., and Magnenat-Thalmann, N. (2017). 20 body movements generation for virtual characters and social robots. *Social signal processing*, page 273. [61](#)
- Beckerle, P., Salvietti, G., Unal, R., Prattichizzo, D., Rossi, S., Castellini, C., Hirche, S., Endo, S., Amor, H. B., Ciocarlie, M., et al. (2017). A human–robot interaction perspective on assistive and rehabilitation robotics. *Frontiers in neurorobotics*, 11:24. [8](#)
- Begum, M., Serna, R. W., Kontak, D., Allspaw, J., Kuczynski, J., Yanco, H. A., and Suarez, J. (2015). Measuring the efficacy of robots in autism therapy: How informative are standard hri metrics’. In *Proceedings of the Tenth Annual ACM/IEEE International Conference on Human-Robot Interaction*, pages 335–342. [13](#), [16](#)
- Bejan, A., Gündogdu, R., Butz, K., Müller, N., Kunze, C., and König, P. (2018). Using multimedia information and communication technology (ict) to provide added value to reminiscence therapy for people with dementia. *Zeitschrift für Gerontologie und Geriatrie*, 51(1):9–15. [46](#), [49](#), [60](#), [126](#), [137](#)
- Berridge, C., Demiris, G., and Kaye, J. (2021). Domain experts on dementia-care technologies: Mitigating risk in design and implementation. *Science and engineering ethics*, 27(1):1–24. [64](#)
- Bharatharaj, J., Huang, L., Mohan, R. E., Al-Jumaily, A., and Krägeloh, C. (2017). Robot-assisted therapy for learning and social interaction of children with autism spectrum disorder. *Robotics*, 6(1):4. [13](#), [14](#), [15](#), [16](#)
- Biswas, M. and Murray, J. (2016). The effects of cognitive biases in long-term human-robot interactions: case studies using three cognitive biases on marc the humanoid robot. In *International Conference on Social Robotics*, pages 148–158. Springer. [25](#)

- Biswas, M. and Murray, J. (2017). The effects of cognitive biases and imperfectness in long-term robot-human interactions: Case studies using five cognitive biases on three robots. *Cognitive Systems Research*, 43:266–290. [25](#)
- Borau, S., Otterbring, T., Laporte, S., and Fosso Wamba, S. (2021). The most human bot: Female gendering increases humanness perceptions of bots and acceptance of ai. *Psychology & Marketing*, 38(7):1052–1068. [50](#)
- Bothe, C., Weber, C., Magg, S., and Wermter, S. (2019). Eda: enriching emotional dialogue acts using an ensemble of neural annotators. *arXiv preprint arXiv:1912.00819*. [79](#)
- Botvinick, M., Ritter, S., Wang, J. X., Kurth-Nelson, Z., Blundell, C., and Hassabis, D. (2019). Reinforcement learning, fast and slow. *Trends in cognitive sciences*, 23(5):408–422. [11](#)
- Bozgeyikli, L., Bozgeyikli, E., Clevenger, M., Raij, A., Alqasemi, R., Sundarrao, S., and Dubey, R. (2015). Vr4vr: vocational rehabilitation of individuals with disabilities in immersive virtual reality environments. In *Proceedings of the 8th ACM International Conference on PErvasive Technologies Related to Assistive Environments*, pages 1–4. [10](#), [15](#)
- Brodaty, H. and Donkin, M. (2009). Family caregivers of people with dementia. *Dialogues in clinical neuroscience*, 11(2):217. [1](#), [43](#), [124](#)
- Brooke, J. (1996). Sus: a quick and dirty usability. *Usability evaluation in industry*, 189. [55](#), [95](#), [133](#)
- Burgio, L. D., Collins, I. B., Schmid, B., Wharton, T., McCallum, D., and DeCoster, J. (2009). Translating the reach caregiver intervention for use by area agency on aging personnel: The reach out program. *The Gerontologist*, 49(1):103–116. [124](#), [125](#)

- Burgio, L. D. and Wynn, M. J. (2021). *The REACH OUT Caregiver Support Program: A Skills Training Program for Caregivers of Persons with Dementia, Clinician Guide*. Oxford University Press. [125](#), [126](#), [128](#)
- Cangelosi, A. and Invitto, S. (2017). Human-robot interaction and neuroprosthetics: A review of new technologies. *IEEE Consumer Electronics Magazine*, 6(3):24–33. [8](#), [24](#)
- Cao, H.-L., Pop, C., Simut, R., Furnemónt, R., De Beir, A., Van de Perre, G., Esteban, P. G., Lefeber, D., and Vanderborght, B. (2015). Probolino: A portable low-cost social device for home-based autism therapy. In *International Conference on Social Robotics*, pages 93–102. Springer. [4](#)
- Cao, S., Qu, L., and Tian, L. (2021). Causal relationships between emotions and dialog acts. In *2021 9th International Conference on Affective Computing and Intelligent Interaction (ACII)*, pages 1–8. IEEE. [77](#)
- Carbo, C. (2019). Cooking and dementia: challenges, concerns and strategies from the caregivers’ perspective. [Accessed January 16, 2022]. [127](#)
- Carbo, D. (2022). Have a family member with dementia cooking safety tips. [Accessed January 16, 2022]. [127](#)
- Carós, M., Garolera, M., Radeva, P., and Giro-i Nieto, X. (2020). Automatic reminiscence therapy for dementia. In *Proceedings of the 2020 International Conference on Multimedia Retrieval*, pages 383–387. [63](#), [67](#)
- Casey, D., Felzmann, H., Pegman, G., Kouroupetroglou, C., Murphy, K., Koumpis, A., and Whelan, S. (2016). What people with dementia want: designing mario an acceptable robot companion. In *International conference on computers helping people with special needs*, pages 318–325. Springer. [18](#), [19](#)
- Castellini, C. (2016). Incremental learning of muscle synergies: from calibration to interaction. In *Human and Robot Hands*, pages 171–193. Springer. [21](#), [22](#)

- Cavallo, F., Esposito, R., Limosani, R., Manzi, A., Bevilacqua, R., Felici, E., Di Nuovo, A., Cangelosi, A., Lattanzio, F., and Dario, P. (2018). Robotic services acceptance in smart environments with older adults: user satisfaction and acceptability study. *Journal of medical Internet research*, 20(9):e264. [27](#), [28](#)
- Cerejeira, J., Lagarto, L., and Mukaetova-Ladinska, E. (2012). Behavioral and psychological symptoms of dementia. *Frontiers in neurology*, 3:73. [67](#)
- Chen, M., Herrera, F., and Hwang, K. (2018). Cognitive computing: architecture, technologies and intelligent applications. *Ieee Access*, 6:19774–19783. [25](#)
- Chevallier, C., Kohls, G., Troiani, V., Brodtkin, E. S., and Schultz, R. T. (2012). The social motivation theory of autism. *Trends in cognitive sciences*, 16(4):231–239. [23](#)
- Chisholm, D., Toto, P., Raina, K., Holm, M., and Rogers, J. (2014). Evaluating capacity to live independently and safely in the community: Performance assessment of self-care skills. *British Journal of Occupational Therapy*, 77(2):59–63. [85](#), [86](#), [94](#), [110](#), [114](#), [115](#)
- Chu, M.-T., Khosla, R., Khaksar, S. M. S., and Nguyen, K. (2017). Service innovation through social robot engagement to improve dementia care quality. *Assistive Technology*, 29(1):8–18. [9](#), [12](#), [13](#), [16](#)
- Chumkamon, S., Hayashi, E., and Koike, M. (2016). Intelligent emotion and behavior based on topological consciousness and adaptive resonance theory in a companion robot. *Biologically Inspired Cognitive Architectures*, 18:51–67. [24](#)
- Clabaugh, C. E., Mahajan, K., Jain, S., Pakkar, R., Becerra, D., Shi, Z., Deng, E., Lee, R., Ragusa, G., and Mataric, M. (2019). Long-term personalization of an in-home socially assistive robot for children with autism spectrum disorders. *Frontiers in Robotics and AI*, 6:110. [11](#)
- Cobo Hurtado, L., Viñas, P. F., Zalama, E., Gómez-García-Bermejo, J., Delgado, J. M., and Vielba García, B. (2021). Development and usability validation of a

- social robot platform for physical and cognitive stimulation in elder care facilities. In *Healthcare*, volume 9, page 1067. Multidisciplinary Digital Publishing Institute. [49](#), [87](#), [126](#)
- Coco, K., Kangasniemi, M., and Rantanen, T. (2018). Care personnel’s attitudes and fears toward care robots in elderly care: a comparison of data from the care personnel in finland and japan. *Journal of Nursing Scholarship*, 50(6):634–644. [28](#), [45](#)
- Coeckelbergh, M., Pop, C., Simut, R., Peca, A., Pinte, S., David, D., and Vanderborght, B. (2016). A survey of expectations about the role of robots in robot-assisted therapy for children with asd: ethical acceptability, trust, sociability, appearance, and attachment. *Science and engineering ethics*, 22(1):47–65. [4](#), [11](#), [18](#), [23](#)
- Conti, D., Di Nuovo, S., Buono, S., Trubia, G., and Di Nuovo, A. (2015). Use of robotics to stimulate imitation in children with autism spectrum disorder: A pilot study in a clinical setting. In *2015 24th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN)*, pages 1–6. IEEE. [13](#)
- Coşar, S., Fernandez-Carmona, M., Agrigoroaie, R., Pages, J., Ferland, F., Zhao, F., Yue, S., Bellotto, N., and Tapus, A. (2020). Enrichme: Perception and interaction of an assistive robot for the elderly at home. *International Journal of Social Robotics*, 12(3):779–805. [40](#)
- Costescu, C. A., Vanderborght, B., and David, D. O. (2015). Reversal learning task in children with autism spectrum disorder: a robot-based approach. *Journal of autism and developmental disorders*, 45(11):3715–3725. [13](#), [15](#)
- Cuevas, P. E. G., Davidson, P. M., Mejilla, J. L., and Rodney, T. W. (2020). Reminiscence therapy for older adults with alzheimer’s disease: a literature review. *International journal of mental health nursing*, 29(3):364–371. [49](#), [62](#)

- Czaja, S. J., Lee, C. C., Perdomo, D., Loewenstein, D., Bravo, M., Moxley, PhD, J. H., and Schulz, R. (2018). Community reach: An implementation of an evidence-based caregiver program. *The Gerontologist*, 58(2):e130–e137. [124](#)
- Darragh, M., Ahn, H. S., MacDonald, B., Liang, A., Peri, K., Kerse, N., and Broadbent, E. (2017). Homecare robots to improve health and well-being in mild cognitive impairment and early stage dementia: results from a scoping study. *Journal of the American Medical Directors Association*, 18(12):1099–e1. [11](#), [14](#), [15](#), [21](#)
- David, D. O., Costescu, C. A., Matu, S., Szentagotai, A., and Doborean, A. (2018). Developing joint attention for children with autism in robot-enhanced therapy. *International Journal of Social Robotics*, 10(5):595–605. [12](#), [13](#)
- de Graaf, M. M., Allouch, S. B., and Van Dijk, J. (2015). What makes robots social?: A user’s perspective on characteristics for social human-robot interaction. In *International Conference on Social Robotics*, pages 184–193. Springer. [24](#)
- Dementia UK (2022). Meaningful activities part four: Reminiscence. [48](#), [51](#)
- Demetriadis, S., Tsiatsos, T., Sapounidis, T., Tsolaki, M., and Gerontidis, A. (2016). Exploring the potential of programming tasks to benefit patients with mild cognitive impairment. In *Proceedings of the 9th ACM International Conference on PErvasive Technologies Related to Assistive Environments*, pages 1–4. [17](#)
- Dennett, D. C. (1989). *The intentional stance*. MIT press. [23](#)
- Derek, M., Chan, J., and Nejat, G. (2012). A socially assistive robot for meal-time cognitive interventions. *Journal of Medical Devices*, 6(1):017559. [85](#)
- Dham, P., Bingham, K. S., Bowie, C. R., Butters, M. A., Fischer, C. E., Flint, A., Herrmann, N., Kumar, S., Mah, L., Mulsant, B. H., et al. (2020). Functional competence and cognition in individuals with amnesic mild cognitive impairment. *Journal of the American Geriatrics Society*, 68(8):1787–1795. [86](#), [114](#)

- Di Nuovo, A., Broz, F., Wang, N., Belpaeme, T., Cangelosi, A., Jones, R., Esposito, R., Cavallo, F., and Dario, P. (2018). The multi-modal interface of robot-era multi-robot services tailored for the elderly. *Intelligent Service Robotics*, 11(1):109–126. [27](#)
- Dickerson, B. C. (2015). Dysfunction of social cognition and behavior. *Continuum (Minneapolis, Minn.)*, 21(3 BEHAVIORAL NEUROLOGY AND NEUROPSYCHIATRY):660. [3](#)
- Dijkstra, K., Bourgeois, M. S., Allen, R. S., and Burgio, L. D. (2004). Conversational coherence: Discourse analysis of older adults with and without dementia. *Journal of Neurolinguistics*, 17(4):263–283. [69](#)
- Doraiswamy, P. M., London, E., Varnum, P., Harvey, B., Saxena, S., Tottman, S., Campbell, P., Ibáñez, A. F., Manji, H., and Al Olama, M. A. A. S. (2019). Empowering 8 billion minds: Enabling better mental health for all via the ethical adoption of technologies. *NAM Perspectives*. [19](#)
- Dragone, M., Amato, G., Bacciu, D., Chessa, S., Coleman, S., Di Rocco, M., Gallicchio, C., Gennaro, C., Lozano, H., Maguire, L., et al. (2015). A cognitive robotic ecology approach to self-configuring and evolving aal systems. *Engineering Applications of Artificial Intelligence*, 45:269–280. [24](#)
- Dubois, M., Claret, J.-A., Basañez, L., and Venture, G. (2016). Influence of emotional motions in human-robot interactions. In *International Symposium on Experimental Robotics*, pages 799–808. Springer. [24](#)
- Eckstein, M., Mamaev, I., Ditzen, B., and Sailer, U. (2020). Calming effects of touch in human, animal, and robotic interaction—scientific state-of-the-art and technical advances. *Frontiers in psychiatry*, page 1153. [137](#), [138](#)

- Elliott, A. F., Burgio, L. D., and DeCoster, J. (2010). Enhancing caregiver health: findings from the resources for enhancing alzheimer’s caregiver health ii intervention. *Journal of the American Geriatrics Society*, 58(1):30–37. [124](#), [125](#)
- Esteban, P. G., Baxter, P., Belpaeme, T., Billing, E., Cai, H., Cao, H.-L., Coeckelbergh, M., Costescu, C., David, D., De Beir, A., et al. (2017). How to build a supervised autonomous system for robot-enhanced therapy for children with autism spectrum disorder. *Paladyn, Journal of Behavioral Robotics*, 8(1):18–38. [3](#)
- Evans, S. C., Garabedian, C., and Bray, J. (2019). ‘now he sings’. the my musical memories reminiscence programme: Personalised interactive reminiscence sessions for people living with dementia. *Dementia*, 18(3):1181–1198. [46](#)
- Family Caregiver Alliance (2022a). Caregiver isolation and loneliness. [Accessed January 16, 2022]. [127](#)
- Family Caregiver Alliance (2022b). Taking care of you: Self-care for family caregivers. [Accessed January 28, 2022]. [127](#)
- Faucounau, V., Wu, Y.-H., Boulay, M., Maestrutti, M., Rigaud, A.-S., et al. (2009). Caregivers’ requirements for in-home robotic agent for supporting community-living elderly subjects with cognitive impairment. *Technology and Health Care*, 17(1):33–40. [42](#)
- Fiske, A., Henningsen, P., and Buyx, A. (2019). Your robot therapist will see you now: ethical implications of embodied artificial intelligence in psychiatry, psychology, and psychotherapy. *Journal of medical Internet research*, 21(5):e13216. [18](#)
- Flandorfer, P. (2012). Population ageing and socially assistive robots for elderly persons: the importance of sociodemographic factors for user acceptance. *International Journal of Population Research*, 2012. [28](#)
- Frith, C. D. and Frith, U. (1999). Interacting minds—a biological basis. *Science*, 286(5445):1692–1695. [23](#)

- Gamborino, E., Herrera Ruiz, A., Wang, J.-F., Tseng, T.-Y., Yeh, S.-L., and Fu, L.-C. (2021). Towards effective robot-assisted photo reminiscence: Personalizing interactions through visual understanding and inferring. In *International Conference on Human-Computer Interaction*, pages 335–349. Springer. [47](#), [48](#)
- Garcia-Sanjuan, F., Jaen, J., and Nacher, V. (2017). Tangibot: a tangible-mediated robot to support cognitive games for ageing people—a usability study. *Pervasive and Mobile Computing*, 34:91–105. [13](#), [16](#)
- Gerling, K., Hebesberger, D., Dondrup, C., Körtner, T., and Hanheide, M. (2016). Robot deployment in long-term care. *Zeitschrift für Gerontologie und Geriatrie*, 49(4):288–297. [19](#)
- Ghafurian, M., Hoey, J., and Dautenhahn, K. (2021). Social robots for the care of persons with dementia: a systematic review. *ACM Transactions on Human-Robot Interaction (THRI)*, 10(4):1–31. [84](#), [103](#), [112](#)
- Gitlin, L. N., Marx, K., Stanley, I. H., and Hodgson, N. (2015). Translating evidence-based dementia caregiving interventions into practice: State-of-the-science and next steps. *The Gerontologist*, 55(2):210–226. [124](#), [125](#)
- Goodman-Casanova, J. M., Dura-Perez, E., Guzman-Parra, J., Cuesta-Vargas, A., and Mayoral-Cleries, F. (2020). Telehealth home support during covid-19 confinement for community-dwelling older adults with mild cognitive impairment or mild dementia: survey study. *Journal of Medical Internet Research*, 22(5):e19434. [77](#)
- Gowans, G., Campbell, J., Alm, N., Dye, R., Astell, A., and Ellis, M. (2004). Designing a multimedia conversation aid for reminiscence therapy in dementia care environments. In *CHI’04 Extended Abstracts on Human Factors in Computing Systems*, pages 825–836. [70](#)

- Grimm, P. (2010). Social desirability bias. *Wiley international encyclopedia of marketing*. [101](#)
- Hargittai, E., Piper, A. M., and Morris, M. R. (2019). From internet access to internet skills: digital inequality among older adults. *Universal Access in the Information Society*, 18(4):881–890. [125](#)
- Haring, K. S., Silvera-Tawil, D., Watanabe, K., and Velonaki, M. (2016). The influence of robot appearance and interactive ability in hri: a cross-cultural study. In *International conference on social robotics*, pages 392–401. Springer. [4](#)
- Hartson, R. and Pyla, P. S. (2018). *The UX book: Agile UX design for a quality user experience*. Morgan Kaufmann. [14](#), [27](#), [44](#)
- Havins, W. N., Massman, P. J., and Doody, R. (2012). Factor structure of the geriatric depression scale and relationships with cognition and function in alzheimer’s disease. *Dementia and geriatric cognitive disorders*, 34(5-6):360–372. [3](#)
- HealthinAging.org (Accessed December 30, 2022). Caregiver guide: Problems of daily living. [84](#)
- Heerink, M., Kröse, B., Evers, V., and Wielinga, B. (2010). Assessing acceptance of assistive social agent technology by older adults: the almere model. *International journal of social robotics*, 2(4):361–375. [28](#), [38](#), [39](#), [55](#), [133](#)
- Heins, S., Dehem, S., Montedoro, V., Dehez, B., Edwards, M., Stoquart, G., Rocca, F., De Deken, P.-H., Mancas, M., and Lejeune, T. (2017). Robotic-assisted serious game for motor and cognitive post-stroke rehabilitation. In *2017 IEEE 5th International Conference on Serious Games and Applications for Health (SeGAH)*, pages 1–8. IEEE. [9](#)
- Hemminahaus, J. and Kopp, S. (2017). Towards adaptive social behavior generation for assistive robots using reinforcement learning. In *2017 12th ACM/IEEE*

International Conference on Human-Robot Interaction (HRI), pages 332–340. IEEE.

[67](#)

Henschel, A., Hortensius, R., and Cross, E. S. (2020). Social cognition in the age of human–robot interaction. *Trends in Neurosciences*. [23](#)

Hofer, J., Busch, H., Šolcová, I. P., and Tavel, P. (2017). When reminiscence is harmful: The relationship between self-negative reminiscence functions, need satisfaction, and depressive symptoms among elderly people from cameroon, the czech republic, and germany. *Journal of Happiness Studies*, 18(2):389–407. [69](#), [75](#)

Huijnen, C. A., Lexis, M. A., and de Witte, L. P. (2016). Matching robot kaspar to autism spectrum disorder (asd) therapy and educational goals. *International Journal of Social Robotics*, 8(4):445–455. [3](#), [22](#)

Hwang, Y., Massimo, L., Aryal, S., and Hodgson, N. A. (2022). The relationship between social isolation and anxiety in people with cognitive impairment in the united states. *International Journal of Geriatric Psychiatry*, 37(2). [77](#)

Ioannou, A., Kartapanis, I., and Zaphiris, P. (2015). Social robots as co-therapists in autism therapy sessions: a single-case study. In *International Conference on Social Robotics*, pages 255–263. Springer. [9](#), [12](#), [13](#), [15](#)

Ishikawa, K. M., Davis, J., Chen, J. J., and Lim, E. (2022). The prevalence of mild cognitive impairment by aspects of social isolation. *PLOS One*, 17(6):e0269795. [76](#)

Javed, H., Cabibihan, J.-J., Aldosari, M., and Al-Attiyah, A. (2016). Culture as a driver for the design of social robots for autism spectrum disorder interventions in the middle east. In *International Conference on Social Robotics*, pages 591–599. Springer. [21](#)

Javed, H., Jeon, M., and Park, C. H. (2018). Adaptive framework for emotional engagement in child-robot interactions for autism interventions. In *2018 15th*

- International Conference on Ubiquitous Robots (UR)*, pages 396–400. IEEE. [10](#), [11](#)
- Jing, H., Lun, X., Dan, L., Zhijie, H., and Zhiliang, W. (2015). Cognitive emotion model for eldercare robot in smart home. *China Communications*, 12(4):32–41. [25](#)
- Johal, W., Calvary, G., and Pesty, S. (2015). Non-verbal signals in hri: Interference in human perception. In *International Conference on Social Robotics*, pages 275–284. Springer. [5](#)
- Jones, A., Küster, D., Basedow, C. A., Alves-Oliveira, P., Serholt, S., Hastie, H., Corrigan, L. J., Barendregt, W., Kappas, A., Paiva, A., et al. (2015). Empathic robotic tutors for personalised learning: A multidisciplinary approach. In *International conference on social robotics*, pages 285–295. Springer. [19](#)
- Kajopoulos, J., Wong, A. H. Y., Yuen, A. W. C., Dung, T. A., Kee, T. Y., and Wykowska, A. (2015). Robot-assisted training of joint attention skills in children diagnosed with autism. In *International Conference on Social Robotics*, pages 296–305. Springer. [2](#), [12](#), [15](#)
- Kalisch, M., Hauser, A., Maechler, M., Colombo, D., Entner, D., Hoyer, P., Hyttinen, A., Peters, J., Andri, N., Perkovic, E., et al. (2021). pcalg: Methods for graphical models and causal inference. *R Package retrieved from https://CRAN.R-project.org/package=pcalg*. [79](#), [80](#)
- Karimah, S. N. and Hasegawa, S. (2021). Automatic engagement recognition for distance learning systems: A literature study of engagement datasets and methods. In *International Conference on Human-Computer Interaction*, pages 264–276. Springer. [83](#)
- Keleman, A. A., Bollinger, R. M., Ances, B. M., and Stark, S. L. (2021). Amyloid accumulation associated with worse performance of complex task. *Alzheimer’s & Dementia*, 17:e054605. [86](#), [114](#)

- Khan, A., Bleth, A., Bakpayev, M., and Imtiaz, N. (2022). Reminiscence therapy in the treatment of depression in the elderly: Current perspectives. *Journal of Ageing and Longevity*, 2(1):34–48. [46](#), [60](#), [64](#)
- Khosla, R., Nguyen, K., and Chu, M.-T. (2017). Human robot engagement and acceptability in residential aged care. *International Journal of Human–Computer Interaction*, 33(6):510–522. [12](#), [13](#), [14](#), [44](#)
- Kim, G. H., Jeon, S., Im, K., Kwon, H., Lee, B. H., Kim, G. Y., Jeong, H., Han, N. E., Seo, S. W., Cho, H., et al. (2015). Structural brain changes after traditional and robot-assisted multi-domain cognitive training in community-dwelling healthy elderly. *PloS one*, 10(4). [12](#), [13](#), [15](#), [17](#)
- Kim, T. and Vossen, P. (2021). Emoberta: Speaker-aware emotion recognition in conversation with roberta. *arXiv preprint arXiv:2108.12009*. [79](#)
- Klapper, A., Ramsey, R., Wigboldus, D., and Cross, E. S. (2014). The control of automatic imitation based on bottom-up and top-down cues to animacy: Insights from brain and behavior. *Journal of cognitive neuroscience*, 26(11):2503–2513. [23](#)
- Knopman, D. S. (2021). Young-onset dementia—new insights for an underappreciated problem. *JAMA neurology*, 78(9):1055–1056. [64](#)
- Knowles, B. and Hanson, V. L. (2018). The wisdom of older technology (non) users. *Communications of the ACM*, 61(3):72–77. [125](#)
- Kobayashi, M., Kosugi, A., Takagi, H., Nemoto, M., Nemoto, K., Arai, T., and Yamada, Y. (2019). Effects of age-related cognitive decline on elderly user interactions with voice-based dialogue systems. In *IFIP Conference on Human-Computer Interaction*, pages 53–74. Springer. [67](#)
- Kohori, T., Hirayama, S., Hara, T., Muramatsu, M., Naganuma, H., Yamano, M., Ichikawa, K., Matsumoto, H., and Uchiyama, H. (2017). Development and

- evaluation of an interactive therapy robot. In *International Conference on Advances in Computer Entertainment*, pages 66–83. Springer. [4](#), [11](#)
- Korchut, A., Szklener, S., Abdelnour, C., Tantinya, N., Hernández-Farigola, J., Ribes, J. C., Skrobas, U., Grabowska-Aleksandrowicz, K., Szczęśniak-Stańczyk, D., and Rejdak, K. (2017). challenges for service robots—requirements of elderly adults with cognitive impairments. *Frontiers in neurology*, 8:228. [11](#), [42](#)
- Kostavelis, I., Giakoumis, D., Malasiotis, S., and Tzovaras, D. (2015). Ramcip: Towards a robotic assistant to support elderly with mild cognitive impairments at home. In *International Symposium on Pervasive Computing Paradigms for Mental Health*, pages 186–195. Springer. [18](#), [21](#), [23](#), [24](#)
- Koster-Hale, J. and Saxe, R. (2013). Theory of mind: a neural prediction problem. *Neuron*, 79(5):836–848. [23](#)
- Kotseruba, I., Gonzalez, O. J. A., and Tsotsos, J. K. (2016). A review of 40 years of cognitive architecture research: Focus on perception, attention, learning and applications. *arXiv preprint arXiv:1610.08602*, pages 1–74. [25](#)
- Kruse, C. S., Fohn, J., Ummunnakwe, G., Patel, K., and Patel, S. (2020). Evaluating the facilitators, barriers, and medical outcomes commensurate with the use of assistive technology to support people with dementia: A systematic review literature. In *Healthcare*, volume 8, page 278. Multidisciplinary Digital Publishing Institute. [1](#), [42](#)
- Kyrarini, M., Lygerakis, F., Rajavenkatanarayanan, A., Sevastopoulos, C., Nambiappan, H. R., Chaitanya, K. K., Babu, A. R., Mathew, J., and Makedon, F. (2021). A survey of robots in healthcare. *Technologies*, 9(1):8. [125](#)
- Larson, E. B. and Stroud, C. (2021). Meeting the challenge of caring for persons living with dementia and their care partners and caregivers: A report from the national

- academies of sciences, engineering, and medicine. *Jama*, 325(18):1831–1832. [124](#), [125](#)
- Law, M., Sutherland, C., Ahn, H. S., MacDonald, B. A., Peri, K., Johanson, D. L., Vajsakovic, D.-S., Kerse, N., and Broadbent, E. (2019). Developing assistive robots for people with mild cognitive impairment and mild dementia: a qualitative study with older adults and experts in aged care. *BMJ open*, 9(9):e031937. [11](#), [40](#)
- Lemaignan, S., Fink, J., Mondada, F., and Dillenbourg, P. (2015). You’re doing it wrong! studying unexpected behaviors in child-robot interaction. In *International Conference on Social Robotics*, pages 390–400. Springer. [25](#)
- Leong, T. W. and Johnston, B. (2016). Co-design and robots: a case study of a robot dog for aging people. In *International Conference on Social Robotics*, pages 702–711. Springer. [19](#)
- Lewis, J. R. (1995). Ibm computer usability satisfaction questionnaires: psychometric evaluation and instructions for use. *International Journal of Human-Computer Interaction*, 7(1):57–78. [95](#), [96](#), [133](#)
- Li, J. (2015). The benefit of being physically present: A survey of experimental works comparing copresent robots, telepresent robots and virtual agents. *International Journal of Human-Computer Studies*, 77:23–37. [2](#)
- Li, Y., Li, K., Ning, H., Xia, X., Guo, Y., Wei, C., Cui, J., and Wang, B. (2021). Towards an online empathetic chatbot with emotion causes. In *Proceedings of the 44th International ACM SIGIR Conference on Research and Development in Information Retrieval*, pages 2041–2045. [77](#)
- Lins, A. A., de Oliveira, J. M., Rodrigues, J. J., and de Albuquerque, V. H. C. (2019). Robot-assisted therapy for rehabilitation of children with cerebral palsy-a complementary and alternative approach. *Computers in Human Behavior*, 100:152–167. [3](#), [6](#), [14](#), [15](#), [16](#), [21](#)

- Liu, Z., Collier, P., Wang, C., Paek, E.-J., Yoon, S.-O., Casenhiser, D., and Zhao, X. (2021). A demonstration of human-robot communication based on multiskilled language-image analysis. In *CHASE 2021: IEEE/ACM Conference on Connected Health: Applications, Systems and Engineering Technologies, Washington D.C.* [1](#)
- Liu, Z., Yang, D., Wang, Y., Lu, M., and Li, R. (2023). Egnn: Graph structure learning based on evolutionary computation helps more in graph neural networks. *Applied Soft Computing*, 135:110040. [84](#)
- Loh, J. (2019). Responsibility and robot ethics: A critical overview. *Philosophies*, 4(4):58. [18](#)
- Lopez-Samaniego, L. and Garcia-Zapirain, B. (2016). A robot-based tool for physical and cognitive rehabilitation of elderly people using biofeedback. *International journal of environmental research and public health*, 13(12):1176. [6](#), [9](#), [17](#), [25](#)
- LoPresti, E. F., Bodine, C., and Lewis, C. (2008). Assistive technology for cognition [understanding the needs of persons with disabilities]. *IEEE Engineering in Medicine and Biology Magazine*, 27(2):29–39. [1](#)
- Lorenz, T., Weiss, A., and Hirche, S. (2016). Synchrony and reciprocity: Key mechanisms for social companion robots in therapy and care. *International Journal of Social Robotics*, 8(1):125–143. [25](#)
- Magyar, J., Kobayashi, M., Nishio, S., Sinčák, P., and Ishiguro, H. (2019). Autonomous robotic dialogue system with reinforcement learning for elderlies with dementia. In *2019 IEEE International Conference on Systems, Man and Cybernetics (SMC)*, pages 3416–3421. IEEE. [67](#)
- Maharani, A., Zaidi, S. N. Z., Jury, F., Vatter, S., Hill, D., and Leroi, I. (2022). The long-term impact of loneliness and social isolation on depression and anxiety in memory clinic attendees and their care partners: A longitudinal actor–partner

- interdependence model. *Alzheimer's & Dementia: Translational Research & Clinical Interventions*, 8(1):e12235. [76](#)
- Manca, M., Paternò, F., Santoro, C., Zedda, E., Braschi, C., Franco, R., and Sale, A. (2021). The impact of serious games with humanoid robots on mild cognitive impairment older adults. *International Journal of Human-Computer Studies*, 145:102509. [2](#), [42](#)
- Marchesi, S., Ghiglino, D., Ciardo, F., Perez-Osorio, J., Baykara, E., and Wykowska, A. (2019). Do we adopt the intentional stance toward humanoid robots? *Frontiers in psychology*, 10:450. [23](#)
- Marino, F., Chilà, P., Sfrazzetto, S. T., Carrozza, C., Crimi, I., Failla, C., Busà, M., Bernava, G., Tartarisco, G., Vagni, D., et al. (2019). Outcomes of a robot-assisted social-emotional understanding intervention for young children with autism spectrum disorders. *Journal of Autism and Developmental Disorders*, pages 1–15. [3](#), [12](#), [13](#), [15](#)
- Matarić, M. J. (2017). Socially assistive robotics: Human augmentation versus automation. *Science Robotics*, 2(4):eaam5410. [24](#)
- Mayo Clinic (2011). Home safety tips: Preparing for alzheimer’s caregiving. [Accessed January 16, 2022]. [127](#)
- McCabe, M., You, E., and Tatangelo, G. (2016). Hearing their voice: a systematic review of dementia family caregivers’ needs. *The Gerontologist*, 56(5):e70–e88. [43](#)
- McCallum, S. and Boletsis, C. (2013). Dementia games: A literature review of dementia-related serious games. In *International conference on serious games development and applications*, pages 15–27. Springer. [2](#)
- McColl, D. and Nejat, G. (2013). Meal-time with a socially assistive robot and older adults at a long-term care facility. *Journal of Human-Robot Interaction*, 2(1):152–171. [85](#)

- Melo, F. S., Sardinha, A., Belo, D., Couto, M., Faria, M., Farias, A., Gamboa, H., Jesus, C., Kinarullathil, M., Lima, P., et al. (2019). Project inside: towards autonomous semi-unstructured human–robot social interaction in autism therapy. *Artificial intelligence in medicine*, 96:198–216. [5](#), [7](#), [9](#)
- Méndez-Molina, A., Morales, E. F., and Sucar, L. E. (2022). Causal discovery and reinforcement learning: A synergistic integration. In *International Conference on Probabilistic Graphical Models*, pages 421–432. PMLR. [83](#)
- Miner, A. S., Shah, N., Bullock, K. D., Arnow, B. A., Bailenson, J., and Hancock, J. (2019). Key considerations for incorporating conversational ai in psychotherapy. *Frontiers in Psychiatry*, 10. [77](#)
- Miskam, M. A., Shamsuddin, S., Yussof, H., Ariffin, I. M., and Omar, A. R. (2015). A questionnaire-based survey: Therapist’s response on emotions gestures using humanoid robot for autism. In *2015 International Symposium on Micro-NanoMechatronics and Human Science (MHS)*, pages 1–7. IEEE. [4](#), [8](#)
- Mois, G., Collete, B. A., Renzi-Hammond, L. M., Boccanfuso, L., Ramachandran, A., Gibson, P., Emerson, K. G., and Beer, J. M. (2020). Understanding robots’ potential to facilitate piano cognitive training in older adults with mild cognitive impairment. In *Companion of the 2020 ACM/IEEE International Conference on Human-Robot Interaction*, pages 363–365. [5](#), [7](#), [17](#)
- Moniruzzaman, M., Rassau, A., Chai, D., and Islam, S. M. S. (2022). Teleoperation methods and enhancement techniques for mobile robots: A comprehensive survey. *Robotics and Autonomous Systems*, 150:103973. [85](#)
- Moon, S. and Park, K. (2020). The effect of digital reminiscence therapy on people with dementia: a pilot randomized controlled trial. *BMC geriatrics*, 20:1–11. [50](#)
- Mori, M., MacDorman, K. F., and Kageki, N. (2012). The uncanny valley [from the field]. *IEEE Robotics & Automation Magazine*, 19(2):98–100. [4](#)

- Motger, Q., Franch, X., and Marco, J. (2022). Software-based dialogue systems: Survey, taxonomy and challenges. *ACM Comput. Surv.* Just Accepted. [77](#)
- Müller, V. C. (2020). Ethics of artificial intelligence and robotics. In Zalta, E. N., editor, *The Stanford Encyclopedia of Philosophy*. Metaphysics Research Lab, Stanford University, winter 2020 edition. [18](#)
- Nault, E., Baillie, L., and Broz, F. (2020). Auditory and haptic feedback in a socially assistive robot memory game. In *Companion of the 2020 ACM/IEEE International Conference on Human-Robot Interaction*, pages 369–371. [8](#), [9](#), [15](#), [21](#)
- Norman, D. (2013). *The design of everyday things: Revised and expanded edition*. Basic books. [48](#), [50](#)
- Norman, K. L., Shneiderman, B., Harper, B., and Slaughter, L. (1998). Questionnaire for user interaction satisfaction. *University of Maryland (Norman, 1989) Disponível em*. [55](#), [95](#), [133](#)
- Nunez, E., Matsuda, S., Hirokawa, M., and Suzuki, K. (2015). Humanoid robot assisted training for facial expressions recognition based on affective feedback. In *International Conference on Social Robotics*, pages 492–501. Springer. [6](#), [8](#), [24](#)
- Orejana, J. R., MacDonald, B. A., Ahn, H. S., Peri, K., and Broadbent, E. (2015). Healthcare robots in homes of rural older adults. In *International Conference on Social Robotics*, pages 512–521. Springer. [8](#), [14](#), [19](#), [22](#)
- Otaki, H. and Otake, M. (2017). Interactive robotic system assisting image based dialogue for the purpose of cognitive training of older adults. In *2017 AAAI Spring Symposium Series*. [3](#)
- Ozcana, B., Caligiorea, D., Fosch-Villarongab, E., Speratia, V., Morettac, T., and Baldassarrea, G. (2016). Designing socially assistive robot (sar) for cognitive child-robot interaction (ccri) with children with autism spectrum disorder-the case of “+

- me. In *2nd International Conference on Social Robots in Therapy & Education*. [6](#), [18](#), [24](#)
- O’Philbin, L., Woods, B., Farrell, E. M., Spector, A. E., and Orrell, M. (2018). Reminiscence therapy for dementia: an abridged cochrane systematic review of the evidence from randomized controlled trials. *Expert review of neurotherapeutics*, 18(9):715–727. [46](#)
- Paletta, L., Fellner, M., Schüssler, S., Zuschneegg, J., Steiner, J., Lerch, A., Lammer, L., and Prodromou, D. (2018). Amigo: Towards social robot based motivation for playful multimodal intervention in dementia. In *Proceedings of the 11th Pervasive Technologies Related to Assistive Environments Conference*, pages 421–427. [3](#), [5](#), [6](#), [7](#), [9](#), [10](#), [14](#), [24](#)
- Pandey, A. K. and Gelin, R. (2018). A mass-produced sociable humanoid robot: Pepper: The first machine of its kind. *IEEE Robotics & Automation Magazine*, 25(3):40–48. [15](#), [29](#), [59](#), [87](#), [126](#), [135](#)
- Paradedda, R. B., Hashemian, M., Rodrigues, R. A., and Paiva, A. (2016). How facial expressions and small talk may influence trust in a robot. In *International Conference on Social Robotics*, pages 169–178. Springer. [24](#)
- Park, S. and Whang, M. (2022). Empathy in human–robot interaction: Designing for social robots. *International Journal of Environmental Research and Public Health*, 19(3):1889. [77](#)
- Peca, A., Coeckelbergh, M., Simut, R., Costescu, C., Pintea, S., David, D., and Vanderborght, B. (2016). Robot enhanced therapy for children with autism disorders: Measuring ethical acceptability. *IEEE Technology and Society Magazine*, 35(2):54–66. [22](#)
- Peleka, G., Kargakos, A., Skartados, E., Kostavelis, I., Giakoumis, D., Sarantopoulos, I., Doulgeri, Z., Foukarakis, M., Antona, M., Hirche, S., et al. (2018). Ramcip-a

- service robot for mci patients at home. In *2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pages 1–9. IEEE. [4](#), [5](#), [6](#), [7](#), [8](#), [9](#)
- Pereira, J., de Melo, M., Franco, N., Rodrigues, F., Coelho, A., and Fidalgo, R. (2019). Using assistive robotics for aphasia rehabilitation. In *2019 Latin American Robotics Symposium (LARS), 2019 Brazilian Symposium on Robotics (SBR) and 2019 Workshop on Robotics in Education (WRE)*, pages 387–392. IEEE. [17](#)
- Pettinati, M. J. and Arkin, R. C. (2015). Towards a robot computational model to preserve dignity in stigmatizing patient-caregiver relationships. In *International Conference on Social Robotics*, pages 532–542. Springer. [24](#)
- Picard, R. W. (2000). *Affective computing*. MIT press. [69](#)
- Pierson, H. A. and Gashler, M. S. (2017). Deep learning in robotics: a review of recent research. *Advanced Robotics*, 31(16):821–835. [25](#)
- Pigini, L., Facal, D., Blasi, L., and Andrich, R. (2012). Service robots in elderly care at home: Users’ needs and perceptions as a basis for concept development. *Technology and Disability*, 24(4):303–311. [42](#)
- Pino, M., Boulay, M., Jouen, F., and Rigaud, A. S. (2015). “are we ready for robots that care for us?” attitudes and opinions of older adults toward socially assistive robots. *Frontiers in aging neuroscience*, 7:141. [60](#)
- Pino, O., Palestra, G., Trevino, R., and De Carolis, B. (2020). The humanoid robot nao as trainer in a memory program for elderly people with mild cognitive impairment. *International Journal of Social Robotics*, 12(1):21–33. [2](#), [13](#), [17](#)
- Prakash, A. and Rogers, W. A. (2015). Why some humanoid faces are perceived more positively than others: effects of human-likeness and task. *International journal of social robotics*, 7(2):309–331. [44](#)

- Price, C. J. (2012). A review and synthesis of the first 20 years of pet and fmri studies of heard speech, spoken language and reading. *Neuroimage*, 62(2):816–847. [23](#)
- Qi, W., Ovrur, S. E., Li, Z., Marzullo, A., and Song, R. (2021). Multi-sensor guided hand gesture recognition for a teleoperated robot using a recurrent neural network. *IEEE Robotics and Automation Letters*, 6(3):6039–6045. [85](#)
- QuestionPro (2021a). Geo-coding. Accessed 08 April 2021. [30](#)
- QuestionPro (2021b). Word cloud. Accessed 20 July 2021. [31](#)
- Rabbitt, S. M., Kazdin, A. E., and Hong, J. H. (2015). Acceptability of robot-assisted therapy for disruptive behavior problems in children. *Archives of Scientific Psychology*, 3(1):101. [7](#), [11](#)
- Radford, A., Kim, J. W., Hallacy, C., Ramesh, A., Goh, G., Agarwal, S., Sastry, G., Askell, A., Mishkin, P., and Clark, J. (2021). Learning transferable visual models from natural language supervision. *arXiv preprint arXiv:2103.00020*. [69](#)
- Rahbar, F., Anzalone, S. M., Varni, G., Zibetti, E., Ivaldi, S., and Chetouani, M. (2015). Predicting extraversion from non-verbal features during a face-to-face human-robot interaction. In *International Conference on Social Robotics*, pages 543–553. Springer. [24](#)
- Rauchbauer, B., Nazarian, B., Bourhis, M., Ochs, M., Prévot, L., and Chaminade, T. (2019). Brain activity during reciprocal social interaction investigated using conversational robots as control condition. *Philosophical Transactions of the Royal Society B*, 374(1771):20180033. [23](#)
- Rehm, M., Krummheuer, A. L., Rodil, K., Nguyen, M., and Thorlacius, B. (2016). From social practices to social robots—user-driven robot development in elder care. In *International Conference on Social Robotics*, pages 692–701. Springer. [19](#)

- Richardson, K., Coeckelbergh, M., Wakunuma, K., Billing, E., Ziemke, T., Gomez, P., Vanderborght, B., and Belpaeme, T. (2018). Robot enhanced therapy for children with autism (dream): A social model of autism. *IEEE Technology and Society Magazine*, 37(1):30–39. [17](#), [18](#), [21](#)
- Riek, L. and Howard, D. (2014). A code of ethics for the human-robot interaction profession. *Proceedings of We Robot*. [19](#)
- Riek, L. D. (2016). Robotics technology in mental health care. In *Artificial intelligence in behavioral and mental health care*, pages 185–203. Elsevier. [19](#), [21](#)
- Riek, L. D. (2017). Healthcare robotics. *Communications of the ACM*, 60(11):68–78. [19](#), [20](#)
- Robinette, P., Howard, A. M., and Wagner, A. R. (2015). Timing is key for robot trust repair. In *International conference on social robotics*, pages 574–583. Springer. [20](#)
- Rodakowski, J., Skidmore, E. R., Reynolds III, C. F., Dew, M. A., Butters, M. A., Holm, M. B., Lopez, O. L., and Rogers, J. C. (2014). Can performance on daily activities discriminate between older adults with normal cognitive function and those with mild cognitive impairment? *Journal of the American Geriatrics Society*, 62(7):1347–1352. [86](#)
- Rogers, Y., Sharp, H., and Preece, J. (2011). *Interaction design: beyond human-computer interaction*. John Wiley & Sons. [50](#)
- Roth, A. R. (2022). Social connectedness and cognitive decline. *The Lancet Healthy Longevity*. [76](#)
- Rudovic, O., Lee, J., Dai, M., Schuller, B., and Picard, R. W. (2018). Personalized machine learning for robot perception of affect and engagement in autism therapy. *Science Robotics*, 3(19):eaao6760. [5](#), [6](#), [10](#), [12](#), [24](#)

- Rudovic, O., Lee, J., Mascarell-Maricic, L., Schuller, B. W., and Picard, R. W. (2017). Measuring engagement in robot-assisted autism therapy: A cross-cultural study. *Frontiers in Robotics and AI*, 4:36. [13](#), [21](#)
- Ruijten, P. A., Haans, A., Ham, J., and Midden, C. J. (2019). Perceived human-likeness of social robots: testing the rasch model as a method for measuring anthropomorphism. *International Journal of Social Robotics*, 11(3):477–494. [50](#)
- Ryan, C. (2018). *Computer and internet use in the United States: 2016*. US Department of Commerce, Economics and Statistics Administration, U.S. CENSUS BUREAU. [28](#)
- Sabal Palms (2020). Movies for seniors with alzheimer’s and assisted living. [50](#)
- Sabbagh, M. N., Perez, A., Holland, T. M., Boustani, M., Peabody, S. R., Yaffe, K., Bruno, M., Paulsen, R., O’Brien, K., Wahid, N., and Tanzi, R. E. (2022). Primary prevention recommendations to reduce the risk of cognitive decline. *Alzheimer’s & Dementia*. [76](#)
- Salem, M., Lakatos, G., Amirabdollahian, F., and Dautenhahn, K. (2015). Towards safe and trustworthy social robots: ethical challenges and practical issues. In *International conference on social robotics*, pages 584–593. Springer. [17](#), [18](#)
- Salichs, M. A., Encinar, I. P., Salichs, E., Castro-González, Á., and Malfaz, M. (2016). Study of scenarios and technical requirements of a social assistive robot for alzheimer’s disease patients and their caregivers. *International Journal of Social Robotics*, 8(1):85–102. [11](#), [19](#), [21](#), [24](#)
- Salvador, M., Marsh, A. S., Gutierrez, A., and Mahoor, M. H. (2016). Development of an aba autism intervention delivered by a humanoid robot. In *International Conference on Social Robotics*, pages 551–560. Springer. [7](#), [15](#)
- Sancarlo, D., D’Onofrio, G., Oscar, J., Ricciardi, F., Casey, D., Murphy, K., Giuliani, F., and Greco, A. (2016). Mario project: A multicenter survey about companion

- robot acceptability in caregivers of patients with dementia. In *Italian Forum of Ambient Assisted Living*, pages 311–336. Springer. [27](#), [28](#), [42](#)
- Sandygulova, A. and O’Hare, G. M. (2015). Children’s perception of synthesized voice: Robot’s gender, age and accent. In *International Conference on Social Robotics*, pages 594–602. Springer. [21](#)
- Sandygulova, A., Zhexenova, Z., Tleubayev, B., Nurakhmetova, A., Zhumabekova, D., Assylgali, I., Rzagaliyev, Y., and Zhakenova, A. (2019). Interaction design and methodology of robot-assisted therapy for children with severe asd and adhd. *Paladyn, Journal of Behavioral Robotics*, 10(1):330–345. [9](#), [13](#), [14](#), [21](#)
- Sanh, V., Debut, L., Chaumond, J., and Wolf, T. (2019). Distilbert, a distilled version of bert: smaller, faster, cheaper and lighter. *arXiv preprint arXiv:1910.01108*. [79](#)
- Saxe, R. and Wexler, A. (2005). Making sense of another mind: the role of the right temporo-parietal junction. *Neuropsychologia*, 43(10):1391–1399. [23](#)
- Scassellati, B., Boccanfuso, L., Huang, C.-M., Mademtzi, M., Qin, M., Salomons, N., Ventola, P., and Shic, F. (2018). Improving social skills in children with asd using a long-term, in-home social robot. *Science Robotics*, 3(21). [4](#), [9](#), [12](#), [14](#), [21](#)
- Schüssler, S., Zuschnegg, J., Paletta, L., Fellner, M., Lodron, G., Steiner, J., Pansy-Resch, S., Lammer, L., Prodromou, D., Brunsch, S., et al. (2020). Effects of a humanoid socially assistive robot versus tablet training on psychosocial and physical outcomes of persons with dementia: Protocol for a mixed methods study. *JMIR research protocols*, 9(2):e14927. [49](#), [87](#), [126](#)
- Schütze, H., Manning, C. D., and Raghavan, P. (2008). *Introduction to information retrieval*, volume 39. Cambridge University Press Cambridge. [31](#)
- Schweitzer, P. and Bruce, E. (2008). *Remembering yesterday, caring today: Reminiscence in dementia care: A guide to good practice*. Jessica Kingsley Publishers. [48](#)

- Seitzer, M., Schölkopf, B., and Martius, G. (2021). Causal influence detection for improving efficiency in reinforcement learning. *Advances in Neural Information Processing Systems*, 34:22905–22918. [83](#)
- Shi, Y., Li, H., Fu, X., Luan, R., Wang, Y., Wang, N., Sun, Z., Niu, Y., Wang, C., Zhang, C., et al. (2023a). Self-powered difunctional sensors based on sliding contact-electrification and tribovoltaic effects for pneumatic monitoring and controlling. *Nano Energy*, 110:108339. [101](#)
- Shi, Y., Li, L., Yang, J., Wang, Y., and Hao, S. (2023b). Center-based transfer feature learning with classifier adaptation for surface defect recognition. *Mechanical Systems and Signal Processing*, 188:110001. [84](#)
- Shibata, T. (2012). Therapeutic seal robot as biofeedback medical device: Qualitative and quantitative evaluations of robot therapy in dementia care. *Proceedings of the IEEE*, 100(8):2527–2538. [2](#)
- Shim, J. and Arkin, R. C. (2016). Other-oriented robot deception: How can a robot’s deceptive feedback help humans in hri? In *International Conference on Social Robotics*, pages 222–232. Springer. [18](#)
- Shukla, J., Barreda-Ángeles, M., Oliver, J., and Puig, D. (2017). Effectiveness of socially assistive robotics during cognitive stimulation interventions: Impact on caregivers. In *2017 26th IEEE international symposium on robot and human interactive communication (RO-MAN)*, pages 62–67. IEEE. [15](#)
- Shukla, J., Cristiano, J., Amela, D., Anguera, L., Vergés-Llahí, J., and Puig, D. (2015). A case study of robot interaction among individuals with profound and multiple learning disabilities. In *International Conference on Social Robotics*, pages 613–622. Springer. [13](#), [15](#), [17](#)

- Small, J. and Ann Perry, J. (2012). Training family care partners to communicate effectively with persons with alzheimer’s disease: The traced program. *Canadian Journal of Speech-Language Pathology & Audiology*, 36(4). [69](#)
- Smith, B. J. and Lim, M. H. (2020). How the covid-19 pandemic is focusing attention on loneliness and social isolation. *Public Health Res Pract*, 30(2):3022008. [76](#)
- Smith, E. R., Broughton, M., Baker, R., Pachana, N. A., Angwin, A. J., Humphreys, M. S., Mitchell, L., Byrne, G. J., Copland, D. A., Gallois, C., et al. (2011). Memory and communication support in dementia: research-based strategies for caregivers. *International Psychogeriatrics*, 23(2):256. [69](#), [75](#)
- Smith, P. G., Morrow, R. H., and Ross, D. A. (2015). Preliminary studies and pilot testing. In *Field Trials of Health Interventions: A Toolbox. 3rd edition*. OUP Oxford. [93](#)
- Social care institute for excellence (2020). Reminiscence for people with dementia. [48](#), [51](#)
- SoftBank Robotics (2021). Pepper android (qisdsk). [Accessed August 29, 2021]. [87](#), [128](#)
- SoftBank Robotics (Accessed April 25, 2022). Engagehuman. [99](#)
- Sonntag, D. (2015). Kognit: Intelligent cognitive enhancement technology by cognitive models and mixed reality for dementia patients. In *2015 AAAI Fall Symposium Series*. [6](#), [9](#)
- Sousa, A. D. (2021). Technology and dementia care—global challenges. In *Dementia Care*, pages 301–310. Springer. [64](#)
- Sung, H.-C., Chang, S.-M., Chin, M.-Y., and Lee, W.-L. (2015). Robot-assisted therapy for improving social interactions and activity participation among

- institutionalized older adults: A pilot study. *Asia-Pacific Psychiatry*, 7(1):1–6. [3](#), [4](#), [8](#), [12](#)
- Sutton, R. S. and Barto, A. G. (2018). *Reinforcement learning: An introduction*. MIT press. [11](#), [71](#)
- Suwa, S., Tsujimura, M., Kodate, N., Donnelly, S., Kitinoja, H., Hallila, J., Toivonen, M., Ide, H., Bergman-Kärpijoki, C., Takahashi, E., et al. (2020). Exploring perceptions toward home-care robots for older people in finland, ireland, and japan: A comparative questionnaire study. *Archives of Gerontology and Geriatrics*, 91:104178. [28](#)
- Taheri, A., Alemi, M., Meghdari, A., Pouretmad, H., Basiri, N. M., and Poorgoldooz, P. (2015a). Impact of humanoid social robots on treatment of a pair of iranian autistic twins. In *International Conference on Social Robotics*, pages 623–632. Springer. [9](#), [12](#), [13](#)
- Taheri, A., Alemi, M., Meghdari, A., Pouretmad, H., and Holderread, S. (2015b). Clinical application of humanoid robots in playing imitation games for autistic children in iran. *Procedia-Social and Behavioral Sciences*, 176:898–906. [2](#)
- Taheri, A., Meghdari, A., Alemi, M., and Pouretmad, H. (2019). Teaching music to children with autism: a social robotics challenge. *Scientia Iranica*, 26(Special Issue on: Socio-Cognitive Engineering):40–58. [4](#), [7](#), [8](#), [9](#), [12](#), [13](#), [14](#), [16](#), [17](#)
- Taheri, A., Meghdari, A., Alemi, M., Pouretmad, H., Poorgoldooz, P., and Roohbakhsh, M. (2016). Social robots and teaching music to autistic children: Myth or reality? In *International Conference on Social Robotics*, pages 541–550. Springer. [12](#)
- Taheri, A., Meghdari, A., and Mahoor, M. H. (2020). A close look at the imitation performance of children with autism and typically developing children using a robotic system. *International Journal of Social Robotics*, pages 1–23. [3](#)

- Tapus, A., Tapus, C., and Mataric, M. J. (2009). The use of socially assistive robots in the design of intelligent cognitive therapies for people with dementia. In *2009 IEEE international conference on rehabilitation robotics*, pages 924–929. IEEE. [72](#)
- Taranović, A., Jevtić, A., and Torras, C. (2018). Adaptive modality selection algorithm in robot-assisted cognitive training. In *2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pages 4456–4461. IEEE. [10](#)
- Tariq, S., Baber, S., Ashfaq, A., Ayaz, Y., Naveed, M., and Mohsin, S. (2016). Interactive therapy approach through collaborative physical play between a socially assistive humanoid robot and children with autism spectrum disorder. In *International Conference on Social Robotics*, pages 561–570. Springer. [9](#), [13](#), [14](#), [16](#)
- Tian, C., Xu, Z., Wang, L., and Liu, Y. (2023). Arc fault detection using artificial intelligence: Challenges and benefits. *Mathematical Biosciences and Engineering*, 20(7):12404–12432. [84](#)
- Tleubayev, B., Zhexenova, Z., Zhakenova, A., and Sandygulova, A. (2019). Robot-assisted therapy for children with adhd and asd: a pilot study. In *Proceedings of the 2019 2nd International Conference on Service Robotics Technologies*, pages 58–62. [3](#), [9](#), [13](#), [14](#), [15](#), [21](#)
- Tokunaga, S., Seaborn, K., Tamura, K., and Otake-Matsuura, M. (2019). Cognitive training for older adults with a dialogue-based, robot-facilitated storytelling system. In *International Conference on Interactive Digital Storytelling*, pages 405–409. Springer. [14](#)
- Trovato, G., Galeazzi, J., Torta, E., Ham, J. R., and Cuijpers, R. H. (2015). Study on adaptation of robot communication strategies in changing situations. In *International Conference on Social Robotics*, pages 654–663. Springer. [17](#)
- Tsardoulis, E. G., Kintsakis, A. M., Panayiotou, K., Thallas, A. G., Reppou, S. E., Karagiannis, G. G., Iturburu, M., Arampatzis, S., Zielinski, C., Prunet, V., et al.

- (2017). Towards an integrated robotics architecture for social inclusion—the rapp paradigm. *Cognitive Systems Research*, 43:157–173. [9](#), [16](#)
- Tsiakas, K., Abujelala, M., and Makedon, F. (2018). Task engagement as personalization feedback for socially-assistive robots and cognitive training. *Technologies*, 6(2):49. [6](#), [21](#)
- Tsiakas, K., Dagioglou, M., Karkaletsis, V., and Makedon, F. (2016). Adaptive robot assisted therapy using interactive reinforcement learning. In *International Conference on Social Robotics*, pages 11–21. Springer. [11](#), [21](#), [22](#)
- Tung, F.-W. (2016). Child perception of humanoid robot appearance and behavior. *International Journal of Human-Computer Interaction*, 32(6):493–502. [4](#)
- University of Pittsburgh, Department of Occupational Therapy (Accessed October 3, 2021). Performance assessment of self-care skills (pass). [99](#)
- Van Bogaert, P., Tolson, D., Eerlingen, R., Carvers, D., Wouters, K., Paque, K., Timmermans, O., Dilles, T., and Engelborghs, S. (2016). Solcos model-based individual reminiscence for older adults with mild to moderate dementia in nursing homes: a randomized controlled intervention study. *Journal of Psychiatric and Mental Health Nursing*, 23(9-10):568–575. [46](#)
- van den Heuvel, R. J., Lexis, M. A., and de Witte, L. P. (2017). Robot zora in rehabilitation and special education for children with severe physical disabilities: a pilot study. *International journal of rehabilitation research. Internationale Zeitschrift fur Rehabilitationsforschung. Revue internationale de recherches de readaptation*, 40(4):353. [12](#), [14](#)
- Vargha, A. and Delaney, H. D. (2000). A critique and improvement of the cl common language effect size statistics of mcgraw and wong. *Journal of Educational and Behavioral Statistics*, 25(2):101–132. [30](#)

- Vaufreydaz, D., Johal, W., and Combe, C. (2016). Starting engagement detection towards a companion robot using multimodal features. *Robotics and Autonomous Systems*, 75:4–16. [24](#)
- Vi, C. T., Takashima, K., Yokoyama, H., Liu, G., Itoh, Y., Subramanian, S., and Kitamura, Y. (2013). D-flip: Dynamic and flexible interactive photoshow. In *International Conference on Advances in Computer Entertainment Technology*, pages 415–427. Springer. [47](#)
- Villaronga, E. F. (2016). What do roboticists need to know about the future of robot law? *ResearchGate. net, novembre*. [18](#)
- Vollmer Dahlke, D. and Ory, M. G. (2020). Emerging issues of intelligent assistive technology use among people with dementia and their caregivers: A us perspective. *Frontiers in Public Health*, 8:191. [47](#)
- Wan, S., Gu, Z., and Ni, Q. (2020). Cognitive computing and wireless communications on the edge for healthcare service robots. *Computer Communications*, 149:99–106. [25](#)
- Wang, R. H., Sudhama, A., Begum, M., Huq, R., and Mihailidis, A. (2017). Robots to assist daily activities: views of older adults with alzheimer’s disease and their caregivers. *International psychogeriatrics*, 29(1):67–79. [84](#), [112](#)
- Wang, S., Bolling, K., Mao, W., Reichstadt, J., Jeste, D., Kim, H.-C., and Nebeker, C. (2019). Technology to support aging in place: older adults’ perspectives. In *Healthcare*, volume 7, page 60. Multidisciplinary Digital Publishing Institute. [125](#)
- Wang, Y., Liu, Z., Xu, J., and Yan, W. (2022). Heterogeneous network representation learning approach for ethereum identity identification. *IEEE Transactions on Computational Social Systems*. [85](#)
- Weiss, W., Fuhrmann, F., Zeiner, H., and Unterberger, R. (2017). Towards an architecture for collaborative human robot interaction in physiotherapeutic

- applications. In *Proceedings of the Companion of the 2017 ACM/IEEE International Conference on Human-Robot Interaction*, pages 319–320. [22](#)
- Wennberg, A., Dye, C., Streetman-Loy, B., and Pham, H. (2015). Alzheimer’s patient familial caregivers: A review of burden and interventions. *Health & Social Work*, 40(4):e162–e169. [124](#), [127](#)
- Whelan, S., Murphy, K., Barrett, E., Krusche, C., Santorelli, A., and Casey, D. (2018). Factors affecting the acceptability of social robots by older adults including people with dementia or cognitive impairment: a literature review. *International Journal of Social Robotics*, 10(5):643–668. [5](#), [27](#), [39](#), [44](#), [60](#)
- Wilkins, J. M. (2017). Dementia, decision making, and quality of life. *AMA Journal of Ethics*, 19(7):637–639. [51](#), [70](#)
- Wiltshire, T. J., Warta, S. F., Barber, D., and Fiore, S. M. (2017). Enabling robotic social intelligence by engineering human social-cognitive mechanisms. *Cognitive Systems Research*, 43:190–207. [25](#)
- Wisniewski, S. R., Belle, S. H., Coon, D. W., Marcus, S. M., Ory, M. G., Burgio, L. D., Burns, R., and Schulz, R. (2003). The resources for enhancing alzheimer’s caregiver health (reach): project design and baseline characteristics. *Psychology and aging*, 18(3):375. [124](#)
- Wong, H. and Zhong, Z. (2016). Assessment of robot training for social cognitive learning. In *2016 16th International Conference on Control, Automation and Systems (ICCAS)*, pages 893–898. IEEE. [13](#)
- Woo, J., Botzheim, J., and Kubota, N. (2017). System integration for cognitive model of a robot partner. *Intelligent Automation & Soft Computing*, pages 1–14. [25](#)
- Wood, L. J., Zaraki, A., Walters, M. L., Novanda, O., Robins, B., and Dautenhahn, K. (2017). The iterative development of the humanoid robot kaspar: An assistive

- robot for children with autism. In *International Conference on Social Robotics*, pages 53–63. Springer. [15](#), [20](#), [22](#)
- Woods, B., O’Philbin, L., Farrell, E. M., Spector, A. E., and Orrell, M. (2018). Reminiscence therapy for dementia. *Cochrane database of systematic reviews*, (3). [46](#)
- Woods, D., Yuan, F., Jao, J.-L., and Zhao, X. (2021a). Social robots for older adults with dementia: A narrative review on challenges & future directions. In *The Thirteenth International Conference on Social Robotics, Singapore*. [1](#), [60](#)
- Woods, D., Yuan, F., Jao, Y.-L., and Zhao, X. (2021b). Social robots for older adults with dementia: A narrative review on challenges & future directions. In *International Conference on Social Robotics*, pages 411–420. Springer. [47](#), [48](#), [77](#), [101](#)
- Woods, R. T., Bruce, E., Edwards, R., Elvish, R., Hoare, Z., Hounscome, B., Keady, J., Moniz-Cook, E., Orgeta, V., Orrell, M., et al. (2012). Remcare: reminiscence groups for people with dementia and their family caregivers-effectiveness and cost-effectiveness pragmatic multicentre randomised trial. *Health Technology Assessment*, 16(48). [69](#)
- Wu, X., Adams, A. E., Komsky, J. C., Saint, S. E., Mackin, T. E., Zamer, J. P., Hedin, D. S., Dahlstrom, R. J., and Beer, J. M. (2021). Socially assistive robots for dementia care: Exploring caregiver perceptions of use cases and acceptance. In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, volume 65, pages 6–10. SAGE Publications Sage CA: Los Angeles, CA. [63](#)
- Wu, Y.-L., Gamborino, E., and Fu, L.-C. (2019). Interactive question-posing system for robot-assisted reminiscence from personal photographs. *IEEE Transactions on Cognitive and Developmental Systems*, 12(3):439–450. [47](#), [48](#)

- Xie, B., Champion, J. D., Kwak, J., Fleischmann, K. R., et al. (2018). Mobile health, information preferences, and surrogate decision-making preferences of family caregivers of people with dementia in rural hispanic communities: cross-sectional questionnaire study. *Journal of medical Internet research*, 20(12):e11682. [124](#)
- Xu, X., Dušek, O., Konstas, I., and Rieser, V. (2018). Better conversations by modeling, filtering, and optimizing for coherence and diversity. *arXiv preprint arXiv:1809.06873*. [83](#)
- Yamazaki, R., Kochi, M., Zhu, W., and Kase, H. (2018). A pilot study of robot reminiscence in dementia care. *International Journal of Biomedical and Biological Engineering*, 12(6):257–261. [47](#)
- Yu, K., Wild, K., Potempa, K., Hampstead, B. M., Lichtenberg, P. A., Struble, L. M., Pruitt, P., Alfaro, E. L., Lindsley, J., MacDonald, M., et al. (2021). The internet-based conversational engagement clinical trial (i-conect) in socially isolated adults 75+ years old: randomized controlled trial protocol and covid-19 related study modifications. *Frontiers in digital health*, 3. [77](#), [78](#), [82](#)
- Yu, R., Hui, E., Lee, J., Poon, D., Ng, A., Sit, K., Ip, K., Yeung, F., Wong, M., Shibata, T., et al. (2015). Use of a therapeutic, socially assistive pet robot (paro) in improving mood and stimulating social interaction and communication for people with dementia: Study protocol for a randomized controlled trial. *JMIR research protocols*, 4(2):e45. [3](#), [12](#), [13](#), [14](#), [16](#)
- Yuan, F., Anderson, J. G., Wyatt, T., Lopez, R. P., Crane, M., Montgomery, A., and Zhao, X. (2020). Feasibility study on robotic care of alzheimer’s. [29](#)
- Yuan, F., Anderson, J. G., Wyatt, T., Lopez, R. P., Crane, M., Montgomery, A., and Zhao, X. (2022a). Assessing the acceptability of a humanoid robot for alzheimer’s

- disease and related dementia care using an online survey. *International Journal of Social Robotics*. [185](#), [187](#), [192](#), [194](#)
- Yuan, F., Anderson, J. G., Wyatt, T. H., Lopez, R. P., Crane, M., Montgomery, A., and Zhao, X. (2022b). Assessing the acceptability of a humanoid robot for alzheimer’s disease and related dementia care using an online survey. *International Journal of Social Robotics*, pages 1–15. [49](#), [59](#), [63](#), [64](#), [77](#), [87](#), [112](#), [114](#), [126](#)
- Yuan, F., Blackburn, J., Condon, C., Bowland, S., Lopez, R., and Zhao, X. (2021a). A social robot-based psycho-educational program to enhance alzheimer’s caregiver health. In *CHASE 2021: IEEE/ACM Conference on Connected Health: Applications, Systems and Engineering Technologies, Washington D.C.* [1](#), [49](#), [87](#), [125](#), [126](#)
- Yuan, F., Boltz, M., Jao, Y.-L., Casenhiser, A., Siddiqi, A., Bray, R., Duzan, J., Crane, M., and Zhao, X. (2022c). Assessment of a humanoid partner for older adults and persons with dementia during home-based activities. In *International Conference on Social Robotics*, pages 587–597. Springer. [100](#), [104](#), [115](#)
- Yuan, F., Klavon, E., Liu, Z., Lopez, R. P., and Zhao, X. (2021b). A systematic review of robotic rehabilitation for cognitive training. *Frontiers in Robotics and AI*, 8:105. [43](#), [77](#)
- Yuan, F., Klavon, E., Liu, Z., Lopez, R. P., and Zhao, X. (2021c). A systematic review of robotic rehabilitation for cognitive training. *Frontiers in Robotics and AI*. [46](#), [47](#), [49](#), [60](#), [62](#), [64](#), [87](#), [112](#), [125](#), [126](#), [137](#)
- Yuan, F., Sadovnik, A., Zhang, R., Casenhiser, D., Paek, E. J., Yoon, S. O., and Zhao, X. (2021d). A simulated experiment to explore robotic dialogue strategies for people with dementia. *arXiv preprint arXiv:2104.08940*. [67](#)
- Yuan, F., Zhang, R., Bilal, D., and Zhao, X. (2021e). Learning-based strategy design for robot-assisted reminiscence therapy based on a developed model for people

- with dementia. In *The Thirteenth International Conference on Social Robotics, Singapore*. [1](#)
- Yuan, F., Zhang, R., Bilal, D., and Zhao, X. (2021f). Learning-based strategy design for robot-assisted reminiscence therapy based on a developed model for people with dementia. In *International Conference on Social Robotics*, pages 432–442. Springer. [47](#), [51](#), [63](#)
- Yun, S.-S., Kim, H., Choi, J., and Park, S.-K. (2016). A robot-assisted behavioral intervention system for children with autism spectrum disorders. *Robotics and Autonomous Systems*, 76:58–67. [13](#)
- Zhao, J. and Lv, Y. (2023). Output-feedback robust tracking control of uncertain systems via adaptive learning. *International Journal of Control, Automation and Systems*, 21(4):1108–1118. [85](#)
- Zheng, Z., Nie, G., Swanson, A., Weitlauf, A., Warren, Z., and Sarkar, N. (2016). Longitudinal impact of autonomous robot-mediated joint attention intervention for young children with asd. In *International Conference on Social Robotics*, pages 581–590. Springer. [13](#), [17](#)
- Zheng, Z., Young, E. M., Swanson, A. R., Weitlauf, A. S., Warren, Z. E., and Sarkar, N. (2015). Robot-mediated imitation skill training for children with autism. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 24(6):682–691. [16](#)
- Zsiga, K., Tóth, A., Pilissy, T., Péter, O., Dénes, Z., and Fazekas, G. (2018). Evaluation of a companion robot based on field tests with single older adults in their homes. *Assistive Technology*, 30(5):259–266. [6](#), [7](#)

Appendix A

Appendix: Tables and Figures

A.1 Study of Understanding User Acceptance and Needs

Table A.1: Response distribution of participants within US

States N = 32	Count	Percentage
AL	7	1.16%
AR	3	0.50%
CA	8	1.33%
CO	3	0.50%
DC	3	0.50%
FL	9	1.50%
GA	6	1.00%
IA	2	0.33%
IL	2	0.33%
IN	2	0.33%
KY	5	0.83%
LA	2	0.33%
MA	3	0.50%
MD	4	0.67%
Continued on next page		

Table A.1 – continued from previous page

States N = 32	Count	Percentage
MI	3	0.50%
MO	1	0.17%
NC	3	0.50%
NJ	1	0.17%
NM	1	0.17%
NV	1	0.17%
NY	3	0.50%
OH	2	0.33%
OK	3	0.50%
OR	1	0.17%
PA	2	0.33%
SC	5	0.83%
TN	485	80.70%
TX	3	0.50%
VA	5	0.83%
WA	1	0.17%
WI	1	0.17%
WV	1	0.17%
Unknown	20	3.31%

Table A.2: Demographic information of participants

Demographic Variables	People with MCI or ADRD $n = 80$	Caregivers $n = 245$	General Public $n = 306$
Gender (n,%)			
Female	44 (55.00%)	184 (75.10%)	177 (57.84%)
Male	35 (43.75%)	58 (23.67%)	124 (40.52%)
Prefer not to answer	1 (1.25%)	0	1 (0.33%)
Other	0	0	1 (0.33%)
Age (years) (n,%)			
Under 50	8 (10.00%)	54 (22.04%)	104 (33.99%)
50-65	17 (21.25%)	86 (35.10%)	52 (16.99%)
65-75	27 (33.75%)	76 (31.02%)	94 (30.72%)
75-85	22 (27.50%)	27 (11.02%)	51 (16.67%)
Above 85	6 (7.50%)	2 (0.82%)	5 (1.63%)
Highest level of education (n,%)			
6th grade or less	0	1 (0.41%)	0
7th-11th grade	2 (2.50%)	0	2 (0.65%)
High school graduate	8 (10.00%)	10 (4.08%)	18 (5.88%)
Some college	20 (25.00%)	53 (21.63%)	54 (17.65%)
College graduate	17 (21.25%)	61 (24.90%)	94 (30.72%)
Post-graduate	33 (41.25%)	120 (48.98%)	138 (45.10%)
Familiarity with technology (Mean $\pm$ SD)			
Smartphones	3.02 $\pm$ 1.02	3.76 $\pm$ 0.49	3.63 $\pm$ 0.64
Tablets	2.80 $\pm$ 1.10	3.52 $\pm$ 0.73	3.40 $\pm$ 0.82
Computers	3.09 $\pm$ 0.99	3.74 $\pm$ 0.49	3.63 $\pm$ 0.57
Robots	1.58 $\pm$ 0.81	1.91 $\pm$ 0.91	1.96 $\pm$ 0.96
Types of caregivers (Multi- ple answer; n,%)			
Continued on next page			

Table A.2 – continued from previous page

Demographic Variables	People with MCI or ADRD $n = 80$	Caregivers $n = 245$	General Public $n = 306$
Informal caregiver	Not applicable	212 (86.53%)	Not applicable
Paid in-home caregiver	Not applicable	13 (5.31%)	Not applicable
Nurse	Not applicable	36 (14.69%)	Not applicable
Therapist	Not applicable	14 (5.71%)	Not applicable
Doctor	Not applicable	8 (3.27%)	Not applicable
Psychologist	Not applicable	2 (0.82%)	Not applicable
Caregiving hours per week (n,%)			
Under 4 hours	Not applicable	141 (57.55%)	Not applicable
4-8 hours	Not applicable	27 (11.02%)	Not applicable
Above 8 hours	Not applicable	72 (29.39%)	Not applicable

Note: Since survey questions are not mandatory, a participant may skip a question accidentally. Therefore, the number of entries of some questions may not equal to the total number of complete responses.

Among caregiver respondents, there were 3 participants who skipped the question associated with gender and 5 participants who skipped the question associated with hours of caregiving.

Among respondents from the general public, there were 3 participants who skipped the question associated with gender.

For the items associated with familiarity with technology (i.e., Rows *Smartphones*, *Tablets*, *Computers* and *Robots*), 1=Not at all familiar, 2=Slightly familiar, 3=Moderately familiar, 4=Very familiar.

Table A.3: Percentage of responses by people with MCI or ADRD.

Item	No=1	Probably not=2	Maybe=3	Probably=4	Yes=5	Mean(SD)
Q1	0	0	11 (13.75%)	13 (16.25%)	56 (70.00%)	4.56 (0.73)
Q2	7 (8.75%)	11 (13.75%)	16 (20.00%)	18 (22.50%)	28 (35.00%)	3.61 (1.33)
Q5	5 (6.25%)	5 (6.25%)	22 (27.50%)	17 (21.25%)	31 (38.75%)	3.80 (1.21)
Q6	3 (3.80%)	4 (5.06%)	13 (16.46%)	34 (43.04%)	25 (31.65%)	3.94 (1.02)
Q7	27 (33.75%)	26 (32.50%)	15 (18.75%)	8 (10.00%)	4 (5.00%)	2.20 (1.16)
Q8	7 (8.86%)	8 (10.13%)	16 (20.25%)	14 (17.72%)	34 (43.04%)	3.76 (1.34)
Q9	2 (2.50%)	4 (5.00%)	18 (22.50%)	28 (35.00%)	28 (35.00%)	3.95 (1.01)

Note: Please see Supplementary Appendix 1 in the work (Yuan et al., 2022a) for Items Q1-Q9.

Table A.4: Percentage of responses to questions about robot acceptance by the caregivers and the general public.

Item	Likert rating					Mean
	1	2	3	4	5	(SD)
A1	9 (3.67%)	56 (22.86%)	24 (9.80%)	109 (44.49%)	37 (15.10%)	3.46 (1.13)
	17 (5.61%)	51 (16.83%)	29 (9.57%)	152 (50.17%)	35 (11.55%)	3.48 (1.10)
A2	25 (10.25%)	56 (22.95%)	38 (15.57%)	89 (36.48%)	29 (11.89%)	3.17 (1.22)
	27 (8.91%)	77 (25.41%)	35 (11.55%)	125 (41.25%)	30 (9.90%)	3.18 (1.20)
A3	6 (2.48%)	18 (7.44%)	45 (18.60%)	110 (45.45%)	54 (22.31%)	3.81 (0.97)
	9 (2.94%)	31 (10.13%)	54 (17.65%)	132 (43.14%)	67 (21.90%)	3.74 (1.02)
A4a	6 (2.45%)	18 (7.35%)	9 (3.67%)	106 (43.27%)	103 (42.04%)	4.17 (0.98)
	12 (3.92%)	10 (3.27%)	19 (6.21%)	117 (38.24%)	145 (47.39%)	4.23 (0.99)
A4b	9 (3.67%)	35 (14.29%)	26 (10.61%)	97 (39.59%)	78 (31.84%)	3.82 (1.14)
	13 (4.26%)	28 (9.18%)	31 (10.16%)	127 (41.64%)	97 (31.80%)	3.90 (1.10)
A4c	18 (7.41%)	50 (20.58%)	37 (15.23%)	76 (31.28%)	60 (24.69%)	3.46 (1.27)
	20 (6.58%)	48 (15.79%)	40 (13.16%)	103 (33.88%)	84 (27.63%)	3.62 (1.24)
Continued on next page						

Table A.4 – continued from previous page

Item	Likert rating					Mean
	1	2	3	4	5	(SD)
A4d	7 (2.87%)	11 (4.51%)	9 (3.69%)	95 (38.93%)	122 (50.00%)	4.29 (0.95)
	6 (1.97%)	19 (6.23%)	19 (6.23%)	112 (36.72%)	145 (47.54%)	4.23 (0.96)
A4e	8 (3.29%)	11 (4.53%)	12 (4.94%)	83 (34.16%)	125 (51.44%)	4.28 (0.99)
	9 (2.94%)	17 (5.56%)	21 (6.86%)	113 (36.93%)	141 (46.08%)	4.20 (1.00)

Note: Please see Supplementary Appendix 2 in the work (Yuan et al., 2022a) for Items A1-A4.

For the same item, the upper and lower row represent the responses from the caregivers and the general public, respectively.

For each item, 1=Extremely unlikely, 2=Somewhat unlikely, 3=Neither likely nor unlikely, 4=Somewhat likely, 5=Extremely likely.

Table A.5: Percentage of responses to questions about robotic functionality by the caregivers and the general public.

Item	Likert rating					Mean
	1	2	3	4	5	(SD)
B1a	14 (5.71%)	18 (7.35%)	31 (12.65%)	81 (33.06%)	93 (37.96%)	3.93 (1.17)
	10 (3.27%)	25 (8.17%)	37 (12.09%)	93 (30.39%)	123 (40.20%)	4.02 (1.10)
B1b	7 (2.86%)	16 (6.53%)	25 (10.20%)	98 (40.00%)	90 (36.73%)	4.05 (1.01)
	4 (1.32%)	18 (5.92%)	27 (8.88%)	150 (49.34%)	89 (29.28%)	4.05 (0.88)
B1c	3 (1.22%)	13 (5.31%)	30 (12.24%)	101 (41.22%)	94 (38.37%)	4.12 (0.91)
	9 (2.94%)	16 (5.23%)	36 (11.76%)	130 (42.48%)	99 (32.35%)	4.01 (0.98)
B1d *	3 (1.23%)	6 (2.46%)	29 (11.89%)	97 (39.75%)	106 (43.44%)	4.23 (0.85)
	5 (1.64%)	23 (7.54%)	27 (8.85%)	134 (43.93%)	105 (34.43%)	4.06 (0.96)
B1e *	2 (0.82%)	7 (2.86%)	12 (4.90%)	57 (23.27%)	164 (66.94%)	4.55 (0.79)
	4 (1.31%)	10 (3.28%)	15 (4.92%)	94 (30.82%)	175 (57.38%)	4.43 (0.84)
B1f *	4 (1.64%)	4 (1.64%)	9 (3.69%)	62 (25.41%)	164 (67.21%)	4.56 (0.79)
	3 (0.98%)	10 (3.27%)	20 (6.54%)	94 (30.72%)	172 (56.21%)	4.41 (0.84)
Continued on next page						

Table A.5 – continued from previous page

Item	Likert rating					Mean
	1	2	3	4	5	(SD)
B1g	0	4 (1.65%)	17 (7.00%)	61 (25.10%)	149 (61.32%)	4.54 (0.71)
	4 (1.31%)	7 (2.29%)	20 (6.54%)	76 (24.84%)	182 (59.48%)	4.47 (0.84)
B2a	5 (2.06%)	4 (1.65%)	8 (3.29%)	51 (20.99%)	171 (70.37%)	4.59 (0.81)
	5 (1.63%)	2 (0.65%)	12 (3.92%)	71 (23.20%)	212 (69.28%)	4.60 (0.75)
B2b	5 (2.05%)	2 (0.82%)	4 (1.64%)	43 (17.62%)	186 (76.23%)	4.68 (0.74)
	4 (1.31%)	3 (0.98%)	4 (1.31%)	54 (17.70%)	235 (77.05%)	4.71 (0.67)
B2c	1 (0.41%)	9 (3.70%)	10 (4.12%)	69 (28.40%)	146 (60.08%)	4.49 (0.79)
	4 (1.31%)	5 (1.64%)	8 (2.62%)	88 (28.85%)	190 (62.30%)	4.54 (0.75)
B2d	2 (0.82%)	3 (1.23%)	9 (3.69%)	67 (27.46%)	162 (66.39%)	4.58 (0.70)
	3 (0.99%)	3 (0.99%)	12 (3.95%)	95 (31.25%)	181 (59.54%)	4.52 (0.72)
B2e *	3 (1.23%)	2 (0.82%)	3 (1.23%)	40 (16.39%)	196 (80.33%)	4.74 (0.65)
	4 (1.31%)	2 (0.65%)	10 (3.27%)	69 (22.55%)	215 (70.26%)	4.63 (0.71)
B2f	1 (0.41%)	7 (2.87%)	18 (7.38%)	63 (25.82%)	153 (62.70%)	4.49 (0.79)
Continued on next page						

Table A.5 – continued from previous page

Item	Likert rating					Mean
	1	2	3	4	5	(SD)
	3 (0.98%)	8 (2.61%)	22 (7.19%)	96 (31.37%)	167 (54.58%)	4.41 (0.82)
B2g ***	1 (0.41%)	7 (2.87%)	7 (2.87%)	55 (22.54%)	172 (70.49%)	4.61 (0.72)
	2 (0.66%)	7 (2.30%)	12 (3.93%)	112 (36.72%)	166 (54.43%)	4.45 (0.74)
B2h *	3 (1.23%)	2 (0.82%)	4 (1.64%)	27 (11.07%)	208 (85.25%)	4.78 (0.63)
	4 (1.31%)	3 (0.98%)	7 (2.29%)	54 (17.65%)	231 (75.49%)	4.69 (0.70)
B2i	1 (0.41%)	9 (3.69%)	15 (6.15%)	66 (27.05%)	149 (61.07%)	4.47 (0.81)
	2 (0.66%)	7 (2.30%)	17 (5.59%)	100 (32.89%)	168 (55.26%)	4.45 (0.77)
B2j	4 (1.64%)	5 (2.05%)	15 (6.15%)	54 (22.13%)	160 (65.57%)	4.52 (0.84)
	4 (1.32%)	7 (2.30%)	20 (6.58%)	85 (27.96%)	180 (59.21%)	4.45 (0.83)
B3a	4 (1.63%)	3 (1.22%)	8 (3.27%)	44 (17.96%)	183 (74.69%)	4.65 (0.75)
	3 (0.98%)	3 (0.98%)	10 (3.27%)	59 (19.28%)	225 (73.53%)	4.67 (0.69)
B3b	2 (0.82%)	4 (1.63%)	9 (3.67%)	54 (22.04%)	173 (70.61%)	4.62 (0.71)
	4 (1.31%)	1 (0.33%)	9 (2.95%)	62 (20.33%)	221 (72.46%)	4.67 (0.68)
Continued on next page						

Table A.5 – continued from previous page

Item	Likert rating					Mean
	1	2	3	4	5	(SD)
B3c	2	1	5	21	215	4.83
	(0.82%)	(0.41%)	(2.05%)	(8.61)	(88.11%)	(0.55)
	4	2	3	41	249	4.77
	(1.31%)	(0.66%)	(0.98%)	(13.44%)	(81.64%)	(0.63)
B3d	3	4	4	47	186	4.68
	(1.22%)	(1.63%)	(1.63%)	(19.18%)	(75.92%)	(0.71)
	2	2	12	68	217	4.65
	(0.65%)	(0.65%)	(3.92%)	(22.22%)	(70.92%)	(0.65)
B3e **	1	8	8	82	145	4.48
	(0.41%)	(3.27%)	(3.27%)	(33.47%)	(59.18%)	(0.75)
	3	5	25	122	144	4.33
	(0.98%)	(1.63%)	(8.17%)	(39.87%)	(47.06%)	(0.78)
B3f	3	17	32	81	95	4.09
	(1.23%)	(7.00%)	(13.17%)	(33.33%)	(39.09%)	(0.99)
	4	9	34	109	112	4.18
	(1.32%)	(2.96%)	(11.18%)	(35.86%)	(36.84%)	(0.89)
B3g	1	6	15	77	122	4.42
	(0.41%)	(2.46%)	(6.15%)	(31.56%)	(50.00%)	(0.77)
	4	1	22	107	146	4.39
	(1.31%)	(0.33%)	(7.21%)	(35.08%)	(47.87%)	(0.77)
B3h	2	4	10	69	153	4.54
	(0.82%)	(1.65%)	(4.12%)	(28.40%)	(62.96%)	(0.73)
	5	5	12	79	192	4.53
	(1.64%)	(1.64%)	(3.93%)	(25.90%)	(62.95%)	(0.80)
B3i	3	6	7	67	155	4.53
	(1.24%)	(2.49%)	(2.90%)	(27.80%)	(64.32%)	(0.78)
Continued on next page						

Table A.5 – continued from previous page

Item	Likert rating					Mean
	1	2	3	4	5	(SD)
	5 (1.64%)	2 (0.66%)	11 (3.61%)	69 (22.62%)	207 (67.87%)	4.60 (0.75)
B3j	3 (1.24%)	3 (1.24%)	13 (5.37%)	49 (20.25%)	166 (68.60%)	4.59 (0.77)
	5 (1.64%)	4 (1.31%)	15 (4.92%)	66 (21.64%)	202 (66.23%)	4.56 (0.80)

Note: Please see Supplementary Appendix 2 in the work (Yuan et al., 2022a) for Items B1-B3.

For the same item, the upper and lower row represent the responses from the caregivers and the general public, respectively.

For each item, 1=Extremely unimportant/ useless, 2=Somewhat unimportant/ useless, 3=Neither important/ useful nor unimportant/ useless, 4=Somewhat important/ useful, 5=Extremely important/ useful.

Asterisks denote statistically significant differences between rating responses of the caregiver group and the other public group (* at 0.05 level, ** at 0.01 level, *** at 0.001 level.)

Table A.6: Percentage of responses to questions about usability and ethical concerns of robots for ADRD care by caregivers and the general public.

Item	Likert rating					Mean
	1	2	3	4	5	(SD)
C1a	0	2 (0.82%)	5 (2.05%)	92 (37.70%)	143 (58.61%)	4.55 (0.58)
	2 (0.66%)	3 (0.99%)	14 (4.61%)	99 (32.57%)	178 (58.55%)	4.51 (0.70)
C1b	0	4 (1.64%)	9 (3.69%)	87 (35.66%)	141 (57.79%)	4.51 (0.65)
	2 (0.66%)	2 (0.66%)	16 (5.26%)	100 (32.89%)	171 (56.25%)	4.50 (0.70)
C1c	1 (0.41%)	0	7 (2.87%)	58 (23.77%)	176 (72.13%)	4.69 (0.57)
	1 (0.33%)	2 (0.66%)	8 (2.63%)	69 (22.70%)	217 (71.38%)	4.68 (0.59)
C1d	2 (0.82%)	0	5 (2.06%)	20 (8.23%)	214 (88.07%)	4.84 (0.52)
	1 (0.33%)	3 (0.99%)	3 (0.99%)	35 (11.51%)	254 (83.55%)	4.82 (0.52)
C1e	1 (0.41%)	2 (0.82%)	9 (3.69%)	82 (33.61%)	148 (60.66%)	4.55 (0.65)
	2 (0.66%)	5 (1.64%)	9 (2.96%)	103 (33.88%)	174 (57.24%)	4.51 (0.71)
C1f **	4 (1.64%)	2 (0.82%)	10 (4.10%)	54 (22.13%)	168 (68.85%)	4.60 (0.76)
	3 (0.99%)	12 (3.96%)	16 (5.28%)	86 (28.38%)	175 (57.76%)	4.43 (0.85)
Continued on next page						

Table A.6 – continued from previous page

Item	Likert rating					Mean
	1	2	3	4	5	(SD)
C1g	2 (0.82%)	3 (1.23%)	3 (1.23%)	52 (21.31%)	179 (73.36%)	4.69 (0.65)
	2 (0.66%)	6 (1.98%)	7 (2.31%)	69 (22.77%)	212 (69.97%)	4.63 (0.70)
C1h	0 (0.99%)	7 (1.32%)	16 (3.95%)	65 (30.92%)	153 (61.18%)	4.51 (0.75)
	3 (0.99%)	4 (1.32%)	12 (3.95%)	94 (30.92%)	186 (61.18%)	4.53 (0.73)
C2	15 (6.12%)	44 (17.96%)	64 (26.12%)	69 (28.16%)	45 (18.37%)	3.36 (1.17)
	22 (7.24%)	74 (24.34%)	75 (24.67%)	74 (24.34%)	46 (15.13%)	3.16 (1.19)
C3 *	7 (2.88%)	55 (22.63%)	56 (23.05%)	74 (30.45%)	34 (13.99%)	3.32 (1.09)
	21 (6.98%)	74 (24.58%)	65 (21.59%)	80 (26.58%)	27 (8.97%)	3.07 (1.14)
C4 **	7 (2.86%)	29 (11.84%)	17 (6.94%)	52 (21.22%)	139 (56.73%)	4.18 (1.16)
	14 (4.62%)	37 (12.21%)	38 (12.54%)	80 (26.40%)	127 (41.91%)	3.91 (1.22)

Note: Please see Supplementary Appendix 2 in the work (Yuan et al., 2022a) for Items C1-C4.

For the same item, the upper and lower row represent the responses from the caregivers and the general public, respectively.

For the last three items (i.e., C2, C3 and C4), 1=Strongly agree, 2=Somewhat agree, 3=Neither agree nor disagree, 4=Somewhat disagree, 5=Strongly disagree.

Otherwise, 1=Extremely useless, 2=Somewhat useless, 3=Neither useful nor useless, 4=Somewhat useful, 5=Extremely useful.

Asterisks denote statistically significant differences between rating responses of the caregiver group and the other public group (* at 0.05 level, ** at 0.01 level.)

Table A.7: The top 10 frequently mentioned words in open-ended comment by caregivers and the general public

Caregivers		General public	
Word	<i>Count</i>	Word	<i>Count</i>
use	37	like	34
patient	36	patient	26
care	34	care	19
help	33	help	18
Alzheimer	31	voice	17
voice	23	need	16
robots	17	Alzheimer	13
assist	16	caregiver	10
dementia	16	cognitive	8
like	16	mild	8

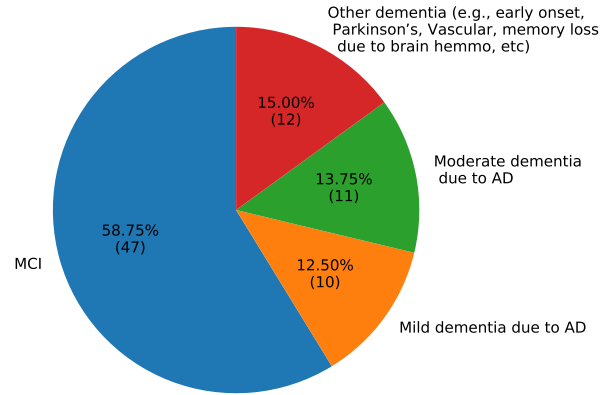


Figure A.1: Disease distribution among patient group

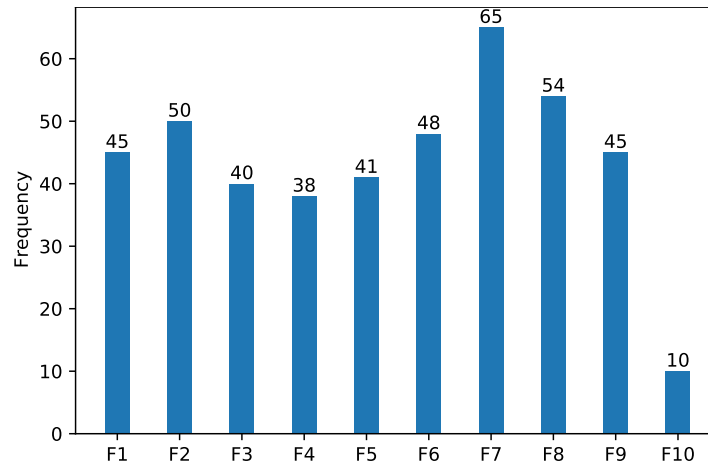


Figure A.2: Functions participants with MCI or ADRD hoped the robot would help with. F1 = Help call family and friends; F2 = Help contact medical services; F3 = Help do shopping; F4 = Help order food; F5 = Help prevent falling; F6 = Remind to turn off stove top; F7 = Remind to take medicine; F8 = Emergency call service; F9 = Keep me company; F10 = Other.

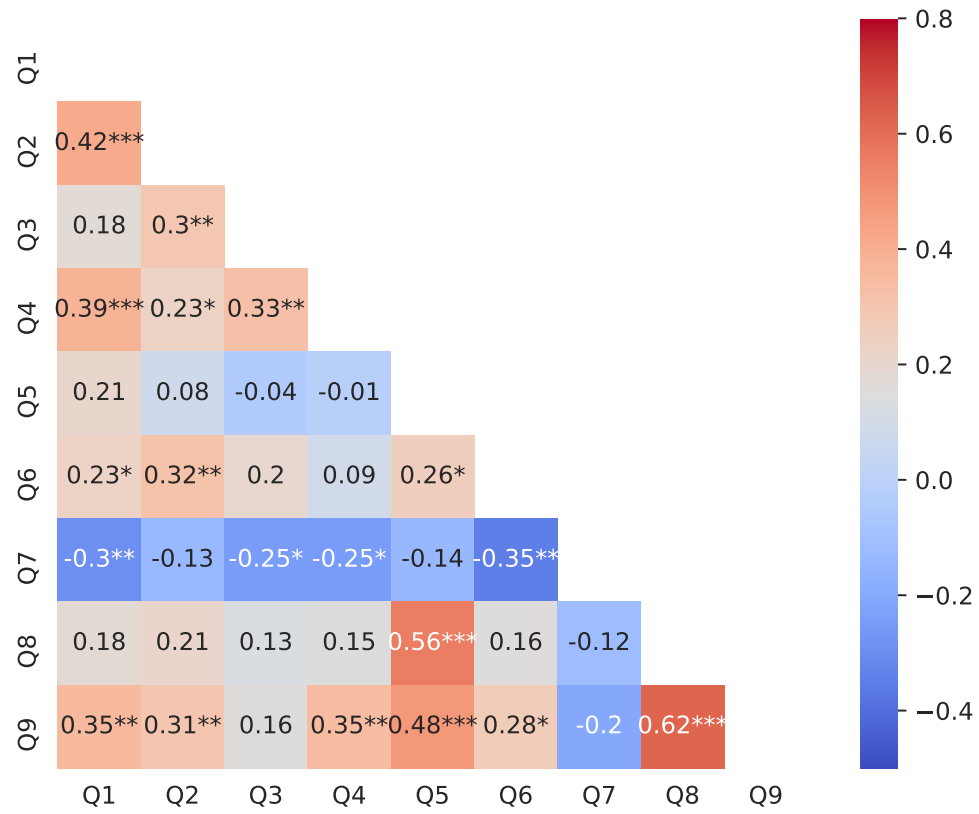


Figure A.3: Correlation map among responses from people with MCI or ADRD. Please See Supplementary Appendix 1 for Items Q1-Q9. Asterisks denote statistically significant relationships between responses to two items (* at 0.05 level, ** at 0.01 level, *** at 0.001 level).

A.2 Study of Robot-assisted Conversational Engagement

Table A.8: Items to evaluate user experience for the RMRT usability study

Item	Construct
<i>Q1</i> : The robot's appearance is pleasing	Usability and UI: Robot's appearance
<i>Q2</i> : The robot's voice is clear	Usability and UI: Robot's voice
<i>Q3</i> : The robot's gestures and other body movements are appropriate	Usability and UI: Robot's body movement
<i>Q4</i> : The robot's tablet screen designs and layout are attractive	Usability and UI: Robot's touchscreen design
<i>Q5</i> : I feel relaxed when talking to the robot	Anxiety
<i>Q6</i> : I would like the robot to be my friend	Social presence
<i>Q7</i> : I would follow the advice of the robot	Trust
<i>Q8</i> : The app is useful	Perceived usefulness
<i>Q9</i> : The app is easy to use	Perceived ease of use
<i>Q10</i> : The app is interesting	Perceived enjoyment
<i>Q11</i> : I would like to use the app in the future	Intention to use
<i>Q12</i> : I would like to recommend the app to others	Willingness to recommend

Table A.9: Descriptive statistics of participants

Demographic variables	Statistic
Gender, ($n = 12$)	n (%)
Female	4 (33.33%)
Male	8 (66.67%)
Age (years), ($n = 12$)	n (%)
50-65	1 (8.33%)
65-75	3 (25.00%)
75-85	7 (58.34%)
Above 85	1 (8.33%)
Highest level of education, ($n = 12$)	n (%)
High school graduate	1 (8.33%)
Some college	4 (33.33%)
College graduate	2 (16.67%)
Post-graduate	5 (41.67%)
Familiarity with technology	Mean $\pm$ SD
Smartphones	2.75 ± 1.22
Tablets	2.42 ± 1.08
Computers	2.73 ± 1.01
Robots	1.00 ± 0

For the items associated with familiarity with technology (i.e., Rows *Smartphones*, *Tablets*, *Computers* and *Robots*), 1 = Not at all familiar, 2 = Slightly familiar, 3 = Moderately familiar, 4 = Very familiar.

Table A.10: Participants' responses to Items Q1-Q12 about system usability and user experience

Groups	Statistic	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11	Q12
People with MCI	Mean	4.50	4.50	4.50	5.00	5.00	4.50	3.50	4.50	5.00	5.00	4.50	4.50
	SD	0.71	0.71	0.71	0	0	0.71	0.71	0.71	0	0	0.71	0.71
	Range	1	1	1	0	0	1	1	1	0	0	1	1
People with ADRD	Mean	4.86	4.29	4.43	4.43	4.14	4.67	4.00	4.43	4.71	4.71	4.57	4.50
	SD	0.38	1.50	1.51	1.51	1.46	0.52	1.41	0.79	0.49	0.49	0.53	0.84
	Range	1	4	4	4	4	1	4	2	1	1	1	2
Informal caregivers	Mean	5.00	4.33	5.00	4.67	4.67	4.67	3.00	5.00	4.67	5.00	4.33	4.67
	SD	0.0	0.58	0	0.58	0.58	0.58	0	0	0.58	0	0.58	0.58
	Range	0	1	0	1	1	1	0	0	1	0	1	1
Overall response	Mean	4.83	4.33	4.58	4.58	4.42	4.64	3.73	4.58	4.75	4.82	4.50	4.55
	SD	0.39	1.15	1.16	1.16	1.16	0.50	1.19	0.67	0.45	0.40	0.52	0.69
	Range	1	4	4	4	4	1	4	2	1	1	1	2

See Table A.8 for Items Q1-Q12.

For the same group, the upper and lower row represent the mean and standard deviation to their responses, respectively.

Scale for each item, 1 = *strongly disagree*, 2 = *somewhat disagree*, 3 = *neither agree nor disagree*, 4 = *somewhat agree*, 5 = *strongly agree*.

Table A.11: Count of functions participants hoped the robot Tammy to have

Groups	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10
People with MCI	2	2	2	1	2	2	2	2	2	0
People with ADRD	7	6	4	4	5	5	6	6	5	1
Informal caregivers	3	3	0	0	2	1	3	3	2	0
Overall response	12	11	6	5	9	8	11	11	9	1

F1 = Help call family and friends; F2 = Help contact medical services; F3 = Help do shopping; F4 = Help order food; F5 = Help prevent falling; F6 = Remind to turn off stove top; F7 = Remind to take medicine; F8 = Emergency call service; F9 = Keep me company; F10 = Other (Play music).

Table A.12: Videos coding for the participant’s interaction with the robot during RMRT for Participant P1.

Topic	Behavior	N_{occur}	Note
1 st topic	Success in choosing a topic	1	
	Laughter	10	
	Nodding	2	
	Failure in using NEXT	2	First time to use the RMRT, still learning
	Success in using NEXT	3	
	Confusion	1	Confused about what to do at the end of the topic
2 nd topic	Success in choosing a topic	1	
	Failure in voice control	1	The robot not ready to catch voice input
	Success in using NEXT	4	
	Nodding	1	
	Success in using MAIN MENU	1	
3 rd topic	Success in choosing a topic	1	
	Failure in voice control	1	
	Success in using NEXT	3	
	Reflection/Thinking	1	When the robot asked P1 to suggest some place
	Laughter	2	
	Tending to shake hands with the robot	1	
	Success in using MAIN MENU	1	
4 th topic	Success in choosing a topic	1	
	Failure in voice control	1	
	Success in voice control	1	
	Success in using NEXT	3	
	Nodding	1	
	Success in using MAIN MENU	1	
5 th topic	Success in choosing a topic	1	
	Failure in voice control	1	
	Success in voice control	1	
	Success in using NEXT	3	
	Success in using MAIN MENU	1	
6 th topic	Failure in choosing a topic	1	P1 didn’t know to scroll up or down the screen
	Success in choosing a topic	1	
	Success in voice control	1	
topic	Continued on next page		

Table A.12 – continued from previous page

Topic	Behavior	N_{occur}	Note
	Success in using NEXT	1	
	Laughter	1	
	Nodding	1	
	Success in using MAIN MENU	1	
7 th topic	Success in choosing a topic	1	Successfully scrolling up the screen
	Ineffective voice control	1	No need of user input in RMRT
	Singing along with the robot	2	
	Laughter	4	
	Success in using NEXT	5	
	Nodding	1	
	Success in using MAIN MENU	1	

Note: Here the voice control was the voice input “Tammy next”.

Table A.13: Videos coding for the participant’s interaction with the robot during RMRT for Participant P2

Topic	Behavior	N_{occur}	Note
1 st topic	Confusion	2	First time to use the RMRT, confused about next step.
	Dysfunction in tapping NEXT	1	P2 with a shaking hand
2 nd topic	Success in choosing a topic	1	
	Failure in voice control	1	
	Laughter	1	Although the robot did not respond successfully
	Success in using NEXT	3	
	Dysfunction in tapping NEXT	1	Due to the shaking hand.
	Success in using MAIN MENU	1	
3 rd topic	Success in choosing a topic	1	
	Laughter	1	
	Success in using NEXT	2	
	Dysfunction in tapping NEXT	1	Due to the shaking hand.
	Success in using MAIN MENU	1	
4 th topic	Success in choosing a topic	1	
	Success in using NEXT	2	
	Not answering but directly tap NEXT	1	
	Forgetting tapping NEXT	1	

Note: Here the voice control was the voice input “Tammy next”.

Table A.14: Videos coding for the participant’s interaction with the robot during RMRT for Participant P3

Topic	Behavior	N_{occur}	Note
1 st topic	Success in choosing a topic	1	
	Failure in voice control	1	Probably low voice or not right time
	Success in using NEXT	5	
	Laugh/giggle/joy	2	
	Tending to shake hand with the robot	1	
	Confusion	1	Confused about what to do at the end of the topic
2 nd topic	Success in choosing a topic	1	
	Ineffective voice input	1	No need of user input in RMRT
	Laugh/giggle/joy	3	
	Eye Contact with the robot	1	
	Success in using NEXT	4	
	Confusion	1	Confused when the robot not responding to her. Forgetting to tap NEXT
	Reflection/thinking	1	The robot asked P3 to tell it her favorite songs

Note: Here the voice control was the voice input “Tammy next”.

Table A.15: Reward components w.r.t. response relevance in reward function R_1 and R_2 .

R_1/R_2	No response (NR)	Irrelevant response (IR)	Relevant response (RR)
a_2	$-2/-2$	0.75/0.75	2/2
a_3	$-2/-2$	1.75/3	3/10
$a_i, i \neq 2, 3$	$-2/-2$	0.3/0.3	0.75/0.75

Table A.16: The PwD-robot interaction during a reminiscence therapy.

Step	State s	Action (PwD's choice)
0	[0, 0, 0]	0
1	[0, 0, 0]	0
2	[0, 1, 0]	0
3	[0, 1, 1]	3
4	[2, 1, 1]	6 $\rightarrow$ (Change picture)
5	[0, 0, 0]	0
6	[0, 1, 1]	3
7	[0, 1, 0]	0
8	[1, 0, 0]	0
9	[2, 0, 0]	0
10	[2, 0, 0]	0
11	[2, 0, 0]	0
12	[2, 0, 0]	0
13	[2, 0, 0]	0
14	[2, 0, 0]	0
15	[2, 0, 0]	0
16	[2, 0, 0]	0
17	[2, 0, 0]	0
18	[2, 0, 0]	0
19	[2, 0, 0]	0
20	[1, 0, 0]	0
21	[1, 0, 0]	0
22	[1, -1, 0]	5
23	[1, 0, 0]	0
24	[1, 1, 0]	0
25	[0, 1, 0]	0
26	[2, 1, 0]	1
27	[2, 1, 0]	1
28	[2, 1, 0]	1
29	[2, 1, 0]	1
30	[2, 1, 0]	1
31	[2, 1, 0]	1
32	[2, 1, 0]	1
33	[1, 1, 0]	0
34	[1, 1, 0]	0
35	[1, 1, 0]	0
Continued on next page		

Table A.16 – continued from previous page

Step	State s	Action (PwD's choice)
36	[0, 0, 0]	0
37	[1, 0, 1]	3
38	[1, 0, 0]	0
39	[0, 0, 1]	4
40	[0, 1, 0]	0
41	[0, 0, 0]	0
42	[2, 0, 0]	0
43	[2, 1, 0]	1
44	[2, 1, 0]	1
45	[2, 1, 0]	1
46	[2, 0, 0]	0
47	[2, 0, 0]	0
48	[2, 0, 0]	0
49	[2, 0, 0]	0
50	[2, 0, 0]	0

Note: A state $s=[Response\ relevance, Emotion\ level, Confusion\ condition]$. A value of 0, 1, and 2 in the 1st component (i.e., *Response relevance*) represent *no response*, *irrelevant response*, and *relevant response*, respectively. A value of -1, 0, and 1 in the 2nd component (i.e., *Emotional level*) represent *negative emotion*, *neutral emotion*, and *positive emotion*, respectively. A value of 0 and 1 in the 3rd component (i.e., *Confusion condition*) represent *unconfused* and *confused*, respectively.

In “Action” Column, a value of 0, 1, 2, 3, 4, 5, and 6 denotes the action, a_1 , a_2 , a_3 , a_4 , a_5 , a_6 , and a_7 , respectively.

Table A.17: Summary statistics of participants' response features

Feature	Mean $\pm$ SD	Median	Range
Joy	0.2325 ± 0.2614	0.1106	0.0007-0.9901
Neutral	0.5230 ± 0.3062	0.5778	0.0008-0.9853
Sadness	0.1287 ± 0.2046	0.0368	0.0006-0.9811
Surprise	0.0107 ± 0.0616	0.0019	0.0001-0.9429
Anger	0.0889 ± 0.1539	0.0357	0.0015-0.9915
Fear	0.0091 ± 0.0349	0.0029	0.0003-0.7065
Disgust	0.0070 ± 0.0282	0.0025	0.0003-0.7837
Length of utterance	23 ± 36	12	1-707

Table A.18: Causal relationship between participants' current response X_t and the backward-looking dialogue act Z_{tb} taken by the moderator occurred more than 5 time in the causal graphs

Edges	Occurrence	Causal Effects
D $\rightarrow$ Agr	5	[2.13, 9.97, 9.94, 4.04, 1.45]
T $\rightarrow$ Ack	7	[0.11, 0.17, 0.13, 0.17, 0.15, 0.25, 0.20]
T $\rightarrow$ App	7	[0.11, 0.10, 0.13, 0.08, 0.11, 0.10, 0.07]
T $\rightarrow$ StaNo	6	[-0.13, -0.19, -0.11, -0.15, -0.18, -0.11]

Table A.19: Causal relationship between participants' current response X_t and the forward-looking dialogue act Z_{tf} taken by the moderator occurred more than 5 time in the causal graphs

Edge	Occurrence	Causal Effects
Sa $\rightarrow$ DYNQ	6	[0.35, 0.61, 0.39, 0.18, 0.48, 0.14]

Table A.20: Causal relationship between participants' current response X_t and following response Y_t occurred more than 5 time in the causal graphs

Edge	Occurrence	Causal Effects
$A \rightarrow nA$	6	[0.21, 0.25, 0.25, 0.47, 0.33, 0.32]
$J \rightarrow nJ$	8	[0.25, 0.22, 0.31, 0.22, 0.31, 0.34, 0.26, 0.43]
$Sa \rightarrow nSa$	9	[0.32, 0.23, 0.34, 0.27, 0.26, 0.25, 0.33, 0.41, 0.39]

Table A.21: Causal relationship between backward-looking dialogue act Z_{tb} from the moderator and participants' following response Y_t occurred more than 5 time in the causal graphs

Edge	Occurrence	Causal Effects
$StaNo \rightarrow nT$	8	[1.67, -0.70, -0.79, -0.61, -0.68, -0.75, -0.74, -0.72]

Table A.22: Causal relationship between forward-looking dialogue act Z_{tf} from the moderator and participants' following response Y_t occurred more than 5 times in the causal graphs

Edge	Occurrence	Causal Effects
$WhQ \rightarrow nT$	7	[3.08, 1.80, 2.48, 2.20, 1.92, 0.85, 1.35]
$YNQ \rightarrow nT$	5	[1.76, 1.42, 1.31, 0.67, 0.59]



Figure A.4: Examples of photos that could be used to assist reminiscing sports. However, the first two pictures on the left could be distracting to PLWD. Comparatively, the picture on the right is appropriate for PLWD during reminiscence..

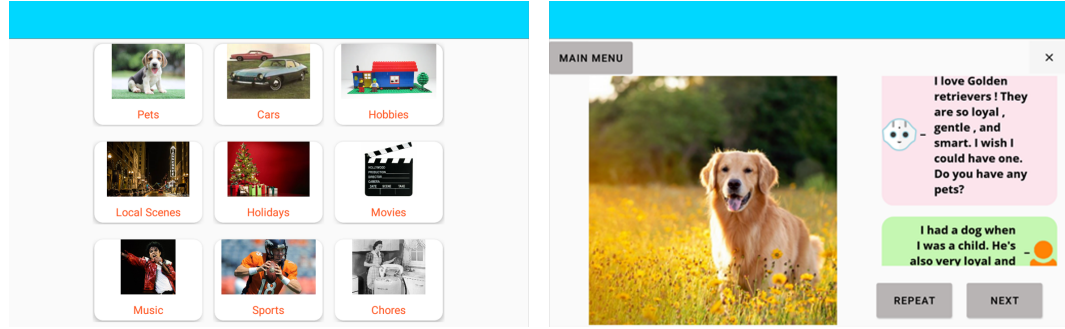


Figure A.5: Screenshot of touchscreen design in the robot for RMRT: (a) The touchscreen design for the topic selection layer. (b) An example of a PLWD-robot conversation.

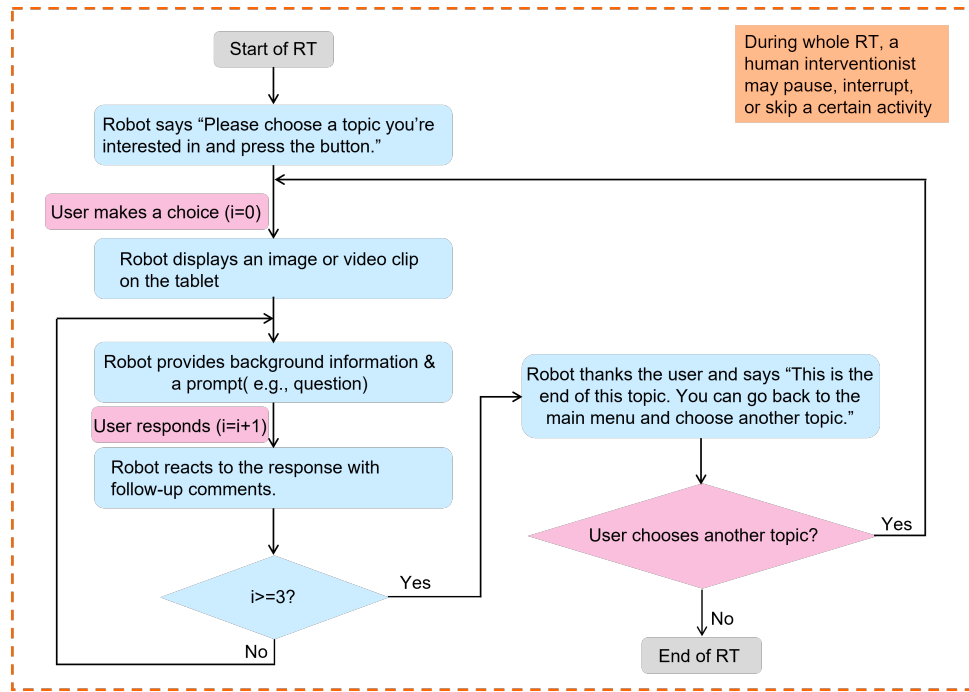


Figure A.6: The flowchart of the robot-mediated reminiscence activity.

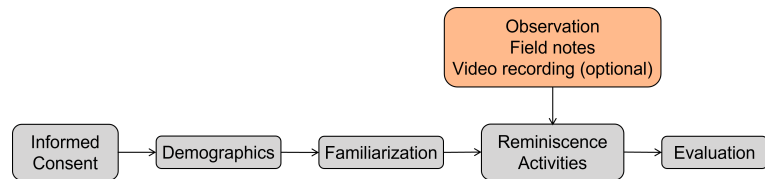


Figure A.7: Experimental procedure for the usability study of robot-mediated reminiscence therapy.

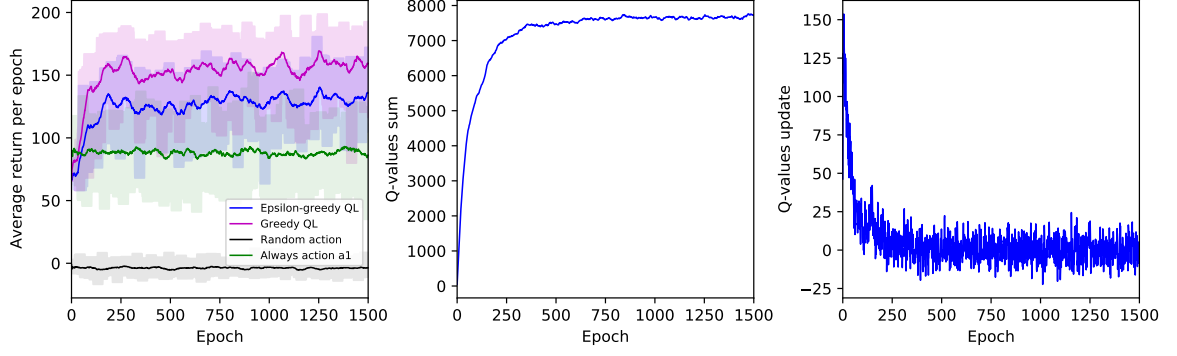


Figure A.8: The learning process by ϵ -greedy Q-learning with reward function R_1 .

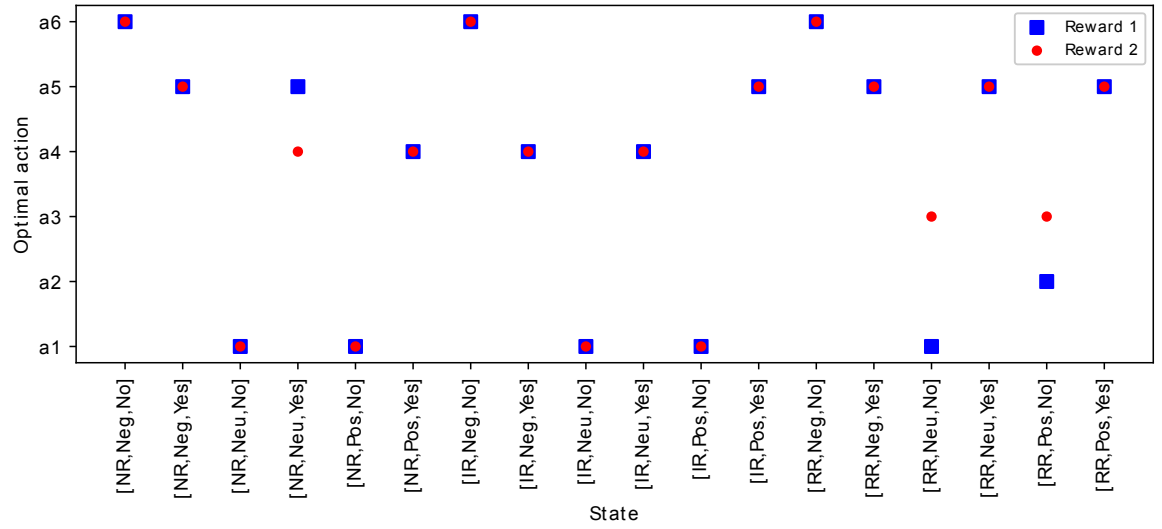


Figure A.9: The most nearly optimal policy π'_* learned by ϵ -greedy QL.

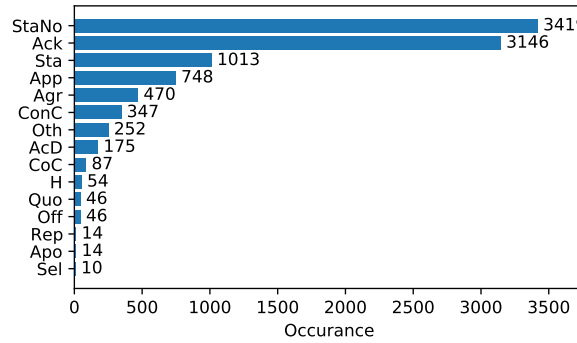
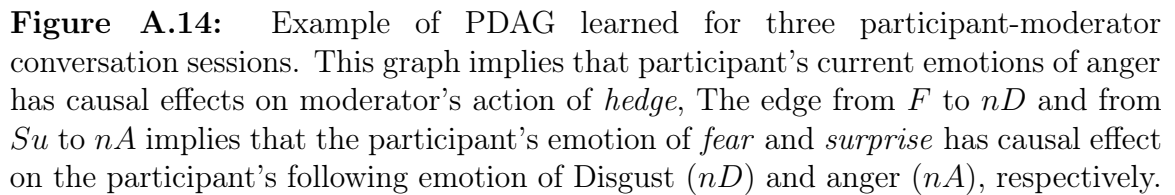
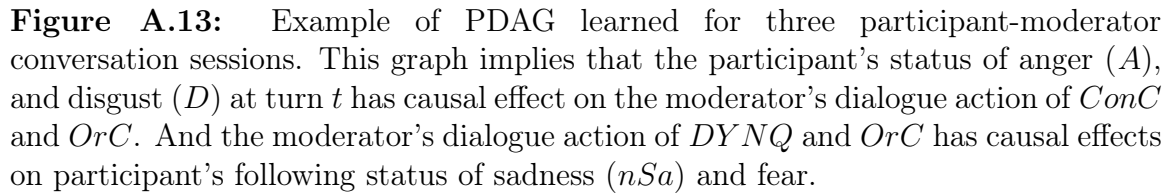


Figure A.10: The occurrence of DA tags with backward-looking function in I-CONNECT conversational dataset.



A.3 Tables and Figures from Study of Robot-assisted Activities of Daily Living

Table A.23: Items to Evaluate User Experience and Satisfaction for the Robot-assisted PASS

Item	Construct
<i>Q1</i> : The robot's appearance is pleasing	Usability and UI: Robot's appearance
<i>Q2</i> : The robot's voice was clear	Usability and UI: Robot's voice
<i>Q3</i> : The robot's gestures and other body movements were appropriate	Usability and UI: Robot's body movement
<i>Q4</i> : The robot's tablet screen designs and layout were attractive	Usability and UI: Robot's touchscreen design
<i>Q5</i> : The information (such as instructions, on-screen messages and body language) provided by the robot was clear	Information quality
<i>Q6</i> : The information provided by the robot was effective in helping me complete the tasks	Information quality
<i>Q7</i> : I felt relaxed when talking to the robot	Anxiety
<i>Q8</i> : I felt relaxed when doing the tasks administered by the robot	Anxiety
<i>Q9</i> : It is easy to understand the robot's instruction and know what to do	Information quality
<i>Q10</i> : I found the system easy to use	Perceived ease of use
<i>Q11</i> : I felt comfortable using this system	System usefulness
<i>Q12</i> : Overall, I am satisfied with this system	Overall satisfaction
<i>Q13</i> : I would follow the advice the robot gives me	Trust

Table A.24: Percentage of responses to Items Q1-Q13 about user experience and satisfaction.

Item	Likert rating					Mean (SD)
	1	2	3	4	5	
Q1	0	0	0	2 (40%)	3 (60%)	4.60 (0.49)
Q2	0	1 (20%)	0	1 (20%)	3 (60%)	4.20 (1.17)
Q3	0	1 (20%)	0	4 (80%)	0	3.60 (0.80)
Q4	0	0	1 (20%)	1 (20%)	3 (60%)	4.40 (0.80)
Q5	0	1 (20%)	0	1 (20%)	3 (60%)	4.20 (1.17)
Q6	0	0	1 (20%)	1 (20%)	3 (60%)	4.40 (0.80)
Q7	0	0	2 (40%)	0	3 (60%)	4.20 (0.98)
Q8	0	0	1 (20%)	1 (20%)	3 (60%)	4.40 (0.80)
Q9	0	1 (20%)	0	0	4 (80%)	4.40 (1.20)
Q10	0	1 (20%)	0	0	4 (80%)	4.40 (1.20)
Q11	0	0	0	1 (20%)	4 (80%)	4.80 (0.40)
Q12	0	0	1 (20%)	0	4 (80%)	4.60 (0.80)
Q13	0	0	1 (20%)	2 (40%)	2 (40%)	4.20 (0.75)

Note: For each item, 1=Strongly disagree, 2=Somewhat disagree, 3=Neither agree nor disagree, 4=Somewhat agree, 5=Strongly agree.

Table A.25: Evaluation Framework for PwD-robot-task-environment transaction during activities of daily living

Construct	Components	Categories
Performance breakdown	Cognitive Domains (DSM-5)	Memory and learning (ML)
		Language (L)
		Executive function (EF)
		Complex attention (CA)
		Social cognition (SC)
	Physical Function	Perceptual and motor functions (PMF)
		Muscular strength/endurance (MSE)
		Coordination, gross/fine motor skills (CGF)
		Balance/fall risk (B/FR)
		Functional mobility (FM)
		Joint flexibility/arthritis limitations (JF)
	Psychosocial	Negative affect (eNeg) e.g., frustration, anger
		Visual engagement
		Verbal engagement
		Behavioral engagement
		Social engagement
	Environment	Environmental Limitation (EL)
	Robot Performance	Robot Malfunction: (RoMal)
		Robot Limitation: (RoLim)
PASS score	Independence	
	Safety	
	Adequacy	

Table A.26: Example of Coding Task Breakdown

Performance breakdown	Time	Cog	Phys	PsySocial	Environment	Robot
Hand on face, looked confused	1:07:30	X		X		
“Yes, Tammi I get the point”	1:08:52	X				
Negative emotion- this is difficult	1:07:12			X		
Robot turned away	1:07:45					X
Slow response, seems confused	1:08:16	X				
Robot interruption of task/no response from participant	1:08:27	X				X
Participant, talking, robot interrupted, F. touches robots head	1:08:48					X
F. turns pill bottle around to show instructions	1:09:43	X				X
F. turns pill bottle around	1:10:53	X				X
F. hands participant materials for 2nd task and reads the instructions.	1:11:15					X

Table A.27: Terms and Definitions used in our Simulating Context

Term	Definition	Example
<i>Scenario</i>	The broad context or setting that includes various tasks, starting from an initial state and ending at a terminal state	Shopping scenario.
<i>Task</i>	Specific objectives within a scenario, often complex and divisible into subtasks.	<i>Task 1</i> : Select 4 items on the shopping list correctly. <i>Task 2</i> : Select the correct cash for the 4 grocery items.
<i>Subtask</i>	Smaller, manageable components of a task.	In Task 1, there are <i>Subtask 1</i> : identifying item one; <i>Subtask 2</i> : picking up item one and gathering it in a location; 3) identifying item two, etc.
<i>Trial</i>	A single attempt or iteration where the PLWD tries to complete the specified subtask, with or without external assistance.	In a subtask of Task 1, if the PLWD picks one item and pauses, a caregiver/assistant might remind them by asking, "Is there anything missing?" prompting the PLWD to check the shopping list.
<i>Timestep</i>	Time steps or moments of interaction between PLWD and an interventionist, occurring under the scenario.	The total timesteps of a scenario equal the sum of trials over all subtasks and tasks.

Table A.28: Definitions and Examples of Assistance Types

Assistance Type	Definition	Example
None	No assistance is provided from the interventionist or robot	
Verbal supportive assistance	Encouragement to initiate, continue, or complete a task	“Keep at it”; “Great”
Verbal non-directive assistance	Cues to facilitate task initiation, continuance, or completion without telling the client exactly what to do; often stated in the form of a question	“Is there anything missing?” “Can you try another way?”
Verbal directive assistance	Verbal statements to initiate, continue, or complete a task	“Check the recipe again”; “The date needs to be filled in on the check”

Table A.29: Probabilistic Transition of PLWD’s cognitive and affective status without external assistance

Status		$Forgetful_t$	$Confused_t$	$Angry_t$	$Disengaged_t$
Base Probability		30%	30%	5%	20%
Probability of mutual influence	$Forgetful_{t+1}$	99%	+7%	+7%	+7%
	$Confused_{t+1}$	+5%	99%	+8%	+10%
	$Angry_{t+1}$	+6%	+8%	100%	+20%
	$Disengaged_{t+1}$	+2%	+2%	+10%	99%

Table A.30: Weight of each reward component

Weight	Value
w_{forget}	-1
$w_{confuse}$	-1
w_{anger}	-5
$w_{disengaged}$	-1
$w_{increasedTrial}$	-1
$w_{subtaskCompleat}$	+50
$w_{subtaskSkip}$	-10
$w_{increasedTimestep}$	-1
$w_{taskCompleat}$	+20
$w_{assist}(a_0)$	0
$w_{assist}(a_1)$	-1
$w_{assist}(a_2)$	-3
$w_{assist}(a_3)$	-5


```

"Recording": {
  "Filename": "4-25-2022_170606_id19_pass2",
  "Status": true,
  "VideoPath": "",
  "VideoStatus": "recording uploaded",
  "patientId": 19
},
"Rotation": {
  "Clockwise": false,
  "Command": false,
  "Counterwise": false,
  "new_dim": 360
},
"Speak": {
  "Content": "This is the end of the task. Thank you.",
  "Pushed": false
},
},

```

Figure A.15: Representation of three JSON branches in the Firebase Realtime Database.

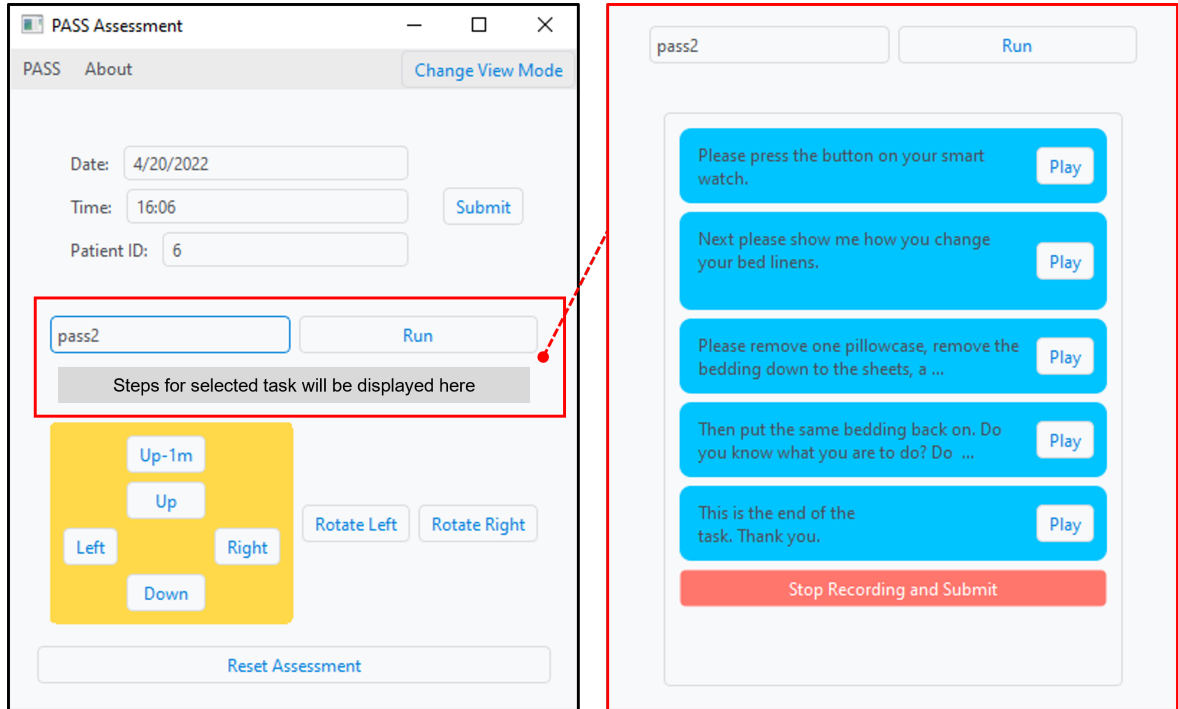


Figure A.16: Experimenter Interface at Startup.

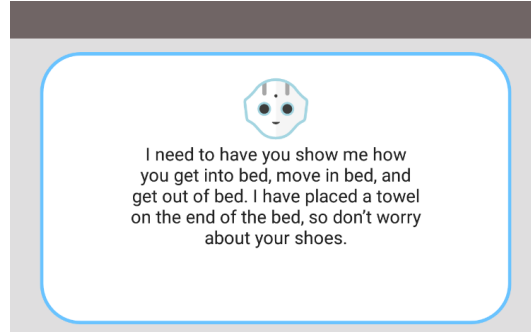


Figure A.17: A screenshot of the graphical user interface in the app Tammy Agent on the robot's tablet.

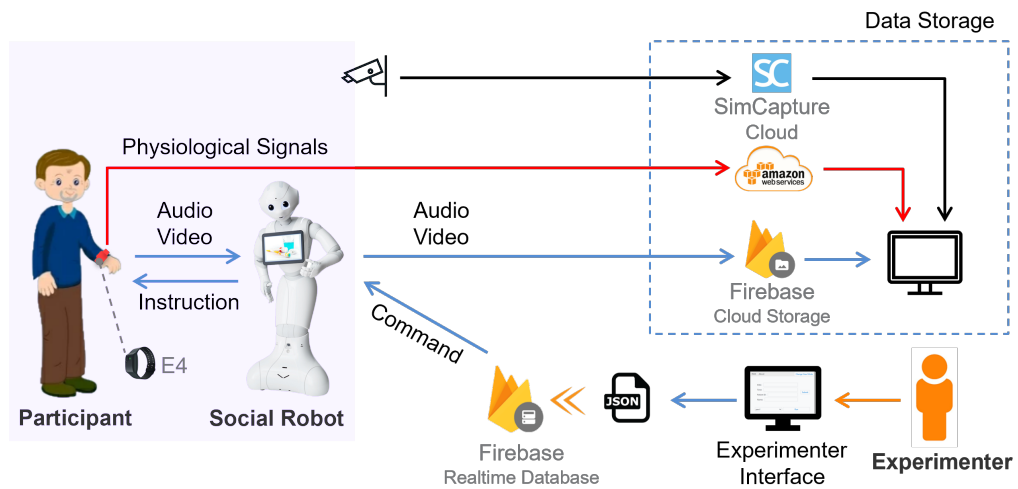


Figure A.18: The diagram illustrating the tele-operated robot-assisted PASS platform.

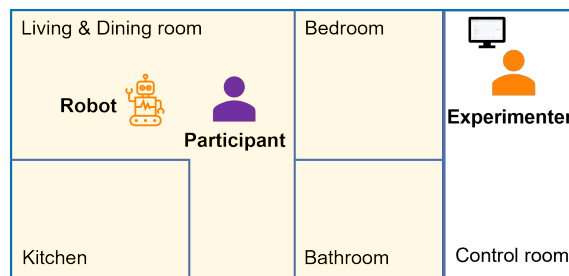


Figure A.19: Illustration of positions of the participant, the robot, and the experimenter during experiments.



Figure A.20: Participants and the Pepper robot during PASS tasks observed through the cameras equipped at Smart Home. The corresponding PASS tasks from left to right are bed mobility, changing bed linen, medication management, and making a sandwich. Participants' faces were clearly recorded, while their faces were blurred here.



Figure A.21: Participants during PASS tasks observed through the camera equipped in the robot's tablet. The corresponding PASS tasks from left to right are changing bed linen, obtaining information from a poster, and making a sandwich. Participants' faces were clearly recorded, while their faces were blurred here.

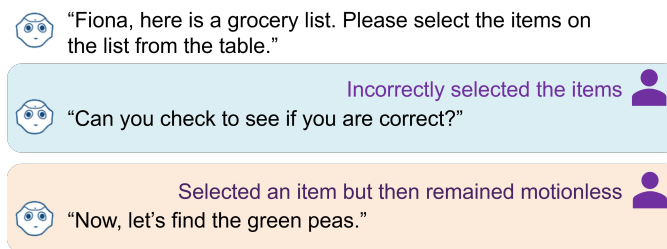


Figure A.22: Examples of scenarios of the robot provide assistance to remind and/or support persons with dementia during daily routine tasks.

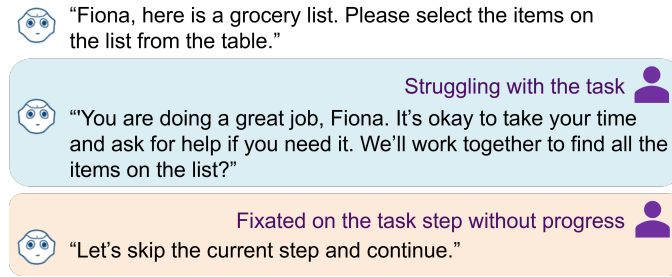


Figure A.23: Examples of scenarios of the robot provide assistance to redirect persons with dementia from performance breakdown during daily routine tasks.

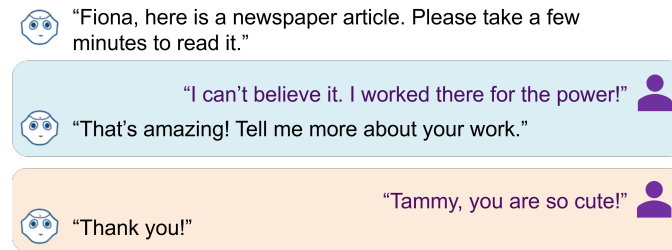


Figure A.24: Examples of scenarios of the robot chatting with a person with dementia during daily routine tasks.

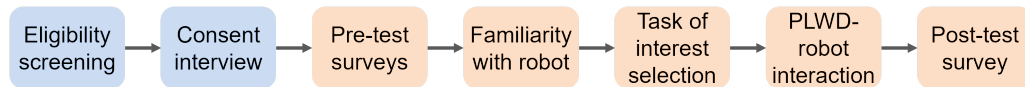


Figure A.25: Illustration of experimental procedure using our robotic platform to guide and assist a person with dementia to perform daily routine tasks.

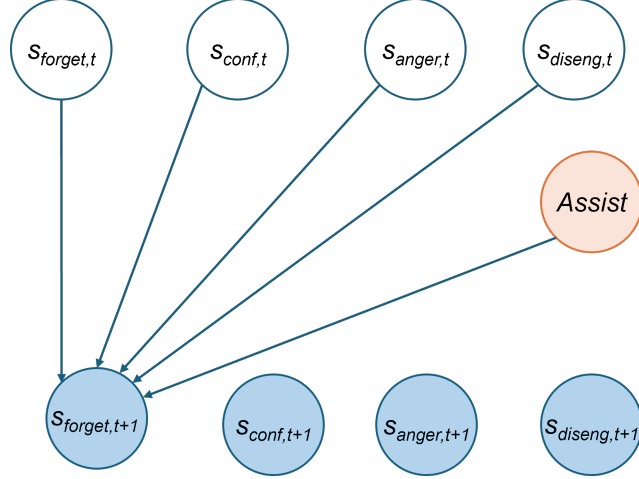


Figure A.26: A graph illustration of how the dynamics of PLWD’s status *Forgetfulness* is simulated. The same mechanics applied to the other three statuses, *Confusion*, *Angry*, and *Disengagement*.

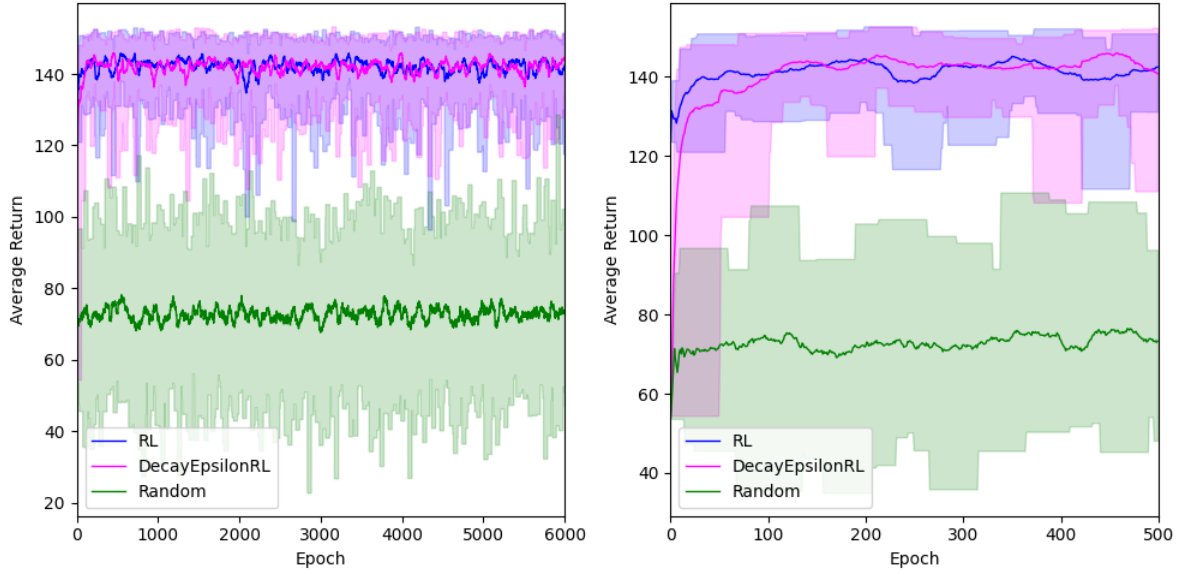


Figure A.27: Average Return from 40 Experiments Using Temporal Optimal Policy π' at the 10th Episode during the training process. This graph compares the performance of constant-epsilon RL (blue), decaying-epsilon RL (pink), and random action selection strategies (green). The returns are calculated by applying the temporal optimal policy extracted at the 10th episode of each epoch, with each strategy’s performance averaged over 40 experimental runs.

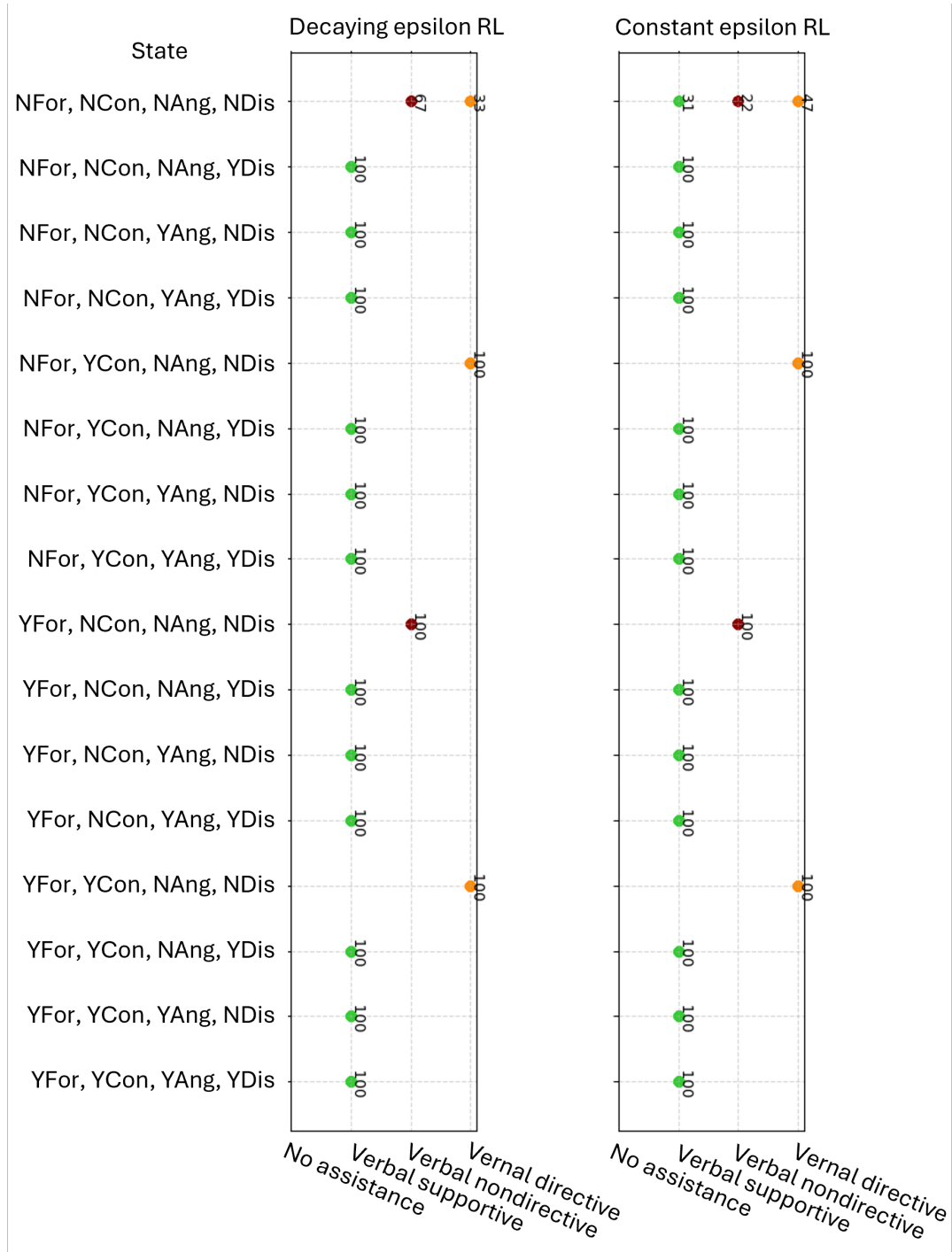


Figure A.28: The optimal policy learned by the decaying epsilon greedy RL agent (right) and the constant-epsilon greedy RL agent (left).

A.4 Tables and Figures from Study of Robot-assisted Psycho-education

Table A.31: Example of follow-up questions and comments during robot-assisted psycho-educational intervention

Question	Follow-up Comment
<i>Do you have any questions or comments to share with me about the bathroom safety?</i>	<i>Thank you. Bathroom safety is very important. I hope the bathroom safety tips here are useful to you. Paying attention to bathroom safety can help a person with dementia maintain his or her independence. And this can also ease your stress of caregiving.</i>
<i>Here is a question for you to think about. How can you incorporate exercise into your routine?</i>	<i>Thanks for your response. Remember, I am here to help you through this journey of caregiving.</i>
<i>After hearing some examples of common behaviors, can you think of times when your loved one exhibited some of these behaviors?</i>	<i>Thanks for your response. As I mentioned, please understand that your loved one is not trying to be difficult. I am also here to help you through these challenges.</i>

Table A.32: Items to evaluate user experience and satisfaction for the robot-assisted psychoeducation

Item	Construct
<i>Q1</i> : The robot's appearance is pleasing	User interface: Robot's appearance
<i>Q2</i> : The robot's voice is clear	User interface: Robot's voice
<i>Q3</i> : The robot's gestures and other body movements are appropriate	User interface: Robot's body movement
<i>Q4</i> : The robot's tablet screen designs and layout are attractive	User interface: Robot's touchscreen design
<i>Q5</i> : It is hard to understand the robot's instruction and know what to do	Information quality
<i>Q6</i> : The module on Alzheimer's and caregiving is useful	Perceived usefulness: Module 1
<i>Q7</i> : The module on safety is useful	Perceived usefulness: Module 2
<i>Q8</i> : The module on healthy lifestyle guide is useful	Perceived usefulness: Module 3
<i>Q9</i> : The module on stress and relaxation is useful	Perceived usefulness: Module 4
<i>Q10</i> : The module on caregiving challenges is useful	Perceived usefulness: Module 5
<i>Q11</i> : This program meets my expectations	Overall user satisfaction
<i>Q12</i> : This program is easy to use	Perceived ease of use
<i>Q13</i> : I would like to recommend the program to others	Willingness to recommend

Table A.33: Descriptive statistics of participants

Demographic variables	<i>n</i> (%)
Gender, <i>n</i> (%)	
Female	5 (55.56%)
Male	3 (33.33%)
Age (years), <i>n</i> (%)	
50-65	1 (11.11%)
65-75	3 (33.33%)
75-85	4 (44.45%)
Above 85	1 (11.11%)
Highest level of education, <i>n</i> (%)	
Some college	4 (44.45%)
College graduate	3 (33.33%)
Post-graduate	2 (22.22%)
Ethnicity, <i>n</i> (%)	
White	5 (55.56%)
African American	4 (44.44%)
Relationship to care recipient	
Relative	1 (11.11%)
Senior companion	2 (22.22%)
Suggest group work	2 (22.22%)
Other	3 (33.33%)
Familiarity with technology, Mean $\pm$ SD	
Smartphones	2.86 $\pm$ 0.90
Tablets	3.00 $\pm$ 1.00
Computers	3.17 $\pm$ 0.75
Robots	1.17 $\pm$ 0.41
Types of caregivers (Multiple answer; <i>n</i> ,%)	
Informal caregiver	7 (77.78%)
Doctor	2 (22.22%)
Not a caregiver	1 (11.11%)
Caregiving hours per week (<i>n</i> ,%)	
Under 4 hours	2 (22.22%)
4-8 hours	2 (22.22%)
Above 8 hours	2 (22.22%)

Note: Since questionnaire questions are not mandatory, a participant may skip a question accidentally. One participant had difficulty reading and skipped most of questions, except questions about age, education, and race.

n = sample size; M = mean; SD = standard deviation.

For the items associated with familiarity with technology (i.e., Rows *Smartphones*, *Tablets*, *Computers* and *Robots*), 1 = Not at all familiar, 2 = Slightly familiar, 3 = Moderately familiar, 4 = Very familiar.

Table A.34: Example of follow-up questions and comments

Participant	Open-ended comment
P1	<i>This program would be very useful in Alzh. Clinics with care partners to utilize to learn about the disease and how to respond. The information is good. Different format, since it is robotics than sitting at a computer screen and reading the information. May the ability to verbally interact more with the caregiver or family.</i>
P2	<i>I believe the robot would significantly help with instructions & retention for the patient. For caregivers (presumably with normal mental status), the information could be given by simple computer presentation. I see the point of the robot will be present for another purpose but not simply to provide info to caregivers.</i>
P4	<i>Will you continue to improve. Tammy's vital information!</i>
P5	<i>The program was presented well. Questions answered clearly. All around great program well done.</i>
P6	<i>I think the program is very interesting and should help a lot.</i>
P7	<i>I like everything that was presented. Very sweat idea.</i>
P8	<i>I have many thoughts on "when the human touch is needed"</i>



Figure A.29: A user testing the psycho-educational program.



Figure A.30: Module selection layer (left) and topic selection layer (right) in the FAIR REACH app.

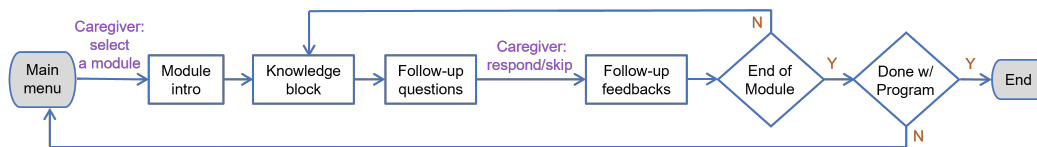


Figure A.31: Schematic flowchart of the FAIR-REACH app.

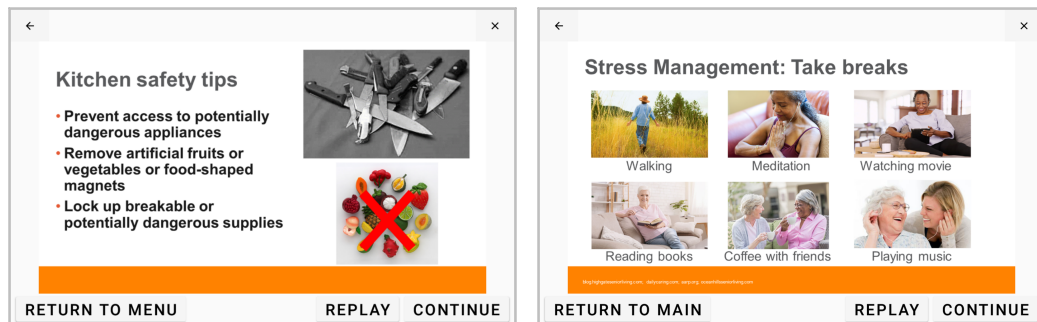


Figure A.32: Screenshots of the GUI design on robot's tablet during presenting psycho-educational materials.

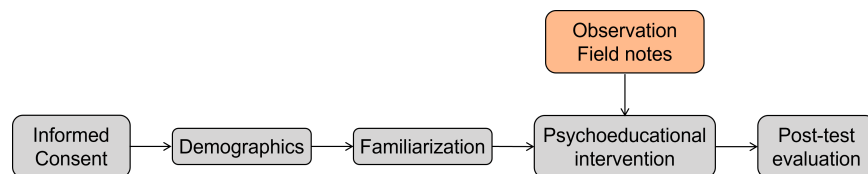


Figure A.33: Experimental procedure for the usability study of robot-assisted psycho-educational program.

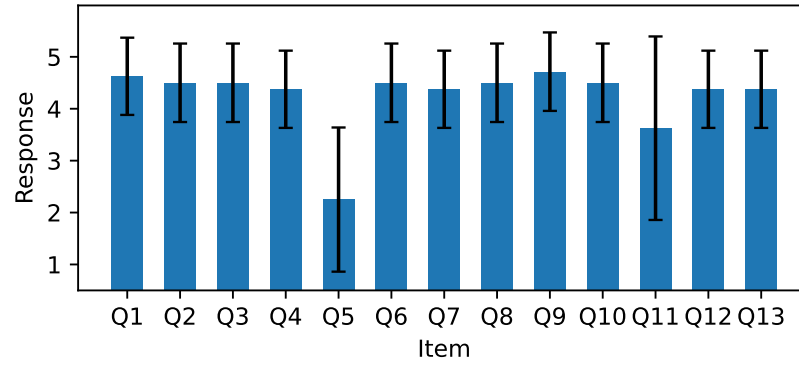


Figure A.34: Participants’ responses about user experience and satisfaction towards the robot-assisted psycho-educational intervention. Please see Table A.32 for Items Q1-Q12. 1=*strongly disagree*, 2=*somewhat disagree*, 3=*neither agree nor disagree*, 4=*somewhat agree*, 5=*strongly agree*.

Vita

Fengpei (Fiona) Yuan is a Ph.D. candidate in the Department of Mechanical, Aerospace, and Biomedical Engineering at the University of Tennessee, Knoxville, focusing on developing SAR and human-centered AI to augment dementia care. Yuan earned her master's in mechanical engineering from the University of Tennessee in 2019 and her bachelor's degree in mechatronics engineering from Harbin Institute of Technology in 2016.