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Enabling Longitudinal Personalized Behavior Adaptation for Cognitively Assistive Robots

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Enabling Longitudinal Personalized Behavior Adaptation for Cognitively Assistive Robots

A dissertation submitted in partial satisfaction of the requirements for the degree Doctor of Philosophy

in

Computer Science and Engineering

by

Alyssa Kubota

Committee in charge:

Professor Laurel D. Riek, Chair
Professor Kamalika Chaudhuri
Professor Virginia de Sa
Professor Elizabeth Twamley

2023

The Dissertation of Alyssa Kubota is approved, and it is acceptable in quality and form for publication on microfilm and electronically.

University of California San Diego

2023

DEDICATION

To my parents, Glenn and Evelyn Kubota,

and my brother, Connor.

EPIGRAPH

Flying makes me a better care provider.

Baymax, Big Hero 6

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ABSTRACT OF THE DISSERTATION

Enabling Longitudinal Personalized Behavior Adaptation
for Cognitively Assistive Robots

by

Alyssa Kubota

Doctor of Philosophy in Computer Science and Engineering

University of California San Diego, 2023

Professor Laurel D. Riek, Chair

Cognitively assistive robots have great potential to improve the accessibility of healthcare services by extending existing clinical interventions to a person's home. This provides a variety of benefits, including extending the reach of professional services, allowing people to engage with these interventions at their own convenience, and reducing risk of exposure to illness at clinics. However, there are many obstacles to deploying these robots longitudinally and autonomously, particularly for populations with lower technology literacy such as older adults. These obstacles include enabling robots to leverage the expert domain knowledge of clinicians and other stakeholders, contextualizing the robot and intervention to the lives of users, and

understanding and adapting to a person's intervention preferences and goals.

The goal of my work is to design systems that enable robots to continuously learn from and adapt to people in real-world environments. In this dissertation, I will describe three main contributions of my work.

First, I developed new methods to recognize complex motion reflective of real-world activities to enable robots to accurately understand human intention. Recognizing human activity can help robots understand a person's state and their reactions to its behavior. My work revealed the complementary strengths of two common sensor modalities for recognizing gross and fine motion, which can be leveraged to recognize complex activities and help robots better understand human intention. In addition, I designed a novel deep learning architecture for recognizing fine motion using nonvisual sensors, enabling robots to recognize human activity in dynamic, privacy sensitive settings such as homes.

Second, I developed the first robotic system (JESSIE) which makes control synthesis accessible to novice programmers, allowing all stakeholders to quickly and easily specify complex robot behaviors through a tangible specification interface. Stakeholders such as clinicians and end users can provide robots with valuable domain and personal knowledge which can inform its behavior. My work revealed key insights regarding how robots can learn and adapt to people with cognitive impairments longitudinally at home. JESSIE makes control synthesis more accessible to novice programmers, enabling stakeholders to imbue robots with their domain knowledge and extend the reach of their work.

Third, I developed an autonomous robot (CARMEN) which extends clinical healthcare interventions to the home, and longitudinally supports goal progress and motivation. In collaboration with clinicians and people with cognitive impairments, I identified interaction design patterns for translating clinical interventions to robots in order to maintain longitudinal engagement and maximize efficacy. Furthermore, I developed a new framework for roboticists creating longitudinal, robot-delivered health interventions with collaborative goal setting capabilities. My work lays the foundation for enabling robots to support motivation and goal achievement throughout a longitudinal intervention at home.

My research contributes to building robotic systems which can longitudinally personalize their behavior to people in real-world environments. My work aims to transform how robots longitudinally interact with people, with the ultimate goal of enabling more safe and effective human-robot interaction, particularly for underserved populations.

Chapter 1

Introduction

Robots are rapidly entering everyday human-centered environments where they have shown great promise for supporting people in their daily lives. For example, robots can provide assistance and improve safety in settings such as hospitals and homes [4, 301, 329, 441], support education for children and healthcare workers [358, 418], and enhance operations such as surgery or manufacturing [95, 145, 220, 373]. The COVID-19 pandemic has highlighted the need for increased access to key services from the home, including quality healthcare and education, particularly for underserved populations such as people with disabilities [22, 260, 302]. For instance, physically and socially assistive robots in the home can deliver personalized physical and cognitive rehabilitation interventions [94, 126, 218, 225, 277, 368, 409, 497], provide social support for care partners [166, 269, 316], and connect students who are physically unable to attend school with their in-person counterparts [456, 483].

In order to successfully support people in real-world settings, robots will need to be able to exhibit personalized actions and behaviors, such as adapting their communication modalities or personality [84, 146]. Personalization is a prominent research area in the field of human robot interaction (HRI), with many HRI researchers exploring how to personalize robots to be more accessible, engaging, and effective [83, 320, 397]. Personalization is particularly important when developing systems for people with disabilities and their care partners, as these populations can have a wide range of physical and cognitive abilities, potential comorbidities, and other personal preferences [5, 447]. Thus, robots will need to consider these preferences and abilities appropriately in order to be more usable and accessible to these populations.

Enabling robot personalization can be difficult as a person's preferences can change due to a variety of factors, including their current context, needs, or mood. Therefore, learning those preferences and adapting to a person can be challenging for a robot to achieve longitudinally and autonomously. This is especially true for people with cognitive impairments, whose abilities and preferences may change as their condition progresses over time [431].

In addition, robot behaviors for clinical applications will need to be grounded in current clinical practice to ensure that they are personalized to a person's current abilities, adhere to the best practices of clinical experts, and maximize accessibility to users. Thus, in order to determine what behavior is appropriate for different people and situations, robots can leverage domain expertise from clinicians, or personal knowledge from family members or care partners. Thus, roboticists as well as robots themselves will need to learn from and engage with all stakeholders, including end-users, family members, care partners, and clinicians, in order to provide a more personalized, effective, and inclusive interaction.

My work is situated in this problem domain of enabling robots to safely and continually learn from and adapt to people in dynamic, real-world environments, such as homes. By incorporating implicit feedback from users (i.e., data obtained via sensors during an interaction) and explicit directives from domain experts such as clinicians (i.e., commands given or programmed into a robot), my work enables robots to support a broader range of people, including those with disabilities.

1.1 Motivation and scope

Many HRI researchers are exploring the deployment of assistive robots to deliver personalized interventions, including for applications such as supporting social and academic learning [227, 341, 369], physical rehabilitation [129, 271], and mental health [15, 226, 401].

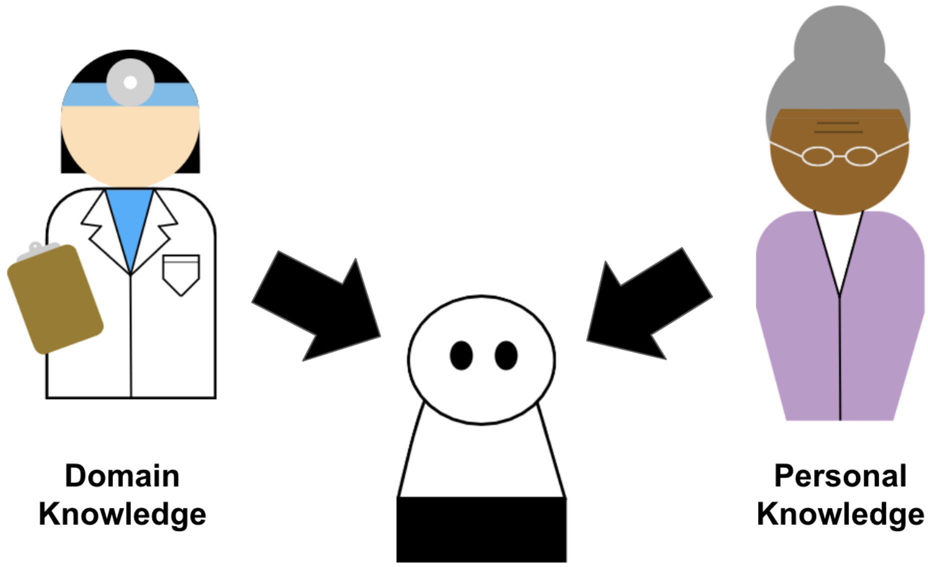


Figure 1.1. Integrating domain knowledge from clinicians and personal knowledge from family members can help maintain engagement and adherence to a robot-delivered intervention longitudinally.

These personalized systems are typically able to adjust features such as intervention content and difficulty, or the frequency of an interaction. They have shown great promise for improving learning and health outcomes.

However, there are still many challenges to deploying these systems autonomously and longitudinally, which are more pronounced when developing them for people with cognitive impairments. First, people with cognitive impairments and their care partners may have low technology literacy, limiting their interactions with a robot. In healthcare contexts, domain and personal knowledge from end users (e.g., patients and people with disabilities), clinicians, and family members can inform robot behavior throughout an intervention, which is essential to maintaining engagement and adherence longitudinally [258] (see Figure 1.1). Neither robot developers nor clinicians can predict how a person's needs may change over time, so these stakeholders may need to program robots to exhibit custom behavior without advanced skills in robotics or programming.

Another key challenge is with regards to real-time personalization, or enabling a cognitively assistive robot (CAR) to understand a person's current context and preferences. A CAR's behaviors may need to vary widely to suit a user's state, such as their mood, abilities, or performance. This is essential for ensuring that a robot's behavior is appropriate for a given user and their current situation, and integrates seamlessly into their existing lives. Doing so can improve accessibility and reduce barriers to use, which can increase engagement with the intervention and ultimately improve its efficacy [83, 253].

Another major challenge is enabling robots to continually learn and adapt to a person over a long period of time, especially as their preferences, goals, and abilities may change over time. In the context of robot-delivered interventions, people may show progress as they continue to engage with the robot. On the other hand, their cognitive impairment may prohibit them from seeing the therapeutic outcomes they would like. Robots will need to recognize these changes and adapt appropriately in order to promote engagement and health outcomes.

Thus, **the research goal of my work is to enable robots to learn from and adapt to people longitudinally in real-world environments**, with a focus on supporting people with cognitive impairments. While there are many dimensions to this problem, this dissertation explores the following aspects:

- How robots can recognize human activity in dynamic, real-world environments.
- How to develop robots to autonomously and longitudinally deliver a cognitive intervention in home settings.
- How novice programmers can create custom programs for social robots.
- How to design social robot behaviors appropriate for people with cognitive impairments.
- How to translate an intervention traditionally delivered by a person in clinic, to be delivered by a robot at home.
- How robots can support key components of longitudinal interventions, including collaborative goal setting.

- How to ethically personalize robot systems for people with cognitive impairments.

1.2 Contributions

The contributions of this work are as follows:

- **Identified how multiple sensor modalities can be combined in a complementary fashion to detect human activity [254].** This study explored the relative efficacies of motion capture cameras and wearable sensors for recognizing both gross (e.g., full body) and fine motion (e.g., hands or fingers). I collected a new dataset of people performing two tasks predominantly characterized by each motion type. Using this data, I employed common classification algorithms for human activity recognition (HAR), and found that motion capture yielded 37% higher accuracy than wearable sensors for gross motion recognition, while the wearable sensor yielded up to 28% higher accuracy for fine motion. This suggests that the sensors offer complementary strengths which can be leveraged to recognize complex activities and help robots better understand human intention.

- **Developed a new deep learning method for automatically recognizing human activity using non-visual sensors in dynamic, real world settings [137].** I designed a hybrid Convolutional Neural Network (CNN) Long Short-Term Memory (LSTM) classifier which captures both convolutional and temporal features from a wearable sensor that gathers both inertial and muscle activity data. The convolutional features represent the state at each timestep, while the temporal features capture how that state evolves over time. I evaluated my system on two publicly available datasets and found that augmenting inertial data with muscle activity yielded 13% higher accuracy than inertial data alone. Moreover, my hybrid architecture outperformed existing state-of-the-art approaches by up to 200%. Thus, my work can enable robots to more robustly recognize human activity in dynamic, privacy sensitive settings such as homes.

- **Developed *CARMEN (Cognitively Assistive Robot for Motivation and Neurorehabilitation)*, a robot which delivers a cognitive intervention autonomously and longitudinally to people with cognitive impairments at home [255].** CARMEN affords people with mild cognitive impairment (MCI) opportunities to learn and practice compensatory strategies that mitigate the effects of impairment (e.g., using a calendar, mindfulness exercises). People with MCI will learn and practice a new compensatory strategy in each interaction with CARMEN. They can then employ these strategies in their real lives, thus minimizing the impact of MCI on daily life. CARMEN is implemented on a tabletop social robot and leverages a tablet display to promote a variety of communication modalities (e.g., visual, auditory, tactile) and accessibility. CARMEN will extend the accessibility of healthcare interventions to the home and ultimately improve health equity.

- **Developed *Just Express Specifications, Synthesize, and Interact* (JESSIE), a new robotic system which enables novice programmers to program social robots by expressing high-level specifications and control synthesis approaches [256].** JESSIE allows users to specify and synthesize personalized behaviors, so programmers can focus on their overarching goals (e.g., which cognitive rehabilitation strategies to practice), rather than specific implementation details. I developed a tangible system which allows programmers to easily express the desired behavior, improving the learnability of the system and the accessibility of control synthesis. As a first version of CARMEN, I demonstrated JESSIE in the context of a robot longitudinally delivering a neurorehabilitative intervention to people with MCI via a home deployed robot. Neuropsychologists, who had no prior experience programming robots, were able to successfully program the robot to deliver interactive cognitive intervention sessions for a person with MCI. JESSIE makes control synthesis more accessible to novice programmers, enabling stakeholders to imbue robots with their domain knowledge and extend the reach of their work.

- **Proposed interaction design patterns for translating an existing clinical intervention**

to a robot in order to maintain longitudinal engagement and maximize efficacy [253]. Using CARMEN as a design probe, I engaged in a collaborative design research process with key stakeholders including clinicians and people with cognitive impairments. I identified design considerations to make robots both physically and cognitively accessible to people with cognitive impairments. This research identified how neuropsychologists envision translating a cognitive training intervention to a CAR, and features the robot intervention needs to be successful, such as supporting goal setting, personalizing content, encouraging real-world transfer, and maintaining engagement longitudinally. We also conducted interviews with people with MCI, the end users of the robot-delivered intervention, which revealed how they envision using the CAR long term at home. This work establishes the foundations of translating neuropsychologist-delivered, clinic-based cognitive interventions to robot-delivered, home-based interventions, and provides a framework to researchers to support this process.

- **Defined a framework for developing longitudinal, robot-delivered health interventions with collaborative goal setting capabilities [255].** This framework comprised design considerations and concrete examples of robot behaviors for the major components of collaborative goal setting which were co-designed with clinicians and people with cognitive impairments. This includes how robots can help users set goals, measure goal progress, deliver intervention content to support transfer to the real world, and motivate people to achieve their goals. My work lays the foundation for enabling robots to support motivation and goal achievement throughout a longitudinal intervention at home.

- **Identified ethical considerations of developing personalized robots for people with cognitive impairments [257].** This work weighed the benefits of personalization with its potential risks, such as risks to a person's safety and autonomy, the potential to exacerbate social isolation, and risks of being taken advantage of due to dark patterns in robot design. We explored ethical considerations for developing personalized CARs, including how a robot can practice beneficence, where responsibility falls if a robot causes harm to a user, and how a user can acquire informed consent from users with cognitive impairments. This work highlighted the challenges that accompany personalized care technologies, and demonstrated the need for continued and critical exploration into the potential consequences of personalizing CARs, particularly for people with cognitive impairments.

1.3 Publications

The work presented in this dissertation is based on the following publications. In addition to these publications, some of the work presented has not yet been published.

1. **Kubota, A.**, Pei, R., Sun, E., Cruz-Sandoval, D., Kim, S., and Riek, L.D. Get SMART: Collaborative Goal Setting with Cognitively Assistive Robots. In Proceedings of the 2023 ACM/IEEE Conference on Human Robot Interaction (HRI). 2023. [Acceptance Rate: 25%]

2. **Kubota, A.**, Cruz-Sandoval, D., Kim, S., Twamley, E., and Riek, L.D. Cognitively Assistive Robots at Home: HRI Design Patterns for Translational Science. ***Best Paper Award Honorable Mention*** In Proceedings of the 2022 ACM/IEEE Conference on Human Robot Interaction (HRI). 2022. [Acceptance Rate: 25%]

3. **Kubota, A.,**, Pourebadi, M., Banh, S., Kim, S., and Riek, L.D. Somebody That I Used to Know: The Risks of Personalizing Robots for Dementia Care. In Proceedings of We Robot. 2021. [Acceptance Rate: 15%]

4. **Kubota, A.** and Riek, L.D. Methods for Robot Behavior Adaptation for Cognitive Neurorehabilitation. In Annual Review of Control, Robotics, and Autonomous Systems. 2021.

5. **Kubota, A.** and Riek, L.D. Behavior Adaptation for Robot-Assisted Neurorehabilitation. In Companion of the 2021 ACM/IEEE International Conference on Human-Robot Interaction. 2021. [Acceptance Rate: 37%]

6. Banh, S., Zheng, E., **Kubota, A.**, and Riek, L.D. A Robot-Based Gait Training System for Post-Stroke Rehabilitation. In Companion of the 2021 ACM/IEEE International Conference on Human Robot Interaction. 2021.

7. **Kubota, A.**, Peterson, E.I., Rajendren, V., Kress-Gazit, H., and Riek, L.D. JESSIE: Synthesizing Social Robot Behaviors for Personalized Neurorehabilitation and Beyond. In Proceedings of the 2020 ACM/IEEE International Conference on Human Robot Interaction (HRI). 2020. [Acceptance Rate: 24%]

8. Taylor A., Lee, H., **Kubota, A.**, and Riek, L.D. Coordinating Clinical Teams: Using Robots to Empower Nurses to Stop the Line. ***Best Paper Award Honorable Mention*** In Proceedings of the ACM Conference on Computer Supported Cooperative Work and Social Computing (CSCW). 2019. [Acceptance Rate: 30%]

9. **Kubota, A.**, Iqbal, T., Shah, J.A., and Riek, L.D. Activity Recognition in Manufacturing: The Roles of Motion Capture and sEMG+Inertial Wearables in Detecting Fine vs. Gross Motion. In Proceedings of the IEEE International Conference on Robotics and Automation (ICRA). 2019.

10. Frank, A., **Kubota, A.**, and Riek, L.D. Wearable Activity Recognition for Robust Human-Robot Teaming in Safety-Critical Environments via Hybrid Neural Networks. In Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS). 2019.

1.4 Ethical procedures

This dissertation describes human subject experiments that have been formally reviewed by the Institutional Review Board (IRB) at the University of California, San Diego. Participants provided informed consent to participate in experimental research in all human subjects experiments. All collected data were appropriately anonymized and securely stored. Participants were compensated for their participation.

1.5 Dissertation overview

The dissertation is organized as follows:

- **Chapter 2** provides a brief overview of related work in the areas of cognitively assistive robots, longitudinal robot behavior adaptation, and compensatory cognitive training.
- **Chapter 3** introduces new methods for enabling robots to recognize human activity using non-visual sensors.
- **Chapter 4** describes the design and implementation of CARMEN, a new robot system which longitudinally and autonomously delivers cognitive neurorehabilitation in home settings.
- **Chapter 5** presents JESSIE, a new robot system which enables novice programmers to create custom programs for social robots.
- **Chapter 6** discusses interaction design patterns and design considerations for translating clinical interventions to robots in order to maintain longitudinal engagement and maximize efficacy.
- **Chapter 7** presents a new framework for developing robot-delivered health interventions with collaborative goal setting capabilities.

- **Chapter 8** discusses ethical considerations for developing personalized robot systems for people with cognitive impairments.
- **Chapter 9** summarizes the main contributions of this dissertation, discusses plans for future work and open questions for the HRI community, and provides concluding remarks.

Chapter 2

Background

2.1 Mild Cognitive Impairment and Neurorehabilitation

2.1.1 Mild cognitive impairment

Dementia is an irreversible syndrome that entails noticeable decline of cognitive function [316, 335]. Approximately 11% of people aged over 65 are impacted by dementia, and each case is unique. Symptoms can range across the spectrum, from early stage (e.g. forgetfulness) to late stage (e.g. difficulty recognizing friends and family). It can affect a person's physical abilities, mental abilities, and behavior, and can lead to hazardous behaviors such as wandering, medication errors, and domestic or financial abuse. Furthermore, the number of people who need support exceed the availability and resources of full-time care providers, and informal care partners (e.g. family) must often assume much of the care responsibility [135, 334], yet are provided few resources to do so, leading to stress and burnout [316]. There are no known cures to slow or prevent its onset which can cause reduced quality of life to family members when adopting the role of informal care partners [444].

Mild cognitive impairment (MCI) is the prodromal, or intermediate, state between normal aging and several neurodegenerative disorders such as Alzheimer's disease and vascular dementia [202, 346]. An estimated 20% of adults aged over 65 experience MCI, approximately 10% of whom convert to some type of dementia each year [62, 202]. To date, no existing pharmacological treatments have proven effective for slowing or preventing this conversion, but

Figure 2.1. Robots used to support people with cognitive impairments vary widely in morphology, including mobile, tabletop, humanoid, mechanistic, and zoomorphic. From left to right: Bandit [439] (Provided by Maja Matarić), Care-O-bot [243] (Provided by Fraunhofer IPA [139]), KOMPAÏ-2 [12] (Provided by KOMPAÏ Robotics [245]), Kuri [256] (Provided by Mayfield Robotics), Mabu [84] (Provided by Catalia Health), PARO [474] (Provided by Carlton SooHoo [339]).

studies suggest that behavioral interventions can help [202].

MCI can affect numerous cognitive domains including memory, visuospatial functioning, complex attention, and executive functions, though not to a level of severity that would warrant a diagnosis of dementia [11, 346]. Studies indicate that many people will remain at the MCI stage without ever converting to dementia, and up to 40% of those with MCI will return to normal levels of cognitive functioning over time [202]. However, as people lose their independence, it can severely impact their quality of life [133, 202]. It can also adversely affect their family members, put strain on their relationship with the person with MCI, and cause stress [17, 111, 143, 202, 316]. This change in lifestyle and role can cause feelings of guilt, anxiety, and depression in a person with MCI and their care partners [17, 143].

2.1.2 Neurorehabilitation

Many researchers have explored strategies to promote the reablement of people with dementia, or mitigating the impact of dementia on their function to promote independence [357]. In particular, non-pharmacological approaches such as behavioral interventions can slow the onset of MCI, which can prolong independence and maintain quality of life [202]. Treatment approaches include cognitive rehabilitation and restoration therapies, which aim to minimize or compensate for lost cognitive function in everyday life. Among the most widely used strategies are compensatory cognitive training (CCT) and restorative cognitive training [202].

CCT teaches a person with MCI metacognitive strategies to help bypass impaired function and minimize its impact on daily life [133, 202]. These strategies may include reorganizing their environment (e.g. always placing their keys next to the door when they return home), integrating new tools into their daily routine (e.g. routinely keep and check a daily planner), and using different skills to compensate for memory difficulties (e.g. using visual imagery or acronyms). Depending on an individual's impacted cognitive abilities, clinicians may prescribe different training regimens to focus on specific skills. CCT has been shown to improve cognitive performance and daily functioning in people with MCI, and these improvements are often sustained even after a person has completed training [202]. In our work, we focus on employing CCT with a robot [256].

In contrast, restorative cognitive training attempts to enhance or restore a person's lost cognitive abilities. It relies on consistent practice and repetition of standardized cognitive exercises designed to target specific skills such as attention or memory, e.g., "drill and practice". While this approach can help strengthen neural circuits and improve a person's performance on similar tasks, these exercises are generally standardized (i.e. not personalized to an individual) and may not be relevant to a person's everyday life [85]. Furthermore, these skills typically do not generalize well (i.e. transfer) to other tasks [202].

2.2 Robots for Neurorehabilitation

Robots have shown great potential to help people across numerous aspects of health and wellness. Examples range across many of settings, including homes, clinics, and hospitals, and different tasks, including reducing clinician workload, supporting people with disabilities, and supporting care partners [115, 248, 316, 348, 350, 375, 376, 405, 474].

Robots for physical neurorehabilitation typically help people by physically supporting or correcting movement with the goal of restoring neuromotor function, e.g., restoring or supplementing limb function in people who had a spinal cord injury or stroke [115, 248, 405]. These robots take many forms, such as robotic arms to help people control their arms and hands to complete activities of daily living (ADL) tasks [248, 405], or exoskeletons to help people walk [115].

Researchers also use CARs to support people's health and prolong their independence by supporting cognitive neurorehabilitation.[1] These robots interact with people through social signals such as speech or gestures. **Figure 2.1** shows a number of examples, which vary in form and function. For example, PARO is a zoomorphic, pet-like robot that has been shown to help reduce negative feelings such as stress and anxiety among people with dementia and their care partners [324, 474], and can also alleviate pain and improve mood [148]. Researchers are also exploring CARs to help people with cognitive impairments learn to manage their condition through cognitive training [94, 256, 350, 436]. They help people practice cognitive skills and social interactions that they can transfer to everyday life [272, 439].

In addition to dementia, researchers have increasingly explored the use of CARs to support people with social and developmental disorders, particularly autistic children or those with attention-deficit/hyperactivity disorder (ADHD) [64, 241, 378, 393] and people with schizophrenia [366, 375, 459]. For instance, autistic children expressed more spontaneous behavior, both nonverbal and emotional, after interacting with a robot mediator which they were able to translate to interactions with another person [92, 150]. Robots can also help improve communication between older adults with schizophrenia and their medical providers, and increase their engagement with recreational activities [375, 459].

2.2.1 Benefits of robots for neurorehabilitation

Robots present many exciting opportunities for supporting rehabilitation. They are a natural fit for the repetitive, task-oriented nature of many cognitive interventions, such as

[1] To our knowledge, there are no commercially available robot systems to deliver cognitive neurorehabilitation at the time of writing.

restorative cognitive training exercises which are often structured. They can also provide real-time, adaptive feedback, providing unique opportunities for rehabilitative therapy.

Robots can enable clinicians to have more meaningful and productive interactions with people even if there is reduced face-to-face interaction overall, such as during the COVID-19 pandemic. They have the potential to enable clinicians to treat more patients, particularly if the robots are deployed longitudinally in a person's home to help observe, assist with ADLs, or extend interventions. Additionally, robots can reduce the cost of treatment for patients, as they take less of a clinician's time [419]. Robots also have potential to provide support to people who live in areas where access to clinicians is limited or nonexistent (e.g., rural areas), and possibly reduce health disparities [166].

While computer-assisted strategies for delivering neurorehabilitation exercises have shown to improve attention, memory, and executive skills in people with memory impairments [25], robots have even greater potential to improve training, as their physical embodiment plays an important role in stroke patient compliance and engagement [121, 438]. Robots can increase engagement and enjoyment in social interactions due to their increased capacity for richer communication as compared to virtual systems [106]. They have many attributes that are important for initiating and sustaining interactions including shared physical context, physical movement, and the ability to appear to be observing a user [240].

A robot can also monitor and assess a person's well-being or task behaviors, which can be shared with their care team, as well as with a user. For example, in the space of cognitive training, a robot could collect information on task performance and progress. It may also infer other attributes such as their level of engagement and interest through gaze tracking, proxemics, or voice recognition. The information that a robot gathers has the potential to provide clinical insights which may help reduce a clinician's cognitive load. Clinicians can use this information to adjust training to match a person's abilities and preferences. They may also use it to help inform a person about their condition or to understand what aspects of the training are most effective. Section 2.4 overviews various behaviors about a person that a robot can sense, as well

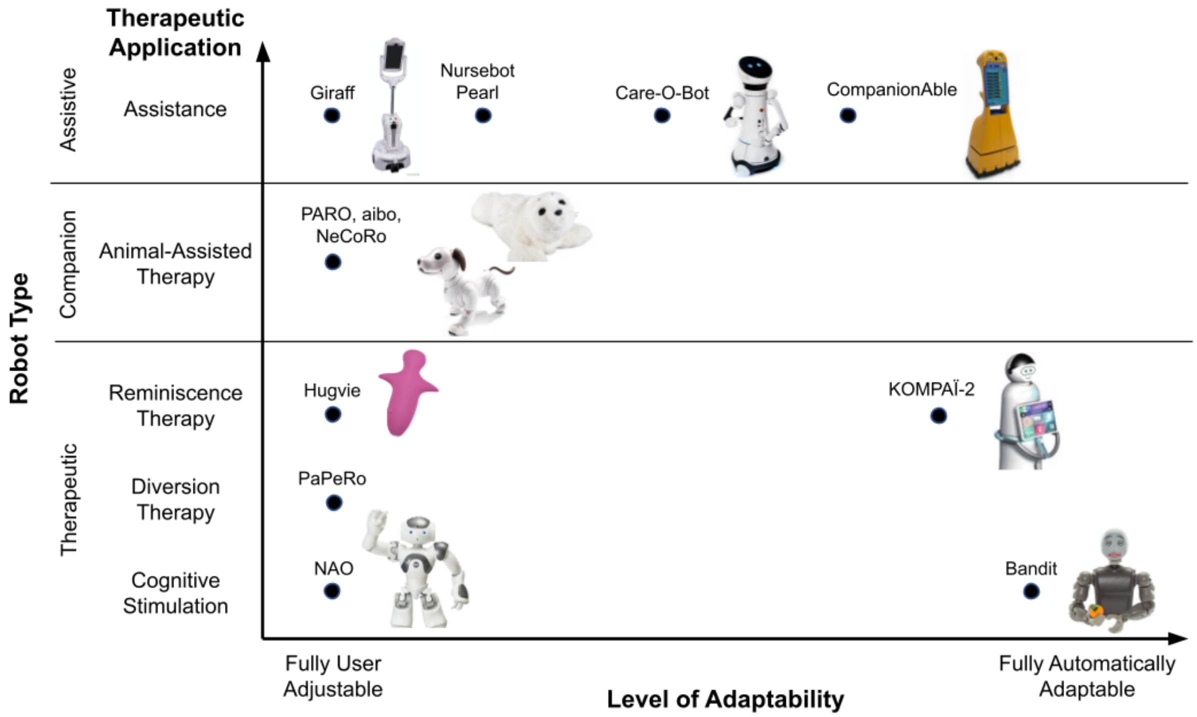


Figure 2.2. Exemplar robots which have been used to support neurorehabilitation and therapy. Specifically for dementia, robots are typically used for assistance, companionship, or therapeutic applications such as animal-assisted therapy or reminiscence therapy. Many are fully user-adjustable, while others can automatically adapt their behavior in response to users. Their morphologies can vary depending on the application, such as mobile robots used to provide physical assistance or tabletop robots used for cognitive therapy. Giraff [323] (Provided by Camanio AB), Care-O-bot [159] (Provided by Fraunhofer IPA [139]), CompanionAble [165] (Provided by Steffen Müller), PARO [474] (Provided by Carlton SooHoo [339]), aibo [434], Hugvie [492] (Provided by ATR Hiroshi Ishiguro Laboratories), KOMPAÏ-2 [12] (Provided by KOMPAÏ Robotics [245]), NAO [350], Bandit [439] (Provided by Maja Matarić).

as how the robot may respond to those behaviors.

2.2.2 Exemplar robots for MCI and dementia

There are many robots to support people with dementia (see **Figure 2.1**). They fill numerous roles such as assistive robots to help users complete ADLs, companion robots for emotional support, or robots to facilitate therapy or coach people practicing cognitive skills. **Figure 2.2** overviews selected robots, some designed specifically for people with dementia and others applied to this space.

They are typically mobile robots that provide monitoring and care, helping to ease the responsibilities of informal care partners (e.g. family, friends), and extending the independence of people with cognitive impairments. Their capabilities may include reminding a person to take medication, facilitating communication between the person and their care network (e.g. video calls with clinicians or family), and delivering cognitive stimulation [165, 323]. Others include walking assistance, fetching items, or setting a table for people with mobility difficulties [159]. These usually occur within a home, though some researchers are also exploring robots that can accompany users on errands outside of the home [348, 435].

Robots may also serve as companions for people with MCI and dementia. Many of these robots have been shown to reduce stress and anxiety while improving relaxation and motivation among people with dementia and their care partners [324, 474]. They can help stimulate interaction and serve as a point of connection between people with dementia and their care partners [474]. Many of these robots resemble animals, making them recognizable even to people with severe memory impairments. For instance, PARO [474] is based on a baby harp seal, and AIBO [434] resembles a dog. These types of robots do not necessarily communicate with people via speech, but can instead move or make sounds in response to stimuli such as touch, sound, or light [474].

These companion robots are often used in therapy. For instance, many of the aforementioned robots serve as safer alternatives to real animals in animal-assisted therapy and activities, often in hospitals and nursing homes [278, 434, 474]. In addition, researchers have explored using PARO to facilitate multi-sensory behavior therapy [70, 387], which stimulates different senses in a controlled setting to reduce agitation in uncontrolled ones.

More recently, researchers have used robots to facilitate reminiscence therapy among people with dementia [12, 492]. Reminiscence therapy aims to help people recall long-term autobiographical memories with the aid of photographs, music, familiar objects, etc. It is highly regarded by participants and therapists, and viewed as enjoyable and effective [487]. The approach is generally conversational, guided by either a human therapist or a robot itself, using a microphone and speaker in the robot to communicate with the person [12, 492]. In robot-guided sessions, a robot relies on user-specific knowledge (e.g. photos from an event, a favorite location) to prompt the user and maintain conversation and memory recollection.

Another role that robots may take for MCI and dementia is that of a coach. These are often used to facilitate and assist with restorative cognitive training exercises. For example, the Bandit robot plays cognitive stimulation games with users, and adjusts the difficulty based on their performance [436]. Similarly, researchers have programmed humanoid robots such as the NAO for clinicians to use to assist with memory training programs [350].

2.3 Principles for Designing Neurorehabilitation Technology

When designing technology for people with disabilities, to ensure it is usable and acceptable, there are three key considerations: personalization, adaptation, and inclusion [375, 485], which are discussed below. Personalization refers to tailoring the system to an individual by considering factors such as their needs, goals, or preferences. Adaptation is the ability for a technological system to automatically modify its behavior to be personalized to an individual. Inclusion means involving stakeholders throughout the process of developing technology, particularly the intended users of that technology. These considerations are particularly important to prevent unexpected consequences on potentially vulnerable populations, such as the exacerbation of disability-based bias [313, 321] (also see Chapter 8).

2.3.1 Personalization and adaptation

In cognitive training and other behavioral treatments, it is critical to personalize training to an individual's preferences, needs, and goals to maximize its applicability to their lives. This may be from simply including their name to adapting to suit their unique preferences and abilities [194]. This is important when developing any technology for people who may not be represented by a "typical" user [485].

Personalization helps improve engagement with training, retention of material, and long-term adherence to a training [25, 202]. These treatments are traditionally led by a human neuropsychologist or cognitive therapist who works closely with a person to determine their needs and goals, and tailor training to them. In fact, early studies on the efficacy of cognition-based interventions suggested that they were ineffective and inappropriate for people at risk of cognitive impairments because they could provoke frustration and depression in both a person and their care partners [17, 412]. This is likely due to the repetition and structure that defined these early interventions (e.g. memorizing and repeating a specific list of words), without a clear connection to an individual's life, abilities, or interests.

Especially when developing technology interventions for health contexts, each individual has unique circumstances that can significantly impact how they interact with the technology. For instance, up to 77% of older adults with MCI may be managing comorbidities (e.g. MCI, diabetes) or have different living situations (e.g. living alone, in a nursing home) [382]. If the system is not personalized to them, it may cause needless stress or frustration for the user and their care partners, or have other detrimental effects on their health. By tailoring the training to an individual, and meeting them where they are in terms of their performance and abilities, modern neurocognitive interventions have shown to be significantly more effective and beneficial for people with cognitive impairments and their care partners as compared to non-personalized interventions [133, 138].

The ability for technology to be personalized calls for the system to either be adjustable by a human, adapt its own behavior, or both. There are many situations in which a clinician, care partner, or user may want to control or adjust a robot's behavior. For instance, with the domain expertise from clinicians and the fundamental personal knowledge from care partners and users, they may already have a good idea of how they want a robot to behave to facilitate and complement the training. Additionally, clinicians and other users may want to modify the system to reflect the training. In a home setting, a user or care partner may want to adjust behavior without the help of a clinician. Thus, any mechanism to manually adjust the system should be easily learnable and usable by all stakeholders.

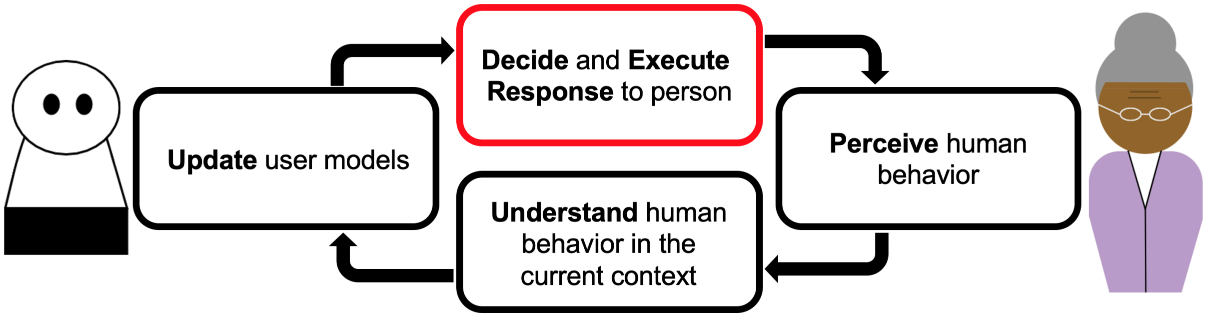


Figure 2.3. The general framework of systems that adapt to users. We focus on Deciding and Executing the robot's response to a person. *Figure inspired by [298].*

There are also situations in which it may be beneficial to automatically adapt to a user. Conditions such as dementia can be progressive, and the person receiving training may be undergoing cognitive changes at a pace that is difficult for others to keep up with. Using a computational model for automatic adaptation may have the advantage of learning and remembering information about a user more quickly and accurately than a person.

Automatic adaptation alleviates the responsibility of continually adjusting a robot's behavior from care partners or clinicians who can then spend more time in face-to-face interactions with an individual. Additionally, studies indicate that older adults prefer assistive systems that allow them to control the system while still being adaptable, over fully adjustable ones [184]. Thus, automatic adaptation to a user can lead to more rapid adjustments to a training regimen which may improve its efficacy and sustain a user's engagement.

In order to automatically adapt to a user, a system must be able to perceive and interpret a person's actions, and respond in a meaningful way (see **Figure 2.3**). This involves considering what a robot will sense about a user and how to obtain that data. For instance, *What sensors will it need and where will they be placed? What information will it infer implicitly (e.g. from sensor data, observations) vs. obtain explicitly (e.g. through questionnaires, surveys)?* Section 2.4 overviews potential sensing modalities and inputs.

Once a robot has this information, it needs to contextualize and understand what it means about a person. This could be their current state (e.g. mood, task performance) or an overarching understanding of the person (e.g. ability level). Finally, robots need to know how to modify their behavior and respond to a user. Roboticists employ numerous computational models to achieve this which we discuss further in Section 2.5.

2.3.2 Inclusive Design, e.g., "Nothing about us without us"

It is important for roboticists and researchers interested in building assistive robots to involve stakeholders throughout the development process. This is exceptionally true while developing a robot to be deployed in a person's home with the goal of supporting their health. These stakeholders may include the primary robot user, their healthcare providers, and their care partners, who may or may not be living with them [111, 316, 376].

Nihil de nobis, sine nobis, or "Nothing about us without us" is a prominent motto of disability activists [72]. It conveys that people with disabilities themselves know what is best for them, and that they are integral in any conversation that may affect their life and community. In other words, they must be consulted regularly throughout the technology development process, from ideation to testing. As roboticists oftentimes develop technology for conditions they have no personal experience with, involving people with disabilities early and often will help avoid making assumptions about the community's goals, ensure their needs are met, and help empower them. This will ensure the maximum utility, usability, and acceptance of the technology by users as well as other stakeholders [267, 376].

When co-designing technology with stakeholders, it is important to be transparent about what the technology is capable of. As there are no known approaches to significantly impact the course of dementia, technology should encourage stakeholders to "live well with dementia" [357]. This means setting realistic expectations about the benefits stakeholders can expect from the technology. For instance, how it could change the roles of clinicians and care partners, the extent of its impact on a user's training process and results, or the data it collects. The onset of the condition being treated is possibly one of the most challenging experiences the stakeholders have undergone, so developers must develop trust and maintain compassion with them throughout the development process.

Additionally, those receiving neurorehabilitation are likely vulnerable populations and do not necessarily have the technological literacy to effectively operate a system. Low technological literacy and cognitive impairment can also impact informed consent [316, 375, 467]. Developers of this technology must be mindful of this and work closely with experts in these communities to protect user privacy while maintaining the system's utility.

2.4 Sensing and Responding to Human Behavior

Modifying robot behavior to be personalized to an individual is crucial for maintaining engagement and ensuring efficacy of the system, particularly for health applications [66, 327]. In order for a robot to effectively adapt its behavior to a user, it must perceive the user's actions and behavior, understand what those mean in the given context, and respond accordingly [134, 438]. Below, we identify some features about people that robots can sense as well as behaviors that robots can modify in order to personalize interactions.

2.4.1 Perceiving and understanding human behavior

Throughout an interaction, there are many ways robots can learn user preferences and abilities. One approach is to first perceive a person's low-level behavior, then infer how those behaviors translate to higher-level attributes. Robots can gather this low-level information via the use of sensors, or through interaction or performance data collected by the system. Examples of low-level behaviors that a robot may gather include their speech (e.g. what they say, how they say it), gestures and movement (e.g. human activity recognition), and physiological signals (e.g. heart or respiration rate). Performance data is typically application specific and depends on the task(s) (e.g. accuracy, time to complete a task).

Some major factors to consider when choosing which sensors to use are what kinds of sensors a robot already has, whether others can be easily placed in the environment, and what kind of information would be worthwhile to collect, process, and possibly store. These sensors

Table 2.1. Robots can use a variety of sensors to perceive low-level interaction data about people, which can be used to infer high-level information about a user's state.

	Behavior Perception	**Common Sensor(s) / Indicator(s)**	**Description**
Low-level	Speech / Prosody	Microphone	Speech is a common means of communicating with a robot. In addition to understanding what a person is saying, their prosody and tone may also convey important information.
	Gesture / Movement	RGB camera, Motion capture, Gyroscope, Accelerometer	Arm and hand gestures are a common means of communicating with a robot, both implicitly (e.g. everyday activities) and explicitly (e.g. specific gestural commands).
	Eye contact / Gaze	Infrared camera, RGB camera	Gaze tracking helps determine where a person is looking.
	Touch	Capacitive touch sensor, Force sensor, Pressure sensor, Strain gauge, Switches	Determining whether a person is touching a robot or where they are touching can add realism to interactions.
	Physiological signals	EEG sensor, EMG sensor, Heart rate monitor, Respiration sensor, Thermometer	Signals generated by a person's body, usually acquired from specialized wearable sensors, can help determine their state.
	Explicit feedback	Questionnaires, Surveys	Asking users for their input directly is a straightforward way to obtain information.
	Task performance	Application specific	In neurorehabilitation, the robot may deliver cognitive training activities with quantifiable scores.
High-level	Engagement	Eye contact, Touch, Speech	Longer and more positive interactions with a robot can help sustain interactions over longer periods of time.
	Mood	Physiological signals, Speech	A user's current mood can help inform how a robot should best interact with them.
	Motor abilities	Touch, Movement	A user's motor abilities can help inform their preferred means of communicating with a robot. For instance, a user with tremors may prefer speaking over pressing buttons.
	Cognitive abilities	Task performance, Speech	A user's cognitive abilities can influence their goals and what treatment regimens may be most effective.

may be on a robot, placed in the environment, or worn by a person. For instance, cameras or microphones may be mounted on a robot or in the environment depending on the context, while physiological or inertial sensors are typically worn by a person.

These sensor and interaction data are relatively low-level and can be used to infer higher level information about a user's state or preferences [386]. For instance, robots can use data they acquire from RGB-D cameras to track a person's gaze or movements, then use these features to infer higher level features such as how engaged or bored they are (e.g. the person is likely to be engaged if they maintain eye contact with the robot and gesture often).

An alternate approach is to ask a user about their preferences such as in a questionnaire or survey [386]. This is a straightforward and direct means of obtaining information that does not require additional sensors. However, it risks people providing their ideal answers rather than completely truthful ones. **Table 2.1** provides an overview of common features to sense about people, both low-level and higher level, for social robots for neurorehabilitation.

Once a robot perceives a person's behavior, the robot must consider how that behavior relates to a) the person's current state and/or b) their overarching condition. How a robot interprets a person's behavior may depend on the application, length of interaction, or other circumstances. It is important for the robot to understand a person's actions and their current state (e.g. mood) in order to maintain natural, real-time interactions. For example, a robot may use a person's body language or task performance to infer if the person is frustrated with or challenged by a cognitive training exercise [438].

Particularly over long-term interactions, such as while completing a cognitive neurorehabilitation session, it is important for the robot to store and update a model of a person, including their preferences, needs, and abilities [386]. A robot can use this model to understand what behavior is typical for a person, track their progress over time, and recognize if they deviate from what is expected (e.g. recognizing if the person is more agitated or more forgetful than usual). Understanding both individual actions and translating them into a more thorough model of a person is important for personalizing robot behavior.

2.4.2 Synthesizing robot behavior in response to people

Effective HRI requires that robots understand people and respond to them. Individual robot actions can be guided by a fundamental model of its interaction style (e.g. personality, role) [66, 327]. In the context of neurorehabilitation, these behaviors can help improve a user's enjoyment of a training regimen and thus its efficacy [256, 386, 455].

Table 2.2. Robots can modify low-level behaviors to personalize high-level aspects of an interaction in order to fulfill a user's preferences and needs.

	Modality	Description
Low-level	Movement / Speed	Movement can be used for mobility, communication, and to help interactions feel natural.
	Speech / Speed / Prosody / Sounds	Speech is a common means of communication for both humans and robots. In addition to dialogue, a robot may adjust speed, prosody, and other sounds to improve clarity / function.
	Screen display	Robots may use a tablet when communicating with a user.
	Facial expressions	Many social robots have faces with dynamic expressions. As people have a tendency to anthropomorphize robots, even those that are not humanoid [499], robots can change their facial expressions to create a more natural and interesting interaction.
	Proxemics	Proxemics is the division of physical space around an agent (classified as intimate, personal, social, and public). A robot can control how physically close it is to a person to convey respect or intimacy.
High-level	Personality	A robot may change its personality to suit a user's preferences. This can be influenced by personal and cultural background. E.g., a robot may adopt a more passive communication style in countries where people tend to have more reserved communication styles [167].
	Initiative	Initiative is whether a robot initiates interaction with a person or vice versa. This may change with a robot's role, such as initiating interaction with a user with more severe MCI.
	Encouragement	Providing encouragement can help a person be more motivated or less frustrated if they experience trouble with the training regimens.
	Personal customization	Integrating personal information into training and therapies can help them be more applicable to a user, improving engagement and efficacy.
	Cognitive customization	Adjusting aspects of a training regimen to suit a person's cognitive abilities can help them practice relevant skills and reduce frustration.
	Primary communication modality	Depending on a user's physical abilities and preferences, a robot may adjust how it receives input from them, such as aural, touch, or visual cues.

When interacting with people, a robot can personalize its behavior in response to a person in numerous ways. At a low level, movement, speech, and visual cues are some major ways a robot can communicate. Movement generally consists of physical motion of the base or limbs. Speech can include dialogue, speed, prosody, tone, or other sounds. Visual cues may be a change of expression, text or images on a tablet, or other cues.

A robot may change its communication modalities based on user abilities or state. For example, a user with tremors may prefer to communicate via speech whereas someone who is non-verbal may prefer a tablet interface. Depending on a robot's capabilities, it may also change its effectors or display to convey emotion or emphasis to enhance an interaction.

These low-level behaviors can be utilized to produce higher-level aspects of the interaction that consider user preferences and needs. By immediately reacting to a person, a robot can create more natural and engaging interactions, such as by maintaining eye contact during conversation. For instance, if a user seems distracted, a robot may change its dialogue and tone to return their attention to the robot. This can help maintain engagement throughout an interaction, thus improving retention of material and overall enjoyment [430].

Similarly, a robot may change longer-term aspects such as its personality. For example, if a person responds better to an encouraging personality than an assertive one, the robot can provide more encouragement throughout training. In this way, a robot can update its model of a person and use it to guide the interactions, modifying its behavior to be more personalized to an individual. This can help maximize a person's adherence to a training regimen and improve their perceptions of the robot [386, 455]. **Table 2.2** overviews some common social robot behaviors that may be altered throughout interactions with a person.

2.5 Common Technical Approaches to Behavior Adaptation

A key element for enabling robots to adapt their behavior to a user is understanding how the data they receive can inform their actions, as well as how a user responds to those actions. There are countless computational methods researchers have used to imbue social robots with this ability, both within and outside of the context of neurorehabilitation. **Table 2.3** provides a summary of common approaches, which are further discussed below.[2]

While perceiving and understanding human behavior is an important aspect of knowing how a robot should respond, the area of human behavior analysis is vast, and approaches may vary widely depending on the behavior being perceived. As this dissertation focuses on methods

[2]As many social behaviors are not robot specific (e.g. dialogue), we also include select systems which were demonstrated on non-physically embodied systems, such as virtual agents.

Table 2.3. Common technical approaches for machines which adapt behavior to people.

Approach / Existing Work	**Strengths**	**Limitations**
Finite State Machines [136, 240, 270, 311]	• Straightforward • Existing libraries for implementation on robots (e.g. SMACH) • Good for structured, short interactions	• Interactions generally cannot be split into discrete states • Intricate interactions may be infeasible to implement • Does not easily allow for complex behaviors or long-term understanding of a user • Does not easily allow for dynamic behavior adaptation
Thresholding [282, 430, 439]	• Good for reacting to continuous streams of data rather than windows of time	• Does not easily allow for complex behaviors or long-term understanding of a user • Does not easily allow for dynamic behavior adaptation
Q-Learning RL and variants (MDP) [39, 74, 130, 142, 155, 234, 252, 284, 293, 341, 350, 362, 377, 455]	• Model-free, or can learn a model about user behavior / preferences	• Assumes the world is fully observable, but a person's preferences cannot always be directly observed • Time and storage intensive which can inhibit real-time interaction • Interactions generally cannot be split into discrete states
RL: POMDP [192, 233, 298, 417, 433]	• Model-free, or can learn a model about user behavior / preferences • Does not assume the world is fully observable which is beneficial as most human preferences cannot be directly observed	• State space becomes intractable for complex interactions • Interactions generally cannot be split into discrete states
Hierarchical RL [32, 67, 185, 348]	• Model-free, or can learn a model about user behavior / preferences • Makes complex (PO)MDPs more manageable • Can handle greater modularity of sensors and behaviors	• Does not take combinations of behaviors into consideration, so it is not guaranteed to find a globally optimum policy • Interactions generally cannot be split into discrete states
Policy Gradient RL [314, 438]	• Naturally handles continuous states and actions	• Difficult to derive an appropriate reward function (i.e. preferences from behavior) • Need to find appropriate parameter values
Inverse RL [50, 68, 423, 488]	• Learns a reward function from a human expert rather than relying on exploration of different behaviors	• Requires feedback from a human expert • Human experts do not necessarily behave optimally or rationally

(Continued on next page)

Neural Networks: MLP [406]	• Hierarchical layers enable high-level feature extraction from raw or low-level input data	• Does not take previous input into account • Requires large amounts of training data which can make it difficult to learn from an individual person • Difficult to optimize hyperparameters
Neural Networks: LSTM [107]	• Hierarchical layers enable high-level feature extraction from raw or low-level input data • Learns temporal features using previous input • Reacts to continuous streams of data rather than windows of time	• Requires large amounts of training data which can make it difficult to learn from an individual person • Difficult to optimize hyperparameters

for robot behavior adaptation, we discuss approaches that assume the human behavior is already recognized, as well as those that embed human perception into their process. For a detailed survey on human behavior analysis, please refer to [340, 493].

2.5.1 Finite State Machines (FSM)

FSMs are a relatively straightforward approach address the behavior adaptation problem [136, 240, 270, 311]. In an FSM, an interaction is broken into states which guide robot behavior. The robot transitions to the next state depending on human and environmental factors.

For instance, Kidd and Breazeal [240] used an FSM on Autom, a robotic weight loss coach. A user would engage in a short conversation with Autom once or twice a day. Its dialogue could vary depending on the time of day, time since the last interaction, and recent data input by a user. Each factor filled in parts of the conversation (e.g. Autom said “Good morning” or “Good evening” depending on the time of day). Notably, the robot’s statements also varied depending on the estimated relationship state between the robot and user, which offered a variety of dialogue to avoid repetition during the six-week study.

This approach is useful for relatively structured and short interactions, many programmers are already familiar with FSMs, and there are a number of existing libraries to implement them on robots (e.g. SMACH (“State Machine,” a Python-based library) [47]). However, not all interactions can be broken into discrete states, and states are generally defined manually so implementing long and involved interactions may be infeasible.

2.5.2 Thresholding

Another approach that roboticists use is thresholding [282, 430, 439]. In this approach, a robot receives sensor data from a user and performs an action if the value crosses a given threshold. Tapus et al. [439] used thresholding on a social robot for people with dementia. It delivered a cognitive game and could adjust the difficulty to improve a person's performance. The robot used an **Accepted Variation Band (AVB)** to automatically adjust the difficulty based on the person's performance, with the goal of minimizing reaction time, maximizing the number of correct answers, and maximizing the difficulty level. If the person's performance (i.e. reaction time, correct answers) improved, the difficulty increased, whereas it decreased if they performed poorly. The authors report increased engagement and improved performance at higher difficulties for people with dementia, highlighting the importance of adjusting to the user's abilities.

Thresholding is advantageous when dealing with a continuous stream of data and reacting in real-time. However, it is best suited for behaviors tied to a specific signal (e.g. increasing voice volume when engagement is low, decreasing task difficulty if performance is low) and does not easily allow for complex reactive behaviors. Additionally, while thresholding enables a robot to react in real-time, it would require another underlying control system, such as those discussed below, to support longer-term understanding about a person.

2.5.3 Reinforcement learning (RL)

In RL, an agent learns how to best interact with its environment to maximize its rewards [426]. RL configurations are generally represented using a Markov Decision Process (MDP) defined as ($\mathscr{S}$, $\mathscr{A}$, $\mathscr{T}$, $\mathscr{R}$, γ) where $\mathscr{S}$ is the set of possible states, $\mathscr{A}$ is the set of possible actions the agent can take, $\mathscr{T}$ is the transition probability function between states, $\mathscr{R}$ is the reward function of the environment, and γ is the discount factor for future rewards [426]. Actions in MDPs can be deterministic (i.e. performing a given action in a given state always leads to the same next state) or stochastic (i.e. the next state is determined by a probability distribution). The agent aims to learn an optimal policy π, or a mapping of states to actions, that maximizes its expected rewards.

Q-learning is a widely used approach to solving MDPs with unknown reward and transition probability functions. Traditionally, a robot can take an action and observe the associated reward, as the environment updates to a new state. Many researchers have applied it to the behavior adaptation problem [39, 74, 130, 142, 155, 234, 252, 284, 293, 341, 350, 362, 377, 455]. For instance, Tsiakas et al. [455] used it to modify the kind of feedback a robot provided based on a person's engagement in a cognitive training session.

Multiple works frame the behavior adaptation problem as a multi-armed bandit problem [39, 142, 480]. The multi-armed bandit problem aims to distribute resources among multiple possible actions with uncertain results in order to maximize the reward, but the current state remains the same. This approach is useful for ensuring that a robot can try each action and observe a person's behavior before relying too heavily on its learned knowledge of the person's reactions to its actions. In behavior adaptation, this can be thought of selecting behaviors in order to maximize a person's engagement, performance, etc.

Numerous algorithms exist to help balance exploration of new or uncertain actions with exploitation of existing or learned knowledge, particularly when the available actions have unpredictable outcomes. For instance, Gao et al. [142] implemented the **Exponential-weight algorithm for Exploration and Exploitation (Exp3)** [14] on a Pepper robot for puzzle solving. The robot would learn the person's preference for supportive behaviors (e.g. give hints, provide encouragement) and respond to a person's performance (measured by the time since they last made an action, total time elapsed, and correct actions).

Q-learning is "model-free," meaning it does not require a preexisting model. This is useful for behavior adaptation where human reactions (i.e. rewards) are difficult to define as a model [377, 455]. However, Q-learning and MDPs have many limitations, such as assuming the world is fully observable, and being time and storage intensive [314, 427, 438]. Real-time behavior adaptation for HRI is not always feasible with this approach as a person's state cannot always be directly observed, and heavy computations may slow a robot's responses. Thus, there are numerous alternatives to address these problems.

When the world is not fully observable, a **Partially Observable Markov Decision Process (POMDP)** is often more suitable. It is defined as ($\mathscr{S}$, $\mathscr{A}$, $\mathscr{T}$, $\mathscr{R}$, ω, $\mathscr{O}$, γ) where $\mathscr{S}$, $\mathscr{A}$, $\mathscr{T}$, $\mathscr{R}$, and γ are the same as in an MDP, ω is a set of observations, and $\mathscr{O}$ is a set of conditional observation properties [413]. The agent does not know its underlying state and must maintain a probability distribution of possible states based on previous observations.

Researchers have used POMDPs for behavior adaptation in health applications such as managing food consumption [298], navigating a robotic wheelchair [433], and helping people with dementia wash their hands by giving visual or verbal prompts [192]. This approach is applicable to behavior adaptation as a person's state is typically unknown and cannot be explicitly observed by a robot (e.g. a frown could express frustration with training or sadness due to external circumstances). However, the state space can become intractable to manage for complex interactions and multiple behaviors which may make real-time responses infeasible.

For complex interactions with numerous human and robot behaviors, researchers have used **Hierarchical RL** [32, 67, 185, 348]. This approach divides the overall MDP into smaller, more manageable ones which simplifies the problem and can help reduce memory requirements [67]. It can also allow for greater modularity of the system's behaviors; for instance, Chan et al. [67] used the MAXQ hierarchical RL approach [109] to abstract their system into a temporal module, state module, and subtask module which each considered and controlled specific behaviors in the context of cognitive training. While hierarchical RL approaches can find the optimal policy for each individual MDP, the global policy is not guaranteed to be optimal as there is no way to consider how behaviors can be combined.

Researchers have also applied **policy gradient reinforcement learning (PGRL)** methods for behavior adaptation [314, 438]. PGRL directly adjusts the policy in relation to the gradient to find a locally optimum policy, defined by behavioral parameters that a robot can adjust. It begins with an initial policy which it evaluates according to the reward function. Then, it perturbs the policy by modifying each parameter. Finally, it evaluates the new policy, and repeats until a local optimum is found.

This approach enables robot learning for continuous states and actions, and can update a robot's behavior in real time which are both important aspects of behavior adaptation in HRI [314]. However, researchers have reported challenges deriving an appropriate reward function to accurately translate user behavior to explicit preferences [314, 438].

A slightly different approach is **inverse reinforcement learning (IRL)** to learn how to behave from an expert agent, assumed to behave optimally [50, 68]. The agent can then use standard RL algorithms following the learned policy to maximize its own reward. In neurorehabilitation, this may entail the robot observing a human therapist guiding the training in order to learn how to respond to a patient in future interactions. However, humans do not always behave rationally or optimally, and it is not always possible to discern an exact policy, so researchers have expanded IRL to help overcome these limitations [423].

Additionally, researchers have worked to infer user preferences solely from observing a user as in **Observational Repeated Inverse Reinforcement Learning (ORIRL)** [488]. In ORIRL, a robot learns a user's preferences by watching them complete different tasks, then leverages those learned preferences when inferring preferences for future activities.

2.5.4 Artificial Neural Networks

Recently, researchers began to leverage advances in neural networks and deep learning for robot behavior adaptation [107, 406]. Neural networks are a broad set of algorithms inspired by biological neural networks that enable agents to recognize patterns in data, generally without having to define underlying task-specific rules. Neural networks have a hierarchical structure where the neurons (a computational unit) of each layer can extract information from the previous one to learn higher-level features. Thus, deep learning approaches with multiple hidden layers have gained popularity for their ability to extract features from raw data without the need for human-defined features, a large source of variation in other learning methods [222].

Senft et al. [406] used a **multilayer perceptron (MLP)** to enable a robot to learn from a therapist how to interact with autistic children. An MLP is a supervised feed-forward neural network composed of multiple perceptrons, or binary classifiers, with a unique set of weights [144]. The use of multiple perceptrons allows the MLP to approximate nonlinear functions for multi-class classification. The MLP used by Senft et al. estimates about the child's engagement level and motivation, labelled with a therapist's resulting action, to train a robot to become progressively more autonomous when responding to the child.

Another neural network architecture used for HRI is **long short-term memory (LSTM) recurrent neural networks (RNN)**. Unlike MLPs and other feed-forward neural networks, RNNs leverage a feedback loop which retains and uses information about previous input when processing future input. They can thus extract temporal features which is especially important when learning over continuous data, as in HRI applications. LSTM networks, composed of LSTM cells, are able to learn long-term dependencies throughout the data stream by implementing an "input gate" and "output gate" to protect stored memory from irrelevant input [190]. This is beneficial in HRI as a person's behavior may be influenced by previous interactions (e.g. a person might perform better on a task after the robot gives encouragement). For example, Dermouche et al. [107] designed an Interaction Loop LSTM model which takes as input the behavior of both the person and robot to continuously adapt to a user.

Neural networks and deep learning approaches have proven successful in a number of areas, but the extensive amount of training data required may make this approach infeasible for learning the behavior of a specific user. Additionally, deep neural networks can be very sensitive to the values of hyperparameters, and care must be taken to avoid overfitting when tuning.

2.6 Chapter Summary

People with cognitive impairments are in a unique position where their needs and preferences may change dramatically over the course of a training regimen. However, existing approaches assume a person's preferences stay constant throughout an interaction, or do not take their preferences into account at all. Thus, they are not necessarily appropriate when working with people with cognitive impairments. The development of new methods that consider a person's dynamic state can help improve the efficacy of robot-assisted neurorehabilitation, for dementia and beyond.

The robots and methods discussed in this review can improve existing cognitive training practices, particularly in longitudinal home settings. By building on these approaches, behavior adaptation methods can enable more engaging interactions between people and robots. Through studies with stakeholders such as people with cognitive impairments, and their clinicians and care partners, robots can improve engagement and adherence to benefit people in countless contexts, from improving adherence to training regimens to bettering their daily life.

This chapter provided a brief discussion of technical concepts and computational methods that are commonly used for adapting robot behavior in the context of neurorehabilitation. My research explores many of these aspects, which informed my work on personalizing robot behavior. The following chapter presents a new method for enabling robots to recognize human activity using non-visual wearable sensors.

2.7 Acknowledgements

This chapter contains material from "Methods for Robot Behavior Adaptation for Cognitive Neurorehabilitation," by A. Kubota and L. D. Riek, which appears in Annual Review of Control, Robotics, and Autonomous Systems, 2021 [258]. The dissertation author was the primary investigator and author of this work.

Chapter 3

Human Activity Recognition with Non-visual Wearable Sensors

Robots demonstrate great potential for decreasing physical and cognitive workload, improving safety conditions, and enhancing work efficiency for their human teammates in a variety of areas including hospitals and manufacturing environments [6,77,326,376]. Particularly in safety-critical environments, robots need the ability to automatically and accurately infer human activity. This will allow them to operate either autonomously or with minimal user input to avoid distracting their human teammates.

Robots can learn valuable information about the activities of their human partners from their motion [90, 214, 216, 261]. Gross motion detection (e.g. movement of the arms, legs, or torso) is the primary area of focus for most human activity recognition (HAR) approaches, traditionally using RGB cameras, depth sensors, or motion capture systems [90, 261]. Thus, robots can recognize gross motion ADLs, such as walking or lifting items, with accuracies of as high as 99% [180, 215, 217, 347].

However, recognizing fine-grained motion (e.g. movement of hands or fingers) is imperative for enabling robots to accurately understand human intention in safety-critical environments. For example, in order to infer what tool a person is using, the robot needs to perceive their hand and wrist motion. However, most conventional sensors do not provide adequate information to accurately detect these movements, so fine-grained activity recognition is unreliable using traditional HAR approaches.

To recognize these minute movements, one approach researchers have employed is hand-centric motion capture [230, 263]. However, motion capture often requires expensive equipment and a cumbersome installation procedure [261]. Furthermore, these sensors are easily occluded in dynamic environments, resulting in reduced recognition accuracy [261].

Thus, many researchers instead employ wearable sensors such as accelerometers, gyroscopes, or surface electromyography (sEMG) sensors for fine-grained motion detection [261,325]. Recent examples include automatically recognizing American Sign Language, identifying gestures to interface with technology, and detecting different types of grasps to control robotic arms [29, 286, 490].

Both motion capture and wearable sensors have proved effective for HAR when recognizing different granularities of motion. However, especially in the context of robotics, their relative efficacy for detecting gross and fine-grained motion is unclear. If their relative capabilities were known in this context, then it may be possible to combine multiple sensor modalities in a complementary fashion to more accurately detect a wider variety of activity.

3.1 Complementary Strengths of Motion Capture and Wearable Sensors

To our knowledge, we are the first to directly compare the efficacy of motion capture and wearable sensors for recognizing gross and fine-grained motion. We employed three common classification algorithms for HAR (support vector machine (SVM), linear discriminant analysis (LDA), *k*-nearest neighbors (*k*-NN)). We chose these classifiers due to their success in recognizing activities using motion capture or wearable sensor data [90,247,261]. To evaluate these modalities on both granularities of motion, we introduce the new MIT-UCSD Human Motion dataset. We used a Vicon motion capture system and a Myo armband to record participants completing two assembly tasks. The first is an automotive assembly task consisting of primarily gross motor movements. The second is a block assembly task which required fine grasping movements.

Our findings will help roboticists understand how motion capture and wearable sensors compare when classifying activities of different motion granularities. In turn, this will unveil which sensors are best suited for detecting activities that are relevant in a given context. Thus, robots can better infer the person's task by utilizing a multimodal system to simultaneously detect gross and fine-grained motion.

3.1.1 Background

Many activities that occur in everyday life (e.g. walking, climbing stairs, lifting objects) primarily entail gross motion. Thus, the majority of HAR algorithms are designed to recognize these activities, typically using data gathered via external sensors such as RGB-D or motion capture systems.

In particular, motion capture has many applications. It can help robots track people and objects in an environment, generally using mounted cameras. For example, unmanned aerial vehicles rely on motion capture data to guide them and prevent collisions while in autopilot [197, 337]. It is also widely used for tracking human activity for applications such as security in public spaces and entertainment [315, 352].

Many researchers have explored using motion capture data to help robots predict gross motion in safety-critical environments such as manufacturing. For example, Unhelkar et al. [460] used a Kinect to create human-aware robots that can safely deliver parts to human workers in an automotive assembly environment. Similarly, Hayes and Shah [180] classified automotive assembly activities using 3D joint locations of people and objects from a Vicon system. Mainprice et al. [292] captured single-arm reaching movements of two people to help robots predict activities in collaborative environments.

However, in many settings, robots need to be able to recognize pertinent activities that involve fine-grained motion, such as grasping. Reliable classification of fine motion is particularly difficult due to the small, ambiguous movements that human hands are capable of [261, 482].

One approach to fine activity classification is using visual data to track hands and objects in the environment. For instance, Lei et al. [273] achieved high classification accuracy of seven kitchen activities by using RGB-D data to track hands interacting with 27 different objects. However, using visual data is not necessarily viable in all settings, especially dynamic and chaotic environments where cameras can often be occluded. Additionally, cameras for motion capture and visual sensing are expensive to install, and their field of view is limited to a constrained physical space.

On the other hand, wearable sensors are mobile and thus can be used to recognize activity anywhere. Thus, body-worn non-visual sensors are another common approach to fine-grained activity recognition. For example, Zhu et al. [498] used data from an inertial measurement unit (IMU) worn on the finger to recognize five different hand gestures. Batzianoulis et al. [29] used arm muscle activity data from sEMG sensors in tandem with finger joint locations to recognize five different types of grasping motions.

A commonly used wearable sensor in recent studies is the Myo armband which measures sEMG and inertial data. Researchers have used it to recognize a wide variety of activities such as ADLs, gym exercises, and wandering behavior in the elderly [247, 453, 454].

All of the aforementioned work used either motion capture or a wearable sensor to recognize gross or fine-grained motion. However, it is unclear whether they could have achieved higher accuracy for their activity set had they used a different sensing modality. Accurate recognition of both gross and fine motion is especially crucial for robots in safety-critical spaces where an error could result in harm to a human partner. To this end, we investigate whether there is an advantage to using one sensor modality over another for recognizing different granularities of motion.

3.1.2 Methodology

In this chapter, we compared the efficacy of motion capture and wearable sensors for recognizing gross and fine-grained motion. We collected the MIT-UCSD Human Motion dataset,

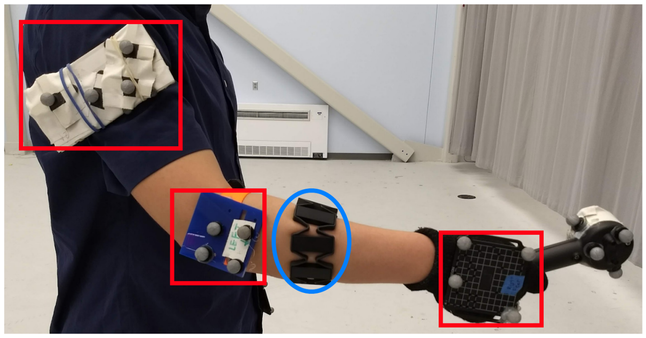


Figure 3.1. Arrangement of sensors on a participant's arm. Vicon markers are in red boxes. Myo is circled in blue.

comprised of two tasks. The first task is an automotive assembly task entailing gross motion, and the second is a block assembly task consisting of fine grasping motion. The automotive task contains four activity classes, and the block task has five. Five participants (two female, three male) performed both tasks. We trained three widely used machine learning algorithms with these data, and used F1 scores as our evaluation metric (see Section 3.1.3). In this section, we describe the data collection procedure, labeling method, and classification algorithms.

3.1.2.1 Data Collection

Sensors

We collected data using a Vicon motion-capture system and Myo armband simultaneously (see Figure 3.1). We placed Vicon markers on the shoulders, elbow, and back of the hand on each of the participants' arms. Participants wore the Myo on the forearm of their dominant arm. We solely tracked participants' arm movements to avoid burdening them with excessive Vicon markers, while still capturing relevant information as they completed activities.

We connected the sensors to a single machine (Intel i7-6820HQ CPU, 16GB of RAM) to ensure a consistent timestamp across all data. We used the Robot Operating System (ROS) (ROS version Indigo) to save time-synchronized data in *rosbag* format. The Vicon has a sampling rate of 120Hz, while the Myo has a sampling rate of 50Hz for IMU data and 200Hz for sEMG data. In accordance with other real-time activity recognition systems, we sampled our data at a consistent

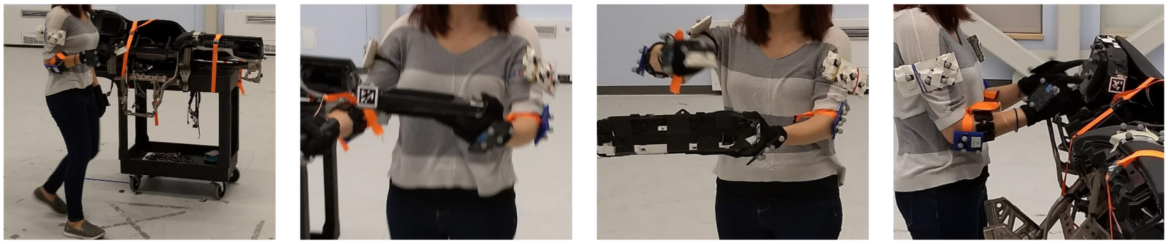


Figure 3.2. Activities from the automotive assembly task. From left to right, top to bottom: *Walking*, *Receiving Part*, *Scanning Part*, *Attaching Part*.

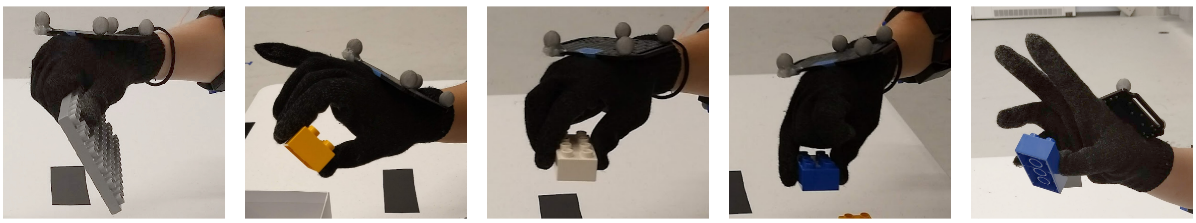


Figure 3.3. Grasping activities in the block assembly task. From left to right: *Palmar*, *Thumb-3 Fingers*, *Thumb-2 Fingers*, *Pincer*, *Ulnar pinch*.

rate of 30Hz in order to reduce the computation required by the systems [172, 180, 333].

Dataset Creation

To evaluate the efficacy of these sensors on different granularities of motion, we constructed the automotive and block assembly tasks to have activities composed of either gross or fine-grained motion respectively.

The automotive assembly task, inspired by the Dynamic-AutoFA dataset, consists of four gross motion activities [180]. As such, no actions in this task depend on dexterous hand or finger movements. The four main activities are *Walking*, *Receiving Part*, *Scanning Part*, and *Attaching Part* (see Figure 3.2, Table 3.1). There are between two and four instances, or occurrences, of each activity throughout the task. Each participant completed five trials (i.e. repetitions of the task) yielding a total of 50 to 100 instances of each activity.

The block assembly task consists of five fine grasping motions. Participants received a box with one flat base block and four rectangular blocks. In order to simulate different dexterous hand movements, we asked participants to grab and affix each block to the structure in a distinct

Table 3.1. Sequence of activities performed in the MIT-UCSD automotive task.

Class	Description
Walk	to dashboard
Scan	dashboard
Walk	to left side of dashboard
Receive	speedometer
Scan	speedometer
Attach	speedometer
Walk	to right side of dashboard
Receive	navigation unit
Scan	navigation unit
Attach	navigation unit
Walk	to exit

manner. The activities in this dataset are *Palmar Grab*, *Thumb-3 Fingers*, *Thumb-2 Fingers*, *Pincer Grab*, and *Ulnar Pinch Grab* (see Figure 3.3, Table 3.2). These grasps are similar to those used in other grasp recognition studies [29, 498]. Each participant completed five trials, performing each grasp once per trial, which yielded a total of 25 instances of each grasp.

We collected data from five participants who engaged in both the automotive and block assembly tasks. Participants were between the ages of 26 and 34, with a mean age of 28.2 years. Two of the five participants were female, and three were male. Four of the participants were right-handed, and one was left-handed.

3.1.2.2 Data Processing and Labeling

Feature Selection

For both the Vicon and Myo data, we use low-level, raw data features in the temporal domain. This is to assess the baseline capabilities of these sensor modalities without the influence of high-level feature selection, which can drastically impact a classifier's accuracy [222]. Data are partitioned using a sliding window technique, with window size of 1 second with 50% overlap.

The Vicon markers provided the 3D position (x-, y-, z- coordinates) of the selected joints

Table 3.2. Grasp types used in the block task. Each grasp used a different combination of fingers.

Grasp Name	Fingers Involved
Palmar	All
Thumb-3 Fingers	Thumb, Index, Middle, Fourth
Thumb-2 Fingers	Thumb, Index, Middle
Pincer	Thumb, Index
Ulnar Pinch	Thumb, Pinky

with respect to the Vicon's internal coordinate system. Since there were six joints (three on each arm), there were a total of 18 of these features in the dataset. We chose to track these joints because they are similar to the arm joints tracked in the Carnegie Mellon University Motion Capture Database [102].

For the Myo data, we collected the linear acceleration, angular velocity, and muscle activity data of each participants' dominant arm. This included x-, y-, and z- linear acceleration, x-, y-, and z- angular velocity, and the eight channels of sEMG data, yielding a total of 14 features. We chose these features to help detect arm position and orientation relative to the wearer, as the Myo does not sense movements relative to the global environment. Additionally, the sEMG signals can help detect differences in hand motion.

Data Labeling

Two annotators manually labeled the data by reviewing recorded video played back from a *rosbag* file. Annotators used a script to record the start and end time of each activity. In order to ensure consistency in our class labels, we conducted inter-rater reliability analysis by computing the two-way mixed intraclass correlation (ICC) for our labeled data. ICC is a measure of similarity between class labels, in our case the similarity of the start and end times of the activities between annotators [170]. Thus, we normalized the timestamps to the start of each trial.

We found Cronbach's $\alpha = .81$ which indicates that our labels were consistent between annotators [440].

3.1.2.3 Classification algorithms

We trained three machine learning classifiers on both datasets to determine which sensor modality is better suited for recognizing gross and fine-grained motion. We used a SVM with a linear kernel function ($C = 1$), LDA, and k-NN ($k = 5$) [343]. We chose these classifiers as they have proven successful in HAR and other applications [90, 261]. As our goal was not to compare the classifiers against each other, we used standard values for additional parameters (e.g. C for SVM, k for k-NN) to simplify the selection process.

SVMs are widely used for pattern recognition, classification, and regression [181]. They use kernel functions to calculate hyperplanes with which to divide training instances into proposed classes. These are then used to classify new instances. They have shown success in high dimensional spaces while producing interpretable results [181, 261].

LDA models training instances parametrically as multivariate means then uses linear decision boundaries to separate them into classes [247]. They inherently handle multiclass data such as ours and do not require hyperparameter tuning.

k-NNs are a type of instance-based learning that classifies new samples as the most prevalent class of the k most similar training instances [261]. We chose $k = 5$ to maintain distinct classification boundaries between classes.

3.1.2.4 Evaluation

To evaluate the relative efficacies of motion capture and wearable sensors, we performed leave-one-out cross-validation for each task (i.e. we tested each individual trial by training the classifier on all other trials of that task and then classified the original trial). In the case where we fused the Vicon and Myo data, we employed early fusion techniques, or combined the features before classification, which showed success in our prior work [331].

We calculated the mean F1 score to evaluate the classification efficacy across all trials of each participant for both tasks (see Table 3.3). As such, the training set is not subject specific, but does contain data from that participant. The F1 score of a class is the average of

Table 3.3. Mean F1 scores obtained for each data modality on each dataset using different classifiers. Across the datasets and sensors, we averaged the F1 scores from every trial. A higher F1 score is better.

	SVM			**LDA**			***k*-NN**		
	Vicon	Myo	Both	Vicon	Myo	Both	Vicon	Myo	Both
Automotive (Gross motion)	**.79**	.42	.43	**.76**	.48	.49	**.88**	.58	.59
Block (Fine-grained motion)	.09	**.37**	.36	.23	**.39**	.36	.32	**.43**	.43

Table 3.4. F-tests of factors. $p \leq .05$ indicates a significant effect on F1 score for individual variables, and significant interaction between variables for multiple. Confidence for all p-values is 95%. r-value is effect size.

Source	p	r
Motion Granularity	$< .001$	0.98
Sensor Modality	$< .001$	0.69
Classifier	$< .001$	0.75
Motion Granularity * Sensor Modality	$< .001$	0.96
Sensor Modality * Classifier	$> .05$	0.21
Motion Granularity * Classifier	$> .05$	0.28
Motion Granularity * Sensor Modality * Classifier	$< .001$	0.54

its classification precision and recall. Its value lies in the range of 0 to 1, where values closer to 1 indicate higher precision and recall. We chose to use the mean F1 score over raw accuracy as our performance measure as it is a better indicator of performance, especially when class distributions are imbalanced [223]. This was the case for the automotive task, since each trial contained up to twice as many more instances of some activities than others.

To determine the significance of our independent variables on our dependent variable (F1 score), we performed a three-way repeated-measures analysis of variance (ANOVA) test. The independent variables we tested were motion granularity (gross or fine), sensor modality (Myo or Vicon), and classifier (SVM, LDA, or k-NN) (see Table 3.4).

3.1.3 Results

Mauchly's Test of Sphericity indicated that all combinations of motion granularity, sensor modality, and classifier violated the assumption of sphericity, i.e. the variances of differences between data of the same participant were not equal. The exceptions to this were Sensor Modality * Classifier), $\chi^2(2) = 1.37$, $p = .504$, and Motion Granularity * Sensor Modality * Classifier, $\chi^2(2) = 0.68$, $p = .712$. Thus, we corrected the degrees of freedom for all other combinations using Greenhouse-Geisser estimates of sphericity. We corrected family-wise error rate in post hoc comparisons using Bonferroni correction.

3.1.3.1 Motion Granularity

Motion granularity had a significant main effect on F1 score. Regardless of the sensor modality or classifier used, the type of motion being classified significantly impacted the F1 score, $F(1,19) = 532.76$, $p < .001$, $r = 0.98$.

3.1.3.2 Sensor Modality

The sensor modality also had a significant main effect on F1 score. Regardless of the motion granularity or classifier, the sensor significantly impacted F1 score, $F(1,19) = 17.08$, $p < .001$, $r = 0.69$.

3.1.3.3 Classifier

We also found that the main effect of the classifier was significant, $F(1.54, 29.24) = 38.07$, $p < .001$, $r = 0.75$. Contrasts between each classifier found that the k-NN achieved higher F1 scores than the SVM, $F(1,19) = 52.22$, $p < .001$, $r = 0.86$, as well as the LDA, $F(1,19) = 29.00$, $p < .001$, $r = 0.78$. The LDA also outperformed the SVM, $F(1,19) = 17.53$, $p < .001$, $r = 0.693$.

3.1.3.4 Motion Granularity * Sensor Modality

There was a significant interaction between the motion type and sensor type, $F(4,19) = 219.39$, $p < .001$. This indicates that the sensor had significantly different effects on the F1 score depending on the motion granularity being recognized, and vice-versa. Contrasts revealed that the Vicon yielded higher accuracy than the Myo for gross motion, but lower accuracy for fine. Conversely, the Myo yielded higher accuracy than the Vicon for fine-grained motion, but lower for gross, $F(1,19) = 219.39$, $p < .001$, $r = 0.96$ (see Figure 3.4a).

3.1.3.5 Sensor Modality * Classifier

There was no significant interaction between sensor modality and classifier, $F(2,38) = 1.83$, $p > .05$, $r = 0.21$. The interaction graph supports this finding (see Figure 3.4b).

3.1.3.6 Motion Granularity * Classifier

There was also no significant interaction between the granularity of motion being classified and the classifier, $F(1.53,29.10) = 3.27$, $p > .05$, $r = 0.28$. The interaction graph supports this finding (see Figure 3.4c).

3.1.3.7 Motion Granularity * Sensor Modality * Classifier

Finally, the was significant interaction between all three of the independent variables, $F(2,38) = 15.34$, $p < .001$, $r = 0.54$. This indicates that F1 score was significantly different for each combination of motion granularity, sensor modality, and classifier. This is reflected in the interaction graphs as the difference in F1 score is consistently greatest between the SVM and k-NN (see Figure 3.4b,c).

3.1.4 Discussion

Our results suggest that motion capture and wearable sensors offer complementary strengths for HAR. Motion capture is more accurate for detecting gross motion, while wearable sensors are more accurate for recognizing fine-grained motion. Our results also indicate that

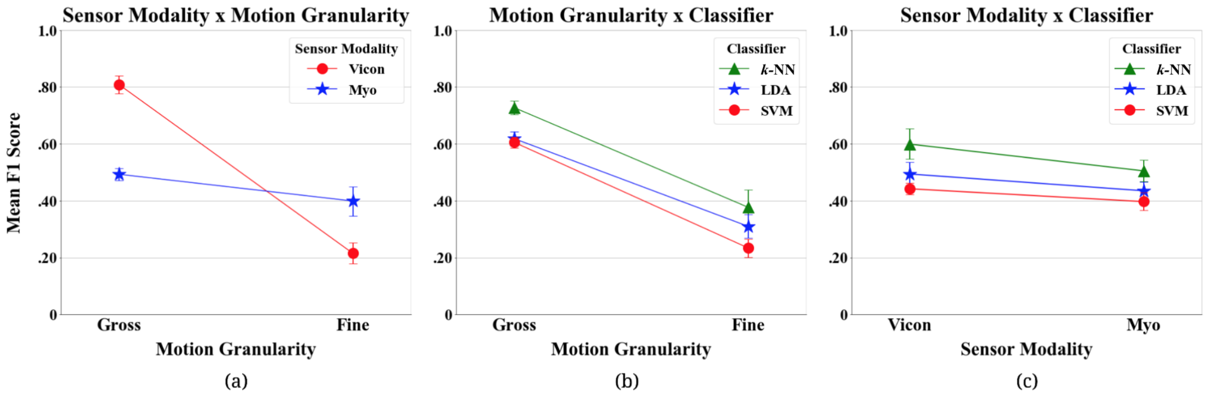


Figure 3.4. Interactions between each pair of variables. The *y*-axis represents mean F1 score over all trials. Similar slopes between lines indicate insignificant interaction between variables. There was significant interaction between sensor modality and motion granularity, and insignificant interaction of classifier with both motion granularity and sensor modality.

both sensor modalities yielded significantly more accurate recognition of gross motion than fine-grained which suggests that fine-grained motion is more difficult to classify than gross.

For gross motion recognition, we found that motion capture data yielded significantly higher accuracy than the wearable sensor data. This may be because the Vicon utilizes 3D position in the environment, so the relative position of the person may help the classifiers more accurately recognize gross motion. For example, the *Receiving Part* and *Attaching Part* activities occur in consistent, but different, locations in the environment. Thus, the classifiers can use the consistent arm positions to distinguish between these two activity classes. On the other hand, the Myo only obtains data relative to the user, so it does cannot distinguish activities in the same way. Arm movement may not be enough information to accurately detect gross body motion.

For recognizing fine-grained motion, we found that the wearable sensor data yielded significantly higher accuracy than motion capture data. The Myo can detect the muscle activity generated by the minute motion variations of each grasp to help the classifiers differentiate between them. In contrast, the Vicon tracks the position of the hands as opposed to the fingers, so the 3D motion it captures is similar between these fine-grained finger activities. Moreover, joints were often occluded from view, resulting in lower accuracy, a known problem when working with visual sensors [171].

Our results also indicate that fine-grained motion is more difficult to classify than gross. Across all classifiers, both the Myo and Vicon yielded lower accuracy on the block assembly task than on the automotive one. This may be because the movements between the grasps were similar (overhand, using some number of fingers) which led to ambiguities in the data. Fine-grained hand motion, as seen in our dataset, can be difficult to discern as it often entails analogous arm motion and muscle activity. In future work, we will explore higher level features and combinations of sensors to more accurately recognize these activities.

Our results also suggest that multimodal sensor fusion resulted in lower classification accuracy than when using a single sensor for both tasks. Prior work in other recognition tasks showed that using similar multimodal approaches can improve classification accuracy, so we expected a similar result here [330, 331]. However, it is possible that the additional modalities contributed more noise than meaningful information, resulting in lower accuracy. In future work, we may be able to mitigate this by performing higher level feature extraction (e.g. mean absolute value for sEMG data, frequency domain features for inertial data), training a deep learning model to extract more significant information, or exploring alternate fusion techniques [331].

Depending on the types of relevant activities in the space, robots may need different kinds of sensor data in order to accurately recognize the intentions of their human counterparts. Our findings can help the robotics community make more informed decisions regarding which sensor modalities would be most beneficial for their specific tasks. This decision depends considerably on which activities are important for robots to recognize as well as the motion granularity of these activities. For instance, if the robot needs to know that a person is lifting a heavy object and may need help, motion capture systems are reliable. On the other hand, wearable sensors would better help a robot to determine which tool to fetch next depending on whether the person is currently assembling a part with a hammer versus a screwdriver.

A limitation of this work is that we only recorded the arm motion of the participants. In many HAR scenarios, movement of other body parts and environmental features can improve activity detection [180]. While it is possible that motion capture would have performed better with more markers, recognizing precise finger movements would still be a challenge due to their close proximity. Therefore, it is unlikely that using more markers would have increased accuracy of fine-grained motion, and improvements in accuracy of gross motion would further support our findings. Additionally, motion capture is not always viable for small tools and parts (e.g. screwdrivers for assembling small electronics). Thus, we subject both the Vicon and Myo to the difficult scenario where only human arm movements are measured.

Our findings suggest promising avenues for improving HAR of complex tasks in safety-critical settings. However, a limitation that should be addressed to improve the robustness of such systems is that we assume the classifier is trained on previous data from each participant, which may not always be the case in real-world scenarios. Additionally, as the amount of training data increases, so does the computational complexity of these classifiers. This is not ideal for a robot that must react quickly in dynamic settings. Therefore, as more data is collected, approaches that can handle larger datasets such as deep learning may be more suitable.

As we continue research in this area, we plan to develop a multimodal system that can leverage the complementary nature of these sensor modalities to recognize both gross and fine-grained motion so robots can better infer human activity. We will also extend our dataset in order to create a more reliable unimodal activity recognition system. Once we have a classifier that can reliably detect human activity, we plan to explore how robots can improve safety conditions for human workers in safety-critical settings.

Our findings can help the robotics community to understand which sensors work best for certain activities. These insights will enable researchers to design algorithms for robots that incorporate complementary multimodal approaches to better recognize activities that entail both motion types. These findings can also help guide both the robotic learning from demonstration and grasping communities as they choose sensor modalities best suited for their contexts. Our findings will help robots infer human intention regardless of the nature of the activities and environment. With the means to accurately distinguish particular activities, they can better support people and improve safety conditions in more specialized, safety-critical settings.

3.2 Multimodal Deep Learning for Fine Motion Recognition

In this section, we present a novel non-visual HAR system to support robust human-robot teaming in safety-critical environments. Our system informs the robot of its teammates' actions through inertial and sEMG signals captured by an unobtrusive armband. This raw multimodal input is processed by an hybrid neural network architecture that leverages the complementary benefits of convolutional and recurrent layers to capture complex spatial and temporal features. We evaluate our work on two datasets representative of tasks performed in safety-critical environments: MIT-UCSD Human Motion [254], which consists of common manufacturing tasks (see Section 3.1.2.1), and MyoGym, a dataset of strenuous exercises demonstrating action primitives for manual labor. Evaluation results show that our system achieves state-of-the-art performance when presented with ample training data of relevant safety-critical tasks.

The contributions of the section are threefold: First, to our knowledge, we are the first to compare the performance of several prominent non-visual HAR classifiers in addressing tasks specific to safety-critical environments, rather than everyday activities such as ADLs. Second, we conduct an analysis of the effect of supplementing inertial data with sEMG on the feasibility of classifying whole-body tasks from single-sensor recordings. Finally, we present a novel wearable non-visual HAR system that leverages hybrid deep learning to improve upon rival algorithms and achieve state-of-the-art human task awareness for robots in these settings.

The approach presented in this section will enable robots to fluently understand and collaborate with human partners on complex, strenuous tasks, and confer the numerous benefits of human-robot collaboration to people in safety-critical environments worldwide.

3.2.1 Background

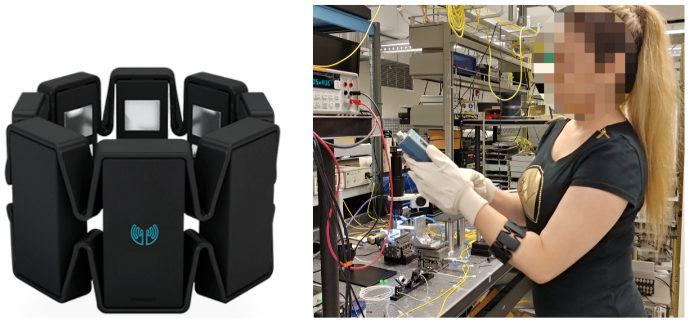
3.2.1.1 Wearable Non-visual HAR Sensors

The most common sensors used for non-visual HAR are IMUs [90, 261]. IMUs measure linear acceleration, rotational acceleration, orientation, or a combination of the three, and are often worn on the limbs or torso. Researchers have also taken advantage of the IMUs found in mobile devices for a variety of studies in-the-wild [90, 261, 325, 462].

A limited number of prior work investigated IMUs for non-visual HAR in safety-critical environments. Stiefmeier et al. [420] fused 27 IMUs and radio-frequency identification sensors to recognize tasks on a car assembly line. Inoue et al. [213] recorded inertial data from multiple accelerometers to recognize a variety of nursing tasks. In contrast to these past systems, which employ complicated and bulky sensor arrays, our approach uses a single armband sensor in order to recognize activities with minimal encumbrance.

Recently, researchers have begun to investigate sEMG sensors for non-visual HAR, either alone or as a supplement to inertial signals. Several groups have employed sEMG in recognition and assessment of ADLs [76], balance [149], and gait [424]. Others have investigated fine hand motions, and have used arm and wrist sEMG to determine hand gestures [390], or to recognize American Sign Language [489]. However, these tasks do not represent the specialized activities or equipment that robots would encounter in safety-critical environments. Furthermore, these systems often utilize numerous obtrusive sensors and are thus not appropriate for use in real-world environments.

In contrast, the Myo armband (see Figure 3.5) is a compact, arm-worn device that houses an 8-channel sEMG and a 9-axis IMU [211]. Recent studies leverage affordable, unobtrusive sensor for exploring multimodal non-visual HAR [2, 247, 254, 453]. Researchers found that augmenting inertial sensors with sEMG sensors from the Myo considerably improves classification accuracy of strenuous exercises [247] and ADLs [453]. However, approaches such as that presented by Koskimäki et al. [247] still exhibit substandard results (up to 72% accuracy),



(a) (b)

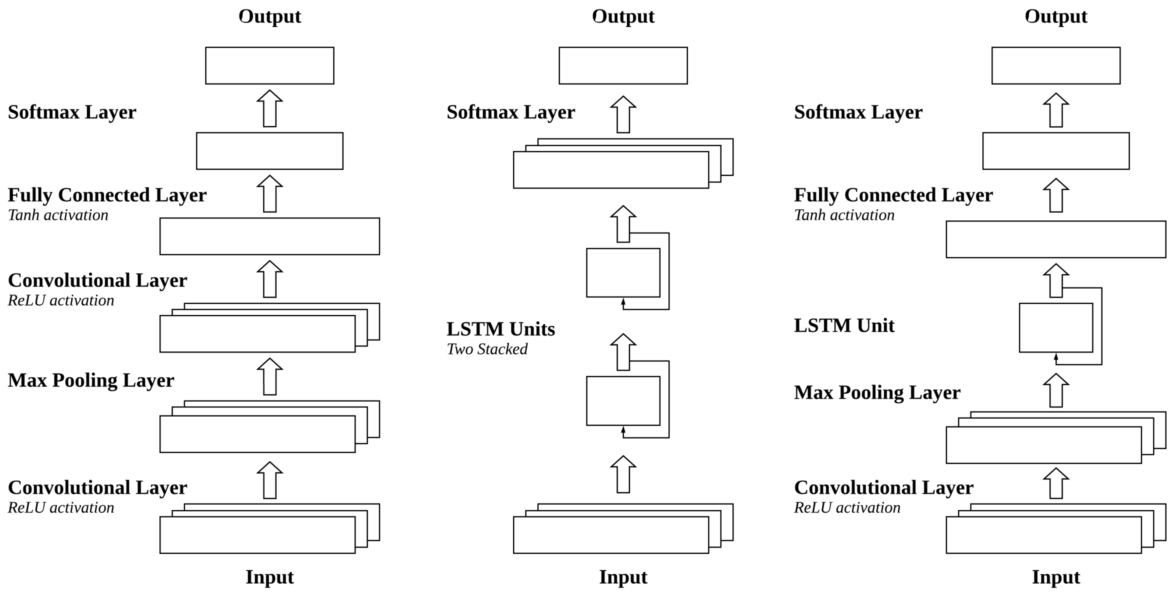
Figure 3.5. (a) The Myo armband can measure sEMG, linear acceleration, and angular acceleration of the wearer's arm movements. (b) Recognizing activities in a manufacturing setting with the Myo.

leaving considerable room for improvement. Totty et al. [453] achieved up to 89.2% accuracy classifying ADL functional groups. However, the approach exhibits several limitations. First, the approach presented is unable to recognize the specific activity performed, but only the high level category (e.g. "no activity", "functional"). In addition, the dataset considered only included basic upper extremity tasks, and does not represent the intensive whole-body tasks relevant to safety-critical environments.

Despite the success of the Myo and of sEMG HAR in general, to our knowledge, there is no work demonstrating a system that can reliably recognize realistic, complex worker tasks performed in real-world environments. The complex networks of sensors suggested in studies such as [76] and [420] are cumbersome and delicate, which makes them unfit for use in real-world environments. Furthermore, none of these studies explored more than a few basic classifiers on inertial+sEMG data. It remains an open question what classification approach is best suited to decoding these complicated multimodal signals.

3.2.1.2 Non-visual HAR Classification

Researchers have employed a variety of classification techniques to address non-visual HAR. One attractive method is LDA as it easily generalizes to multiclass classification and does not require hyperparameter tuning [247]. Another widely-used approach is k-NN, which



(a) CNN **(b) LSTM** **(c) Hybrid CNN-LSTM**

Figure 3.6. The architectures of the deep HAR models used in this work. For clarity, the input vectors displayed represent a single time window in a batch. (a) The CNN extracts local patterns among multiple data channels. (b) The LSTM network identifies important temporal features. (c) The hybrid CNN-LSTM identifies temporal patterns using convolutional features.

classifies new instances as the most common class of the *k* most similar training samples. *k*-NNs produce noteworthy results for inertial non-visual HAR of ADLs compared to other popular algorithms [388, 453].

Recently, successes in areas such as image and speech recognition have inspired researchers to employ deep learning for non-visual HAR. Deep learning approaches mitigate the need for hand-crafted features, which are difficult to design for mobile and wearable sensor streams [179]. The most common deep learning approaches for non-visual HAR are convolutional neural networks (CNN) and recurrent neural networks (RNN) [172]. CNNs construct spatial features from signals by taking convolutions of input channels at each timepoint. On the other hand, RNNs extract temporal features, i.e. how the evolution of the signal over time informs the prediction. Long short-term memory (LSTM) networks, the most widely used RNN, improve upon traditional RNNs by selectively truncating error gradients in backpropagation to allow the network to learn long-term dependencies in input signals [190].

Table 3.5. Mean F1 scores obtained for each data modality on each dataset for each classifier. Across the classifiers, data modality, and dataset, we averaged the F1 scores from every trial. A higher F1 score is better.

	MIT-UCSD Human Motion					**MyoGym**				
	CNN-LSTM	CNN	LSTM	*k*-NN	LDA	CNN-LSTM	CNN	LSTM	*k*-NN	LDA
Inertial+sEMG	**.35**	**.36**	.22	.31	**.33**	**.84**	**.39**	**.28**	.36	**.74**
Only Inertial	.31	.36	**.24**	**.35**	.30	.84	.38	.23	**.39**	.69

CNNs have become popular in non-visual HAR for applications such as classifying ADLs (c.f. [494]) and fall detection (c.f. [238]). In addition, the ability to leverage the temporal structure of activity signals makes LSTMs a promising tool for non-visual HAR of tasks with complicated, time-dependent patterns [172]. Other recent work uses a combination of convolutional and recurrent layers for non-visual HAR (c.f. [172]). These combined CNN-LSTM architectures capitalize on the CNN layers' ability to extract convolutional features that best represent the state at each timestep, from which the LSTM layers learn the temporal evolution of that state over the input sequence. While CNN-LSTMs are rather new to non-visual HAR, they can achieve state-of-the-art accuracy on non-visual data [172].

3.2.2 Methodology

In this section, we expand upon past work in the following ways. First, we evaluate the performance of several prominent non-visual HAR algorithms on realistic worker tasks to determine the most effective techniques for use in real-world environments. In particular, we investigate three deep learning approaches (CNN, LSTM, CNN-LSTM) and two machine learning classifiers (*k*-NN, LDA). Second, we investigate the promise of supplementing inertial wearable sensors with sEMG across each dataset, task, and algorithm. Finally, we present and validate a cohesive non-visual HAR system that employs a single, practical armband sensor to effectively classify tasks, enabling fluent HRI in these spaces.

3.2.2.1 Datasets and Preprocessing

We evaluate our system on two datasets representative of tasks common in safety-critical environments: MIT-UCSD Human Motion (see Section 3.1.2.1) [254] and MyoGym [247]. MyoGym includes 10 participants performing 30 strenuous gym exercises, representative of lifting, pushing, and carrying tasks. All data in both datasets were collected by a Myo armband worn on the dominant forearm, and contain 6-channel inertial (tri-axial accelerometer, tri-axial gyroscope) and 8-channel sEMG data collected at 50 Hz.

Data were segmented into 50% overlap 1 second and 1.5 second input windows for MIT-UCSD and MyoGym, respectively. We use a shorter window for MIT-UCSD due to shorter task durations. We standardized each input channel of each train set to $\mu = 0$ and $\sigma = 1$ over all training data. To simulate real-time performance, we standardized test data to $\mu = 0$ and $\sigma = 1$ with a moving window of data points in the past 1 second. Because data in MyoGym were collected continuously through all 30 exercises, the *null* class represents approximately 78% of all training data. To discourage the trivial solution (i.e. always predicting the majority class), we reduced the number of *null* class instances through random undersampling of *null* sequences.

3.2.2.2 Classifiers

We built three neural network classifiers to perform non-visual HAR: a CNN, an LSTM, and a hybrid CNN-LSTM. We aimed to minimize variation due to arbitrary hyperparameter choices (e.g. number of layers, activation functions) by making analogous design choices across networks. In this way, we ensure that differences in classification accuracy are more closely tied to the type of network than differences in these hyperparameters. Each network was designed with two convolutional or recurrent layers, a fully connected layer, and a softmax output layer (see Figure 3.6). We use two feature-extracting layers for each network to control for layer ordering effects and isolate the effect of layer type on classification.

All kernels use a stride of 20 ms, the sample rate of the Myo. Convolutional layers used a kernel of 500 ms for MIT-UCSD, and a kernel of 1200 ms for MyoGym. We chose these relatively large kernels to simulate temporal memory in convolutional layers. Per convention, we apply a max-pooling layer between convolutional layers. This layer uses a kernel size of 40 ms. LSTM layers contained 64 hidden units, and fully connected layers contained 1000, as chosen by cross-validation. Convolutional, LSTM, and fully connected layers were activated with ReLU functions, and output layers used softmax activation for classification.

In order to compare to existing literature, we tested each dataset on an LDA (see [247]) and a k-NN ($k = 5$) (see [254, 453]). Since these classifiers cannot autonomously select informative features from data, we extracted 57 linear acceleration features, 54 angular velocity features, and 112 sEMG-based features as input, as recommended by Koskimaki et al. [247]. In contrast, our network algorithms were only fed raw data. This allows us to compare the efficacy of expert-recommended features against those generated autonomously by NNs for classifying real-world tasks.

3.2.2.3 Evaluation

All classifiers were trained separately on both datasets until convergence. We evaluated performance metrics based on leave-n-trials-out cross-validation. In order to ensure sufficient training data was available, we used $n = 1$ for MIT-UCSD, and $n = 3$ for MyoGym. We did not perform resampling or class-balancing on the test data to simulate a robot perceiving human actions in real-time.

We report micro-F_1 score as our evaluation metric, as it more faithfully represents classification performance across unbalanced classes compared to accuracy and macro-F_1 score. To analyze the variation in outcome measures, we performed a three-way repeated-measures ANOVA across classifier, data modality, and dataset.

3.2.3 Results

All effects are reported significant at $p < 0.05$. Mauchly's tests indicated that that the assumption of sphericity was violated for the main effect of classifier, as well as the interac-

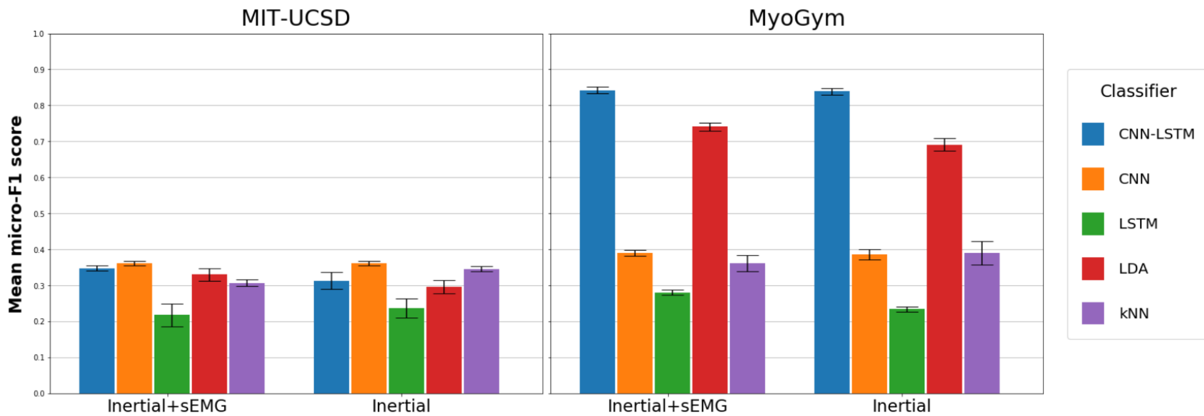


Figure 3.7. Average micro-F1 scores (across all trials) for the classifier type and sensor data channels, separated by dataset.

tion effects of classifier and data modality, and that of classifier and dataset. We corrected for this using Greenhouse-Geisser estimates of sphericity. Each of our measures had a significant main effect on F1 score (classifier: $F(2.06, 267.36) = 472.1$, modality: $F(1, 130) = 5.9$, dataset: $F(1, 130) = 642.3$). There were also significant interaction effects between modality and classifier, $F(2.79, 362.76) = 10.9$, between dataset and classifier, $F(1.952, 253.76) = 359.7$, and between modality and dataset $F(1, 130) = 35.1$. This suggests that the type of sensing capabilities as well as dataset have different effects on classification accuracy depending on the classifier used.

Contrasts reveal that the CNN-LSTM performed significantly better than the other classifiers overall on the MyoGym dataset. This architecture performed consistently better than the LSTM and k-NN across all evaluations. The CNN-LSTM also performed significantly better than the LDA on MyoGym when sEMG was present, but saw no significant improvement over LDA in the other scenarios. On MIT-UCSD, there was no significant advantage shown using CNN-LSTM instead of LDA or CNN. There was no significant difference between the performance of the CNN-LSTM and LDA or CNN on the MIT-UCSD dataset. The classifier's performance decreased slightly but significantly across both datasets when no sEMG signal was available, suggesting our system performs adequately even with less information available.

The average F1 score for the MIT-UCSD dataset across all classifiers and modalities was

$31.2 \pm 5.0\%$, significantly lower than the performance on the MyoGym dataset ($51.6 \pm 23.6\%$.). All classifiers performed significantly better on the MyoGym dataset or had no significant change. Including sEMG in training and classification had significant overall positive effect on F1 score across classifier. The inclusion of sEMG significantly assisted every classifier except the overall performance of the LSTM, and the performance of the CNN on the MIT-UCSD dataset.

3.2.4 Discussion

Our evaluation suggests that a hybrid CNN-LSTM architecture offers superior identification of safety-critical tasks in a realistic environment compared to prominent rival techniques. We found that CNN-LSTM architecture excels in environments that exhibit strenuous pushing, pulling, and lifting tasks, attaining 84% accuracy across 30 different actions on the MyoGym dataset. Additionally, the hybrid architecture is on par with other state-of-the-art classifiers over the MIT-UCSD dataset. This suggests that the combination of convolutional and recurrent layers with forearm sEMG and inertial signals is a promising approach for supporting robot understanding of complex human activities in real-world environments.

Although popular in recent literature, our evaluation suggests that *k*-NN is unsuited to non-visual HAR in real-world environments, even when aided by expert feature selection. This is interesting, as it has been widely validated as a suitable means for identifying ADLs [254, 388, 453]. This implies that more specific, alternative approaches, such as a hybrid CNN-LSTM, may be necessary to support safe and robust non-visual HAR in safety-critical and other complex environments. Tasks in real-world environments are complex and stochastic, and take even humans substantial time to learn when newly introduced [465]. In order to ensure safe and accurate non-visual HAR, it is important not to take a previously successful classifier's effectiveness for granted. Instead, one must evaluate all robot systems on realistic data for the target environment.

Beyond classifiers, our results also suggest benefits of supplementing inertial data with sEMG. We found that sEMG signals were informative for pushing and pulling tasks, and assisted most classifiers in broadly categorizing tasks that involved targeted hand movements, such as assembling blocks. They also helped in discerning between tasks with similar movements, such as reaching forward to receive an automobile part versus doing so to install it in the dashboard.

However, one limitation of this work is that due to the small size of the MIT-UCSD dataset (approximately 4000 1-second sequences), the relative performance of each classifier is difficult to gauge. In particular, the CNN-LSTM still has significant room for improvement, as it is widely known that neural networks require substantial training data to learn informative features. This premise is supported by the poor performance of the other classifiers when trained on this dataset. Nevertheless, given our system requires only an unobtrusive wearable sensor to gather data, a real-world implementation should have little issue collecting ample training data for robust performance.

While we found that sEMG signals are beneficial in some cases, sEMG had a detrimental effect when classifying tasks that involved raising the arms and lifting. Furthermore, several deep learning approaches performed worse when sEMG was included, suggesting that the additional modalities may confound classification on smaller or more intricate datasets. Caution and careful testing should be used when exploring whether sEMG sensing benefits future non-visual HAR applications. Future work will explore several avenues for expanding this non-visual HAR system. As the purpose of this work was to identify the most effective technique for safety-critical environments, we performed no hyperparameter optimization. Moving forward, we will fine-tune hyperparameters and explore other neural network architectures. In addition, in order to continue developing systems that perform in real-world environments, we intend to to gather a larger dataset of real-world manufacturing and clinical tasks. We will make these datasets publicly available to empower the robotics community to investigate non-visual HAR in real-world environments.

3.3 Chapter Summary

In this chapter, we introduced new methods for recognizing human activity in dynamic environments. This work enables robots to infer the intentions of the people around them by recognizing a variety of motion using non-visual sensors. We also proposed a novel non-visual HAR system that aims to to support robot integration into real-world environments by enabling robust identification of human activity. To our knowledge, this system is the first non-visual HAR approach that is able to robustly identify complex full-body tasks using a single, unobtrusive sensor feasible for real-world use in safety-critical environments. With the ability to more accurately distinguish between complex activities, robots will no longer be excluded from human-dense, safety-critical environments. Through our work, researchers will be able to develop advanced robots that can improve health and quality of life of the millions of workers worldwide. The next chapter focuses on a robot platform that we developed which can learn from and adapt to people when delivering cognitive training.

3.4 Acknowledgements

I thank Tariq Iqbal for providing his expertise in conducting quantitative research and assistance with data collection. I would also like to thank Julie Shah for providing access to her equipment and lab space where we collected data. I also thank Andrea Frank for her assistance with algorithm ideation and development.

This chapter contains material from “Activity recognition in manufacturing: The roles of motion capture and sEMG+inertial wearables in detecting fine vs. gross motion,” by A. Kubota, T. Iqbal, J. A. Shah, and L. D. Riek, which appears in Proceedings of the IEEE International Conference on Robotics and Automation (ICRA) [254]; and “Wearable activity recognition for robust human-robot teaming in safety-critical environments via hybrid neural networks,” A. Frank, A. Kubota, and L. D. Riek, which appears in Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) [137]. The dissertation author and Andrea

Frank were the primary investigators and authors of this work.

Chapter 4

Cognitively Assistive Robot for Motivation and Neurorehabilitation (CARMEN)

Many types of robots exist to cognitively and socially assist people with cognitive impairments. These *robot-delivered health interventions* have many benefits, including the potential to expand access to healthcare by extending it into a person's home, reducing treatment time and cost, and prolonging a person's independence [154]. Robots can provide support on multiple dimensions, including socially and cognitively.

Robots can also provide social support and provide non-pharmaceutical therapeutic interventions for people with cognitive impairments. Often, zoomorphic robots such as PARO or AIBO act as companions, or therapists may use them to augment interventions such as animal-assisted therapy or multi-sensory behavior therapy [205, 319]. These robots can help reduce negative feelings such as stress and anxiety among people with cognitive impairments and caregivers, and even improve their mood [148, 212, 324, 338].

Researchers have also explored the use of CARs to support cognitive training and cognitive stimulation among people with cognitive impairments which can help slow the progression of their disease [258, 466]. These robots can remind users of appointments, medication, and dietary requirements to reduce reliance on their memory [322]. In addition, they may assist users with cognitive training games to support their memory, or accompany human clinicians with memory training programs [350, 436]. Researchers are also exploring the use of robots to teach people with cognitive impairments metacognitive strategies which help strengthen memory, planning, and executive functioning in order to help them manage their impairment in their daily life [256]. Often, the cognitive support that an assistive robot provides can extend or supplement a health intervention.

For the past several years, our team has worked with neuropsychologists to develop CARs that deliver CCT [204] autonomously and longitudinally to people with MCI at home. In this chapter, we introduce CARMEN, a cognitively assistive robot which autonomously and longitudinally delivers cognitive training to people with MCI in home settings. Our system helps users practice cognitive strategies to strengthen skills such as planning and executive functioning.

4.1 Design Requirements

In developing CARMEN, we collaborated closely with clinical researchers and people with MCI to ensure that the robot would be physically and cognitively accessible for this population, as well as useful as an intervention tool. Our explorations into this space revealed major design requirements which we considered as we developed the system (see Chapters 5, 6, and 7). These included delivering intervention material autonomously, requiring minimal internet connection, being robust over the course of the intervention, supporting multiple communication modalities, and having few physical components.

4.1.1 Autonomous Intervention Delivery

Our prior work with stakeholders revealed that it is important that people can use CARMEN in their homes without constant mediation from researchers or clinicians. While our clinical collaborators expressed interest in manually adjusting a robot's behavior in order to better suit a person's goals or abilities, robots should also interact with a person and deliver intervention content autonomously. Thus, CARMEN needs to automatically start running the intervention upon startup, and advance between different cognitive strategies and areas in alignment with the original ME-CCT manual. This allows for a more streamlined and straightforward experience, which is particularly important for people with low technology literacy, to help reduce frustration and minimize barriers to using the system.

Intelligent and autonomous behavior adaptation of a system is also crucial for maintaining adherence and maximizing efficacy to longitudinal interventions such as ME-CCT [258]. Therefore, a key feature of CARMEN will be a machine learning algorithm that enables it to automatically learn a person's preferences and abilities, and adjust its behavior (e.g. intervention content, communication modality) accordingly.

4.1.2 Limited Internet Connectivity

Many people with MCI are older adults who may not have reliable internet access in their homes [175]. In addition, disability status and health problems are known factors which reduce internet adoption [175]. Therefore, to improve accessibility and ensure that CARMEN will be usable in real world settings, it needs to perform most of its processing locally in order to minimize its reliance on internet connectivity. Keeping CARMEN primarily offline will also minimize its vulnerability to security threats, which is important to protect the privacy of users in sensitive spaces such as their homes.

However, due to the longitudinal nature of cognitive interventions such as ME-CCT, the amount of data that CARMEN gathers throughout the intervention may be too large to be stored locally. Furthermore, the machine learning models we expect to develop and train using this data may require large amounts of processing time and power. To balance these considerations, we perform certain real-time capabilities (e.g. speech synthesis, adaptive robot behaviors) locally on the robot. Once a day, CARMEN opens a secure connection to communicate data with a remote supercomputer where we store data that the robot collects and update our machine learning models.

4.1.3 Longitudinally Robust

CARMEN will need to be able to work robustly throughout the duration of an intervention, in our case approximately eight weeks. It is important that robots will execute their tasks as expected so that people with MCI will not have to troubleshoot problems or contact researchers often. Our clinical collaborators provided suggestions for supporting troubleshooting, including providing written instructions and having a phone help line. But to minimize frustration for users, we designed CARMEN to be robust over a long period of time.

4.1.4 Straightforward Physical Setup

Our studies with stakeholders revealed that people with MCI may have difficulty maintaining focus, so systems with multiple components could cause confusion or break concentration. Therefore, we aimed to keep the physical setup of CARMEN as straightforward as possible, including keeping the hardware compact and with no additional components that a user might need to keep track of or maintain. In addition, we adopted a plug-and-play system with minimum human intervention to set up and start to use the robot.

4.1.5 Accessible Communication Modalities

People with MCI are often older adults and may have varying physical and cognitive abilities which can impact how they can comfortably interact with technology. For example, people with MCI may experience tremors which can make it difficult to press buttons, or they may have audio or visual impairments.. Therefore, these systems need to support multiple communication modalities to improve accessibility for people with different physical abilities and preferences. Designers should take steps to make robots both physically and cognitively accessible for communication with people with MCI, which we adopted while designing CARMEN [253, 363].

For example, to support physical accessibility, our clinical collaborators indicated that many of the best technology design practices for older adults are also applicable for people with MCI. These included having options for large font sizes for text, high contrast visuals, loud volumes for speech and sounds, and using large buttons with adequate spacing between them. At the same time, they expressed the importance of letting people adjust these settings to match their abilities and preferences [253].

In addition, people with MCI may have difficulty with verbal comprehension or memory [299]. Therefore, to improve clarity and comprehensibility of CARMEN, we kept its vocal utterances short and concise [93]. We also implemented means to have CARMEN repeat information, and let people advance through the intervention at their own pace.

4.1.6 Approachable Physical Appearance

The aim of CARMEN is to be deployed in a person's home longitudinally, and ideally maintain engagement and adherence with the intervention throughout its deployment. Research shows that the physical appearance of a robot can significantly impact the acceptance and use by older adults, with many older adults rejecting systems that were too human-like or implied any disability [108]. Our initial explorations also indicate that people with MCI may see robots as a companion throughout the intervention, and care should be taken to avoid Turing Deceptions (i.e. when someone mistakes interactions with a robot for those with a person) when designing robots for people with cognitive impairments [257, 376].

However, the "face-to-face" nature of interactions with robots has been shown to improve intervention outcomes, engagement, and trust of the system [57]. Therefore, we aimed to make CARMEN's appearance anthropomorphic and approachable, but not overly realistic.

4.2 CARMEN System Architecture

We envision CARMEN will serve as a tool to supplement cognitive training at home in between weekly appointments with a human clinician. Depending on a person's needs and their confidence with each cognitive strategy, they may interact with CARMEN to practice the strategies multiple times each week throughout the intervention. We define each of these interactions as a *session*. During each session, the robot will explain a cognitive strategy and

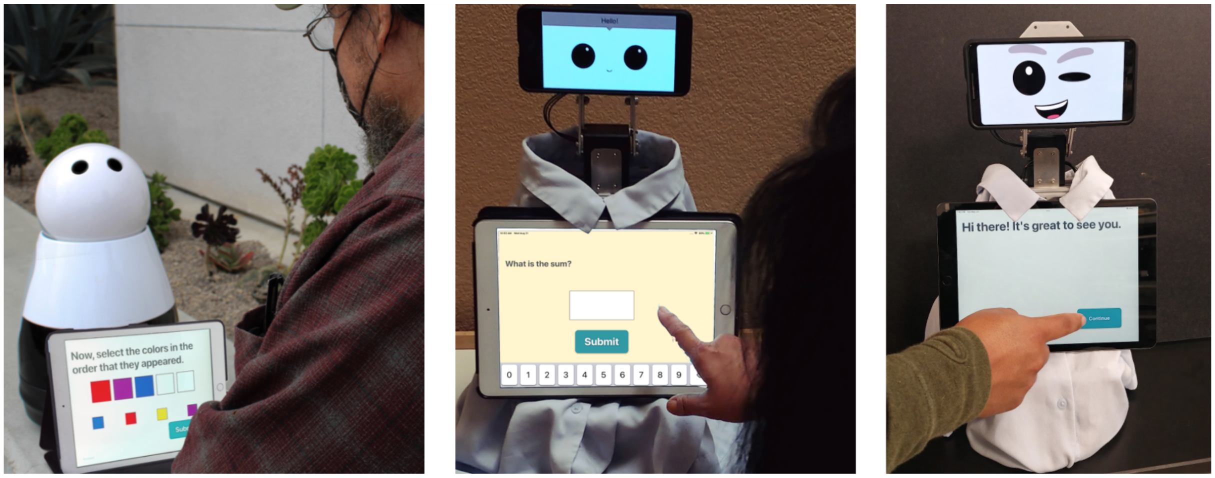


Figure 4.1. Design iterations of our robot CARMEN which delivers cognitive interventions longitudinally to people with MCI. The robots help users practice cognitive strategies with activities to minimize the impact MCI on daily life [204].

give the person an opportunity to practice that strategy via one or more *activities*. It will collect interaction and performance data from the person which it will use to update its behavior for the next session in order to support the user's engagement and goals.

We describe the hardware and software components of CARMEN below.

4.2.1 Hardware

CARMEN is a system which comprises a social robot platform coupled with a tablet to support multimodal communication and promote accessibility. We have explored multiple robot embodiments for the system, including the Kuri and FLEXI [10] platforms (see Figure 4.1). For customizability purposes, we decided to primarily develop CARMEN based on the FLEXI platform.

FLEXI is a low cost, open source social robot embodiment kit [10]. It is a tabletop social robot designed to be customizable so HRI researchers can use it for a broad range of applications. The tablet provides an avenue for the robot to display visual information to users, and enables users to communicate with the robot via the touch screen (e.g. pressing buttons, on-screen keyboard). FLEXI also leverages a smartphone which displays its face.

To support movement, FLEXI has four degrees of freedom. One motor at the base enables it to swivel left and right, one in the neck allows it to lean forward and back, and a two-joint motor in the head allows it to tilt and rotate its face.

We made several modifications to the original FLEXI system to better suit our needs.. While the FLEXI uses a Microsoft Surface Tablet, we use a MeLE mini PC running Ubuntu so CARMEN can utilize ROS [364]. We integrated an Apple iPad as the tablet interface which connects to the mini PC via a websocket, and replaced the smartphone with an LCD monitor to minimize wireless connections between physical components. We also developed an alternative system to control the face locally, as the original FLEXI system requires an internet connection for this functionality. In addition, we connected an external speaker and microphone to support verbal communication and sounds with users. Finally, we enclosed the hardware in a 3D printed case to secure all of the components.

To support longitudinal machine learning, CARMEN also has software which runs on two supercomputer systems. First is Expanse [421], a high performance computing (HPC) cluster which will support our longitudinal machine learning objects by helping both train and update our machine learning models to adjust the robot's behavior to suit a person's preferences and abilities. CARMEN also communicates with Jetstream2 [173], a virtual data container where we run a database that stores user interaction data.

4.2.2 CARMEN Software

There are three main software components of CARMEN that control each hardware component, as well as transfer data between them (see Figure 4.2). We split these into the physical robot platform, the tablet, and the supercomputer.

CARMEN runs Ubuntu 20.04 LTS, ROS Noetic. ROS is a middleware which abstracts software from the hardware and allows programs to be platform agnostic. In addition, different processes can be modularized using ROS nodes, which can communicate with one another by passing messages.

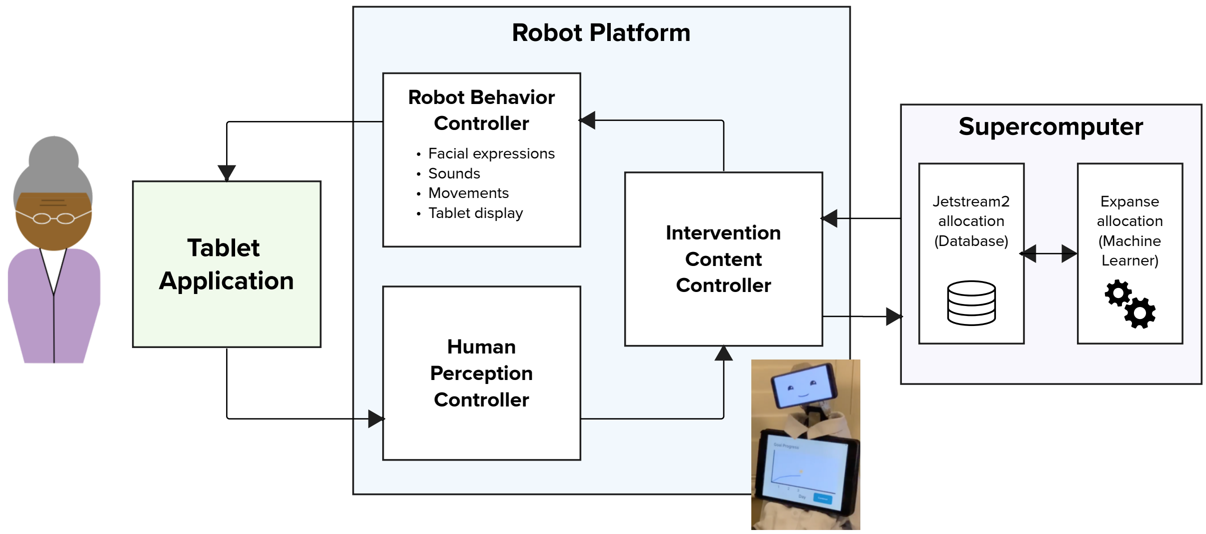


Figure 4.2. CARMEN has three main software components which control the physical robot platform, the tablet application, and communication with supercomputers.

CARMEN itself has three main types of software modules, each of which we implemented as ROS nodes. We categorize these into intervention content modules, robot behavior modules, and human perception modules. In order to enable CARMEN to be extensible to multiple robot platforms, we abstract the intended behaviors from the specific robot implementation, and run just a single node that is specific to the current hardware.

4.2.2.1 Intervention content modules

Intervention content modules control details related to the neurorehabilitation intervention itself. These details include the order in which the robot presents cognitive training strategies for users to practice, the activities used to practice those strategies, and the difficulty of those activities.

We specify the overall order of the strategies in a configuration file (YAML), which follow the order in which people with MCI learn them in the in-person intervention.

Each session follows the same general template which we implement as a finite state machine (FSM) (see Figure 4.3). We refer to this FSM as the Navigation Controller, as it guides the user through each part of the session. The states include 1) greeting the person, 2) giving an

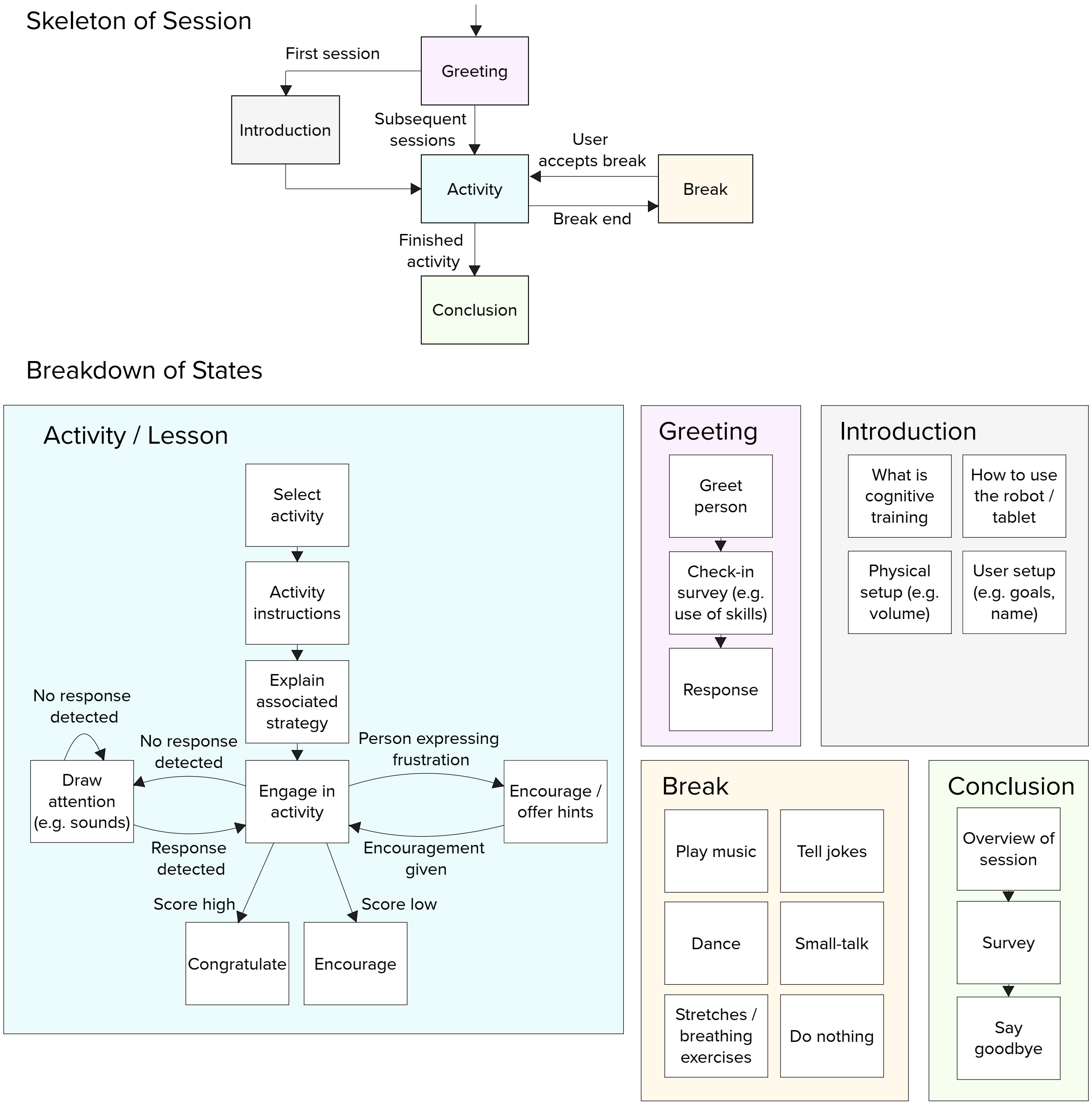


Figure 4.3. Each session with CARMEN follows the same general structure, which we implement as an FSM.

overview of that day's cognitive strategy, 3) giving instructions for the activity they will use to practice that strategy, 4) running the activity, 5) providing feedback about their performance on the activity, and 6) concluding the session. Edges correspond to the conclusion of the previous state.

Each state of the FSM is written as its own ROS node which is executed by the Navigation

Controller at the appropriate point The specific activity and its difficulty are determined at the beginning of each day based on the person's preferences and their performance on previous activities.

4.2.2.2 Robot behavior modules

Robot behavior modules work in real time to control how the robot behaves, including what it says, what it displays on the tablet, and how it moves, facial expressions it makes. Each of these components (speech, tablet display, motor movement, facial expressions) work in tandem to create different animations which the robot can execute to convey different emotions or personality traits when interacting with users.

Speech

Throughout the session, the robot speaks to the user and displays the words it says on the tablet in order to support multimodal communication. This also enables the user to reread what the robot said if they forgot or could not understand its speech.

We use a ROS service to handle the text to be spoken and/or displayed, which we refer to as the Dialogue Controller. The ROS node that is actively running (as defined by the current state) sends a message to the Dialogue Controller in JSON format. This message specifies 1) the text, 2) whether that text should be spoken aloud, displayed on the screen, or both, and 3) how the user can provide input back to the robot (e.g. buttons, keyboard).

The Dialogue Controller then forwards the message to the Speech Controller and Tablet Controller, which handle communication between the robot and their respective components. Upon receiving a response from the user, the Dialogue Controller will send the user's response back to the current active node, and the session will proceed.

CARMEN uses the CereVoice SDK for text-to-speech synthesis, and more details about the tablet application can be found in Section 4.2.2.4.

Motor movement

In order to control CARMEN's movement, we leverage the Dynamixel motors SDK

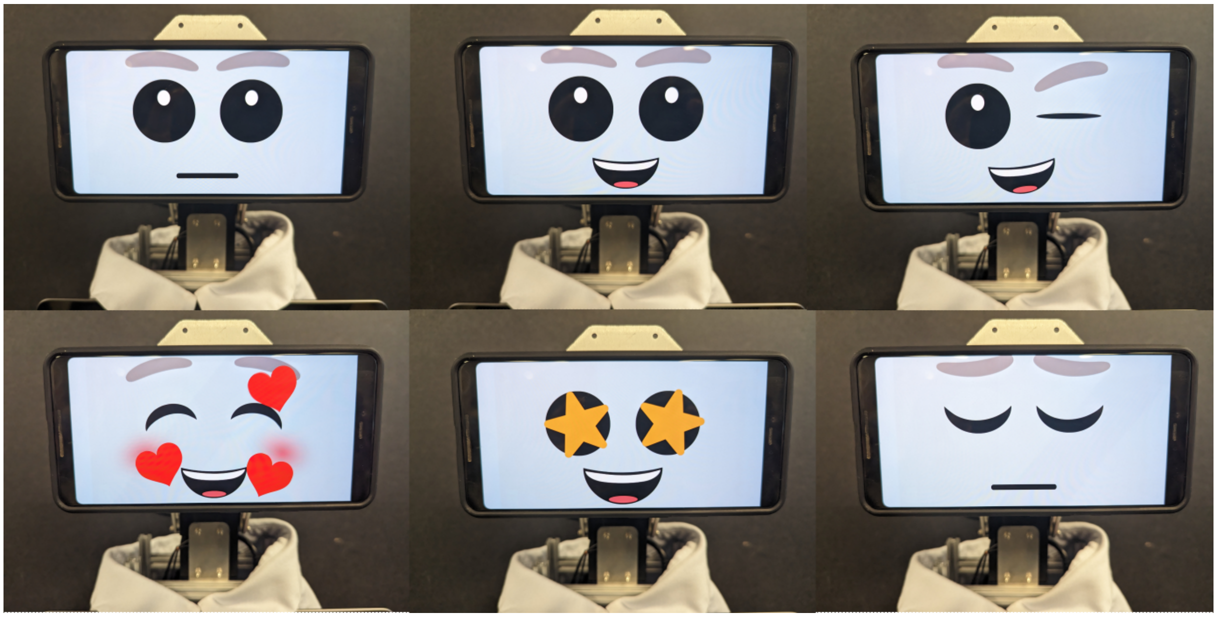


Figure 4.4. CARMEN displays different facial expressions.

which we access via a custom wrapper class. We wrote this class in order to more easily program the motors and create custom movements for different animations. We also limit the speed at which the motors can move as well as their range of rotation to minimize the risk of user harm and motor burnout.

Facial expressions

CARMEN exhibits different facial expressions on the smartphone display in order to convey different emotions. There are two main components to CARMEN's face. First, we developed a front-end module to design and display different facial expressions, including different types and animations for eyes, mouth, and eyebrows (see Figure 4.4). This front-end module is implemented with PixiJS (a 2D WebGL renderer) and AngularJS (a Javascript framework).

Second, we created a back-end module that runs fully locally on CARMEN to serve and manage the front-end module. The back-end module allows REST API and websocket connections using NodeJS. Thus, to control which expression is currently displayed, a script sends a POST request to set the desired expression. Then the back-end uses websockets to

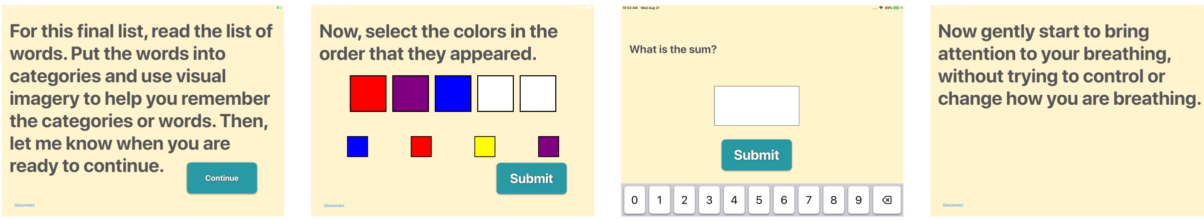


Figure 4.5. Images from activities that users can complete to practice cognitive training strategies. From left to right: Word Game, Color Game, Number Game, Mindful Breathing Exercise.

communicate with the front-end client to display the proper facial expression animation.

4.2.2.3 Human perception modules

Human perception modules enable CARMEN to receive and respond to input from the user. At this time, CARMEN supports input via the tablet, which can be a button response or keyboard input depending on the type of activity (more details about each activity and possible responses can be found in Section 4.2.2.4). These responses may provide the robot with a variety of information, including a person's intention to advance to the next set of dialogue, their responses to an activity, or adjustments to system settings. The tablet will automatically send these interactions back to the Tablet Controller.

4.2.2.4 Tablet Application

We developed a web application through which users can interact with CARMEN on a tablet. The tablet serves two main functions. First, it displays the text that the robot speaks so users can follow along more easily. Second, it provides a means for users to interact with the robot throughout a session, including advancing to the next set of dialogue and completing activities with the robot.

We developed the application using Flutter. It connects to the system via a websocket.

We programmed four main activities that users can engage in to practice the cognitive training strategies. These include the Word Game, Color Game, Number Game, and Mindful Breathing Exercises (see Figure 4.5).

- In the Word Game, the robot gives a list of words which are spoken aloud, displayed on the tablet, or both, and the user can type as many words as they remember via the tablet keyboard.
- In the Color Game, the robot shows a series of colors, and asks the user to input them on the tablet in the order that they appeared.
- In the Number Game, the robot speaks aloud a series of numbers, and the user has to add the two most recent numbers, and type them in with a numeric keyboard.
- In the Mindful Breathing Exercise, the robot talks the user through a mindfulness exercise to help them relax and focus.

The Word Game, Number Game, and Mindful Breathing Exercise were drawn directly from ME-CCT and are employed by human clinicians when delivering the intervention. The Color Game was an activity that we co-designed with our clinical collaborators while exploring additional ways that people can practice each cognitive strategy (see Chapter 6). We worked closely with clinicians to translate these activities so the robot could conduct them effectively and accessibly. In addition, each activity can be personalized to suit a person's goals and abilities (e.g. which strategies they practice, difficulty or duration of the activity).

4.2.2.5 Data Collection and Processing

Throughout each session, CARMEN collects interaction and performance data from users in order to help learn their preferences and abilities, and adjust its behavior and intervention content for the next session. Interaction data includes the frequency with which the user engages with the robot, the duration of the session, and the date and time of the session. Performance data includes which activity they completed, how long it took them to complete that activity, and their score on that activity if applicable. After each session, CARMEN saves the collected data locally.

At the end of each day, the robot runs a scheduled job to securely transfer the interaction data file into a central location on a Jetstream2 allocation. Once all files from each robot have been sent over, another job on the allocation runs a script that takes each data file from each robot, and inserts them into a SQLite database.

4.3 Chapter Summary

This chapter introduced CARMEN, a new robot system that delivers a cognitive intervention autonomously and longitudinally to people with cognitive impairments at home. Thus, people with cognitive impairments can practice compensatory strategies and transfer them into their life. This work provides the basis for my subsequent work, which focuses on how stakeholders can program robots like CARMEN.

4.4 Acknowledgements

I thank Dagoberto Cruz-Sandoval and Anya Bouzida for their assistance with robot system development. This chapter contains material which is currently being prepared for submission for publication. The dissertation author was the primary investigator and author of this work.

Chapter 5

Control Synthesis for Accessible Robot Programming

Healthcare is an important domain to support key stakeholders by creating customized robot programs [23, 100, 101]. Thus, HRI researchers are exploring robots to fill these care gaps, particularly home-based social robots deployed longitudinally [16, 23, 30, 69, 82, 99, 183, 360, 380, 385, 394, 410, 437].

As HRI researchers collaborate with clinicians, community health workers, and family members, many have reported challenges stymieing their progress [18, 32, 182]. First, they lack the tools to enable clinicians to create tailored, personalized interventions and modify robot behavior at a high level. Personalization is critical in any robotics healthcare application, as no care receiver is the same and requires uniquely tailored interventions to support their health. Another challenge is that HRI researchers must manually and painstakingly create customized programs for each stakeholder domain, limiting the scalability and potential impact of their work.

Most stakeholders, particularly clinicians, lack the time to learn how to program robots to exhibit custom behavior, especially if they must consider each individual action the robot should perform (e.g. what to say, how to move). This can cause unusable code or unexpected robot behavior, and must be extensively tested, else risks unintended consequences on potentially vulnerable populations.

While prior work exists to support novice programmers via visual, aural, and tactile

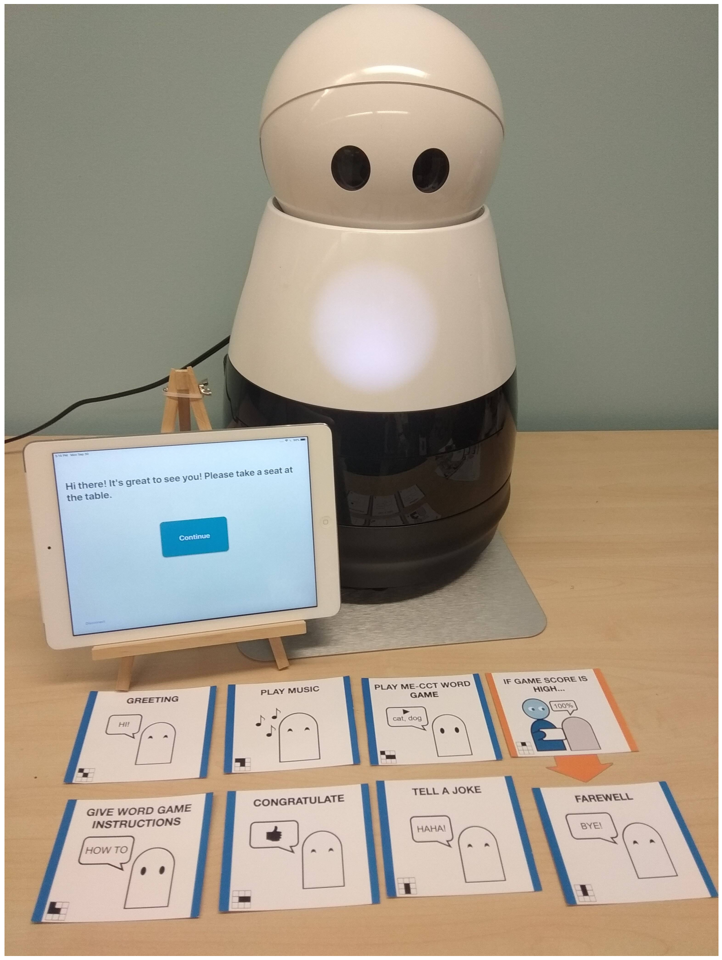


Figure 5.1. JESSIE employs control synthesis with a tangible front-end to enable people to create customizable programs for social robots within the context of neurorehabilitation.

languages (i.e., via End-user programming) [28, 81, 289, 342, 403, 404], these frameworks are almost entirely procedural, require understanding code structure, and do not allow high level specification of desired behavior, including constraints on the robot's actions. For example, a novice user can typically program a sequence of actions (e.g. pick, then move, then place), but implementing multiple conditions and constraints on behavior is more difficult (e.g. pick, place, and play music if the user is bored, and turn on lights if it is dark). For complex behaviors, users would have to compose constructs such as *if* statements and *for* loops, which can be difficult and error prone even in end-user programming contexts.

To address this gap, we leverage our prior work on control synthesis for robot behavior from high-level specifications [249, 486]. Such techniques and tools take a description of robot behavior, typically in temporal logic, and automatically synthesize a robot controller guaranteed to satisfy the task, if one exists. Control synthesis enables users to reason about the overall behavior, then automatically creates the specific implementation for the robot. It automatically transforms complex behaviors (e.g. sequences of actions, reactions to external events, constraints on robot behavior) into code. It removes the burden of deciding a program structure, which is non-trivial and difficult for non-programmers, and eliminates implementation errors. However, using existing control synthesis tools requires understanding of temporal logic and typically lack an interface to easily to express the desired behavior, prohibiting novice users from taking advantage of control synthesis.

To address these gaps, we present JESSIE (Just Express Specifications, Synthesize, and Interact), an end-to-end system that enables programmers of any level to quickly and easily program social robots to exhibit complex behaviors. JESSIE leverages existing control synthesis methods coupled with an accessible high-level specification interface to enable users to specify and synthesize social robot controllers which afford personalized activities, reactions, and behavioral constraints. Thus, users need not concern themselves with specific implementation details or individual robot actions, and can instead focus on overarching goals (e.g. therapeutic).

To demonstrate our approach, we implemented our system on a Kuri robot in the context of developing cognitive training treatments for people with MCI. We evaluated JESSIE with six neuropsychologists, its envisioned end-users. Overall, participants without prior programming experience successfully created personalized, interactive therapies for people with MCI, and reported positive comments with regard to its usability. Furthermore, they gave suggestions for improvement including increased support for personalization, varying the robot's status, and collaborative goal setting (see Section 5.4).

The contributions of this chapter are as follows: First, we present an end-to-end system that allows non-programmers to specify complex robot behavior through a tangible interface, and automatically generates the associated robot control. This will help inform future real-world

HRI research by enabling on-the-fly robot customization. Second, we demonstrate JESSIE in the context of cognitive training for MCI, an important application area for social robotics. We report our findings from our evaluation with six neuropsychologists, representative end-users who did not have prior programming experience. To our knowledge, this is the first evaluation of a control synthesis framework by end-users. Third, we demonstrate the reproducibility and extensibility of the system by executing a clinician-created behavior on another platform, the TurtleBot 2. Finally, as an artifact to support reproducibility for other HRI and robotics research contexts, all software, documentation, and supplemental materials discussed in this chapter are available as open-source at https://github.com/UCSD-RHC-Lab/JESSIE.

5.1 Background

5.1.1 Control Synthesis

Control and program synthesis are techniques to automatically transform high-level specifications into control or programs guaranteed to satisfy the specification. In robotics, researchers typically use different temporal logics to express tasks and automatically transform them into robot behaviors [250]. Thus, users can reason about the robot's overall task rather than implementation details.

In this work, we build on reactive synthesis from linear temporal logic (LTL) specifications [120]. Roughly speaking, LTL formulas are composed of atomic propositions (Boolean variables), logical and temporal operators as follows:

$$\varphi ::= \pi \mid \neg\varphi \mid \varphi \vee \varphi \mid \bigcirc \varphi \mid \varphi \,\mathcal{U}\, \varphi$$

where "not" ($\neg$) and "or" ($\vee$) can be used to create "and" ($\wedge$) and "implies" ($\rightarrow$), and the temporal operators "next" ($\bigcirc$) and "until" ($\mathcal{U}$) can be used to create "eventually" ($\Diamond$) and "always" ($\Box$).

The formal semantics of LTL formulas can be found in [120]. Intuitively, a formula $\bigcirc\varphi$ is true if φ is true in the next time step, $\Box\varphi$ is true if φ is always true during the execution, and

$\Diamond\varphi$ is true if at some point in the execution, $\Diamond\varphi$ is true.

LTL allows users to encode assumptions about the behavior of the robot's environment (e.g., the state of the person with MCI) and requirements on the robot behavior (e.g., if the person with MCI is not engaged, play music). Furthermore, there exist algorithms that automatically transform an LTL formula into a finite state controller [250] that is then used for robot control. For computational reasons, we use the GR(1) fragment of LTL [46] as the underlying formalism.

We leverage free and open-source tools for LTL synthesis and execute the resulting controller with ROS [365]. For LTL synthesis, we use slugs [118], which computes a symbolic representation of the controller from the specification. At runtime, slugs provides the next state for LTLstack [486] to execute.

LTLstack is a tool for mapping the propositions in the LTL formula to ROS nodes and executing the synthesized controller. At each time step, LTLstack reads information from the sensor nodes, finds the next state in the controller, and activates behavior nodes.

5.1.2 End-User Programming

End-user programming methods enable those with limited or no programming experience to write programs, and provide visual, aural, tangible, and tactile interfaces for programming [24,28,81,198,289,342,403,404]. A main concept in end-user programming is empowered computing – allowing users to personalize systems to their needs and preferences [141]. They are used widely in educational contexts [156,196,309,428], and are used in HRI, home automation, and healthcare contexts [51,58,65,91,100,152,157,200,300,332,353,398,403]. However, these methods are typically procedural, so users require a basic understanding of coding constructs. Thus, creating a correct implementation with the desired behavior is highly dependent on the user's coding skills. For simple behaviors (e.g. sequencing actions), users of all levels can produce programs with minimal instruction. However, increasing complexity of implementation (i.e. there are conditionals and possibly conflicting behaviors) can lead to incorrect programs and excessive testing before achieving the desired behavior.

In robotics, visual programming environments are the most commonly employed end-user programming technique [8, 91, 100, 110, 151, 152, 200, 285, 300, 332, 354]. For instance, Choregraphe [356] is used to program robots such as Nao, and TagTrainer [446] is used to create rehabilitation exercises. Visual programming environments such as these require users to reason about the implementation of the code - *for* and *while* loops, *if* statements, etc. In contrast, JESSIE provides a specification interface to the user and automatically generates the code implementation. Reasoning at the specification level enables users to specify constraints, such as what the robot should not do, reactions to external events (without worrying about the code structure to implement them), sequences, conditionals, etc. While anything specified in JESSIE can be written as code in a visual programming environment, reasoning about the required behavior rather than the implementation of the behavior lowers the barrier of entry for end-users, such as therapists, to create custom robot behavior.

While there is recent work on incorporating formal methods (e.g. model checking for verification, satisfiable modulo theories (SMT) solvers for synthesis) into such languages [353, 354], the use of reactive synthesis as we employ in this work (i.e. generating a controller with multiple possible correct executions rather than a trace) has not been demonstrated.

Due to disparate backgrounds of stakeholders in our application domain, including people with low technology literacy [71, 283], we implement a card-based tangible specification interface inspired by prior work [24, 45, 81, 196, 198, 289, 309, 403, 404]. Tangible end-user programming systems typically feature icons on blocks that are strung together in sequence, similar to what JESSIE supports, but unlike our work, tend to be procedural. While a few tangible end-user programming approaches have been demonstrated in therapeutic contexts [48, 105], to our knowledge making control synthesis accessible to this population is unexplored.

5.2 System Overview

JESSIE enables end-users to specify high-level robot behavior, such as constraints and reactions, and automatically generates and executes a robot controller using LTLstack. It comprises ROS nodes representing sensor information and behaviors for a social robot, made accessible to users through a tangible specification interface. We implemented JESSIE in the context of cognitive training programmed by neuropsychologists and delivered via a Kuri robot.

5.2.1 Proposed Approach

JESSIE is comprised of LTL synthesis with a tangible specification front-end to enable novice programmers to leverage control synthesis to program robots via high-level specifications. These specifications enable programmers to define desired robot behavior without grappling with unfamiliar code or creating the implementation. Additionally, the synthesis approach is correct-by-construction, so the generated controller is guaranteed to satisfy the specification, eliminating "bugs" that may be introduced by novice programmers.

One goal for our specification interface is to clearly convey the possible robot actions and behaviors, as well as how each one fits in the overall program execution. As people may not be familiar with the robot's capabilities or fundamental computer science concepts (e.g. conditionals), we abstracted these ideas in an intuitive form while still communicating the robot's possible behaviors. In neurorehabilitation, the ability to quickly develop unique programs is essential for clinicians to create customized programs for each individual they work with, each with distinct needs and preferences.

5.2.2 Computational Back End

5.2.2.1 Specification to Execution Flow

Figure 5.2 summarizes our use of LTL synthesis via a specification interface. First, the end-user programmer uses our tangible interface (see Section 5.2.4) to define the robot

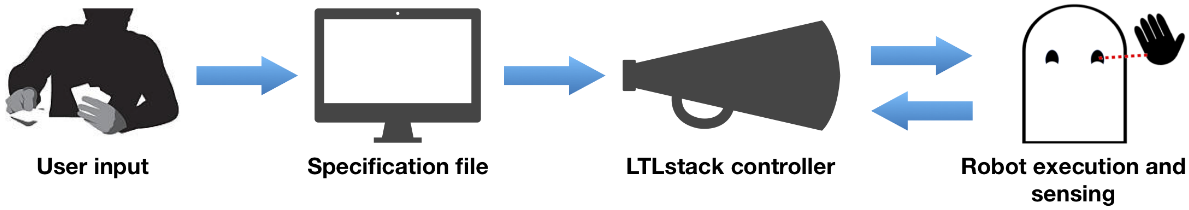


Figure 5.2. Overview of JESSIE. Users specify the robot's activities and behaviors with our tangible interface. A specification file is then created which includes the desired sensor and actuator nodes, the robot's initial conditions, event ordering, and sensor-reaction maps. LTLstack then synthesizes a controller to execute the associated ROS nodes.

behavior through activities, or *activity modules* (e.g. play music, play a number game) (see Section 5.2.2.2). They can also specify constraints for behaviors (e.g. congratulate the user only when they achieve a high score on a game). Then, JESSIE automatically transforms these activities and constraints into LTL specifications by reading the identifying QR tags to determine the order in which the cards were placed. LTLstack [486] then calls slugs [118] and synthesizes a controller to execute the specified activity nodes and reactive behaviors based on sensor input at runtime (see Section 5.2.2.3).

5.2.2.2 ROS Nodes

The specifications are transformed into LTL formulas over a set of atomic propositions. These propositions are grounded to sensor data and robot behaviors, used to execute the controller. We consider three types of propositions and their grounding as ROS nodes: *Activity module* nodes represent behaviors the robot can execute during the session (e.g. give a greeting, practice number game). *Activity completion* nodes signal the completion of activity modules. *Sensor* nodes are associated with stimuli the robot should respond to (e.g. whether the person touched the robot).

Activity modules represent a particular action which clinicians can have the robot execute. They choose the order of activities for interactive sessions (e.g. they can create a program to first play a number game then congratulate the person with MCI on their performance). These modules consist of dialogue, movement, and other actions. For instance, the *Greeting* module utilizes Kuri's ability to move its head, speak, and play sounds to convey excitement about meeting the person. In the *Mindfulness exercise* module, Kuri asks the person with MCI to close their eyes, then talks them through a script to improve self-awareness. When executed, each activity varies in duration, spanning from between a few seconds to up to ten minutes.

Clinicians can also use activity modules to specify robot reactions to sensor stimuli. For instance, rather than always congratulating the person with MCI after a game, clinicians may choose to do so only if they scored above some threshold. We created 14 activity modules, including cognitive training games and mindfulness exercises developed with input of our clinical collaborators [203], giving greetings, providing instructions, and delivering cognitive assessments.

Each activity module node has a corresponding completion node to signal when that activity has completed. While these nodes are necessary for LTLstack to transition between a sequence of activities, we automatically create and link one to each activity. Thus, users need not worry about their implementation or execution.

Sensor nodes enable the robot to perceive its environment. They leverage Kuri's built-in sensors to translate environmental data to a higher-level understanding of the person interacting with it. For instance, the *If tactile interaction...* node uses Kuri's capacitive touch sensor to detect when the person is physically interacting with it.

While we created these nodes specifically for our platform and application domain (see Section 5.2.3), researchers can create other ROS nodes and cards for their desired application and platform by following the guide in our supplementary materials. We demonstrated the reproducibility of our system by implementing ROS nodes for a TurtleBot 2, and synthesizing and executing programs clinicians created for the Kuri. Actions and stimuli are mapped to the new platform (e.g. TurtleBot made a sound whereas Kuri nodded its head). These nodes can be found in our supplemental materials to enable a side-by-side comparison. Note that no other files were modified to execute our approach on a new platform.

5.2.2.3 Synthesis and Execution

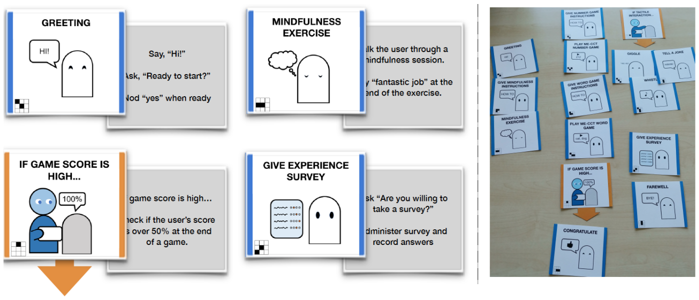
For control synthesis and execution, we used LTLstack, which consists of ROS packages for running with correct-by-construction controllers [486]. It takes a mapping between propositions and ROS nodes and a slugs specification file (LTL formula), and generates and executes an associated controller by listening to sensor and completion nodes and activating activity nodes. The specification file encodes the constraints and requirements that should be satisfied throughout the program's execution, including environment assumptions and system guarantees [46, 118].

To our knowledge, JESSIE is the first end-to-end reactive synthesis framework demonstrated in an HRI context, and the first evaluated by end users. This evaluation informs future control synthesis specification and framework design (see Section 5.4).

5.2.3 Platform

JESSIE is intended to facilitate reproducibility and systems engineering in HRI, and thus is intended to be used on any platform and within any context. In this work, we demonstrated our system on Kuri, a social robot from Mayfield Robotics (see Figure 5.1), in the context of neurorehabilitation. It contains a multitude of sensors to perceive its environment, including an RGB-D camera, microphones, and bump and touch sensors. It can communicate through numerous modalities, such as expressive eyes, a multi-color chest light, speech, motion, and sound. To minimize the risk of older adults tripping over Kuri, we deploy it as a tabletop robot, though it is capable of being mobile as well. Kuri runs ROS Indigo on Ubuntu 14.04.

We developed an iPad application (iPad Air, iOS 12.4.1) that connects to Kuri via a websocket as another means of interaction. Clinicians do not interact directly with the Kuri or iPad; they control the behavior and display by selecting which activities to execute.



Order of activity modules

$\neg greetingComplete \implies \neg minfulnessInstructions'$
$\neg minfulnessInstructionsComplete \implies \neg minfulnessExercise'$
$\neg mindfulnessExerciseComplete \implies \neg numberGameInstructions'$
$\neg numberGameInstructionsComplete \implies \neg numberGame'$
$\neg numberGameComplete \implies \neg wordGameInstructions'$
$\neg wordGameInstructionsComplete \implies \neg wordGame'$

Sensor nodes and reactive behaviors

$(scoreHigh' and \neg congratulateComplete') \implies congratulate'$
$(tactileInteraction' and \neg giggleComplete') \implies giggle'$

Figure 5.3. Left: Example cards and descriptions from our tangible specification interface. Blue cards are activities the robot can do; orange cards represent stimuli the robot can sense and react to. **Right**: A program created by a clinician and a partial implementation in LTL. Programmers lay out activity module cards in the order of execution they desire, in addition to reactions to stimuli.

5.2.4 Tangible Specification Interface

We created a tangible specification interface as an intuitive way to program social robots via control synthesis. Users simply input actions and reactions, with no need for extensive training or external programmers. Thus, clinicians can create custom treatments for people with MCI via high-level specifications without altering source code.

We designed the interface to be both intuitive and descriptive so it is easy to learn while encompassing the actions of an interaction. Each card depicts a symbol and short descriptor (Figure 5.3, left) that represents actions programmers may include, associated with ROS activity module and sensor nodes described in Section 5.2.2.2. Activity module nodes are blue, and sensor nodes are orange. The arrow on sensor nodes reflects conditionality, analogous to the logical "implies" symbol. Each card has a unique marker to facilitate the automatic translation from cards to specifications to code.

Programmers may place activity cards in any order, from top-to-bottom, left-to-right (Figure 5.3, right). Sensor cards can be placed anywhere, as they run in parallel with main activity modules. Users simply place the desired reaction below the sensor card, such that the arrow points to it. Then, the sensor nodes will allow the robot to react to the associated stimuli throughout program execution.

5.3 Evaluation

To evaluate the JESSIE system and determine how to improve it, we conducted a study with six neuropsychologists interested in using it. We assessed the system's usability, specifically for clinicians with no programming experience. We taught participants how to use our specification interface to create a program, then allowed them to design their own sessions for people with MCI to complete with Kuri. Our study was approved by the UC San Diego Institutional Review Board, under protocol number 181341.

After giving informed consent, we introduced participants to Kuri and gave an overview of the study. As most participants did not have experience with robots, we showed them a video demonstrating some capabilities they can use in their programs. We then explained how to use our tangible interface, computer science concepts (e.g. conditionals), and actions Kuri can perform.

We then began the programming phase. We asked participants to create an interactive session for a person with MCI they are working with and encouraged them to ask the researcher for help if needed. We recorded the time it took participants to complete their programs. Then, they watched Kuri execute their program[1]. To conclude the session, we conducted an open interview to receive feedback on our system, including ease of use, how often they would recommend people interact with it, and other features they would like implemented in the future, and they completed written questionnaires.

We employed mixed methods approaches in our data collection and analysis. Quantitative measures included the System Usability Scale (SUS) score [61] which measures perceived usability, task completion time, and card usage. Qualitative measures included post-study interviews and researcher observations of challenges participants faced during the study. Questions we asked included *Would you consider using this kind of system to support your work?, What other*

[1] Automatically generating specifications from the tangible interface was not fully implemented during evaluation, so a researcher conducted a manual translation. Automatic translation is now complete and available in our open-source code.

features would you like to see implemented?, and *Did you feel like you could express the robot behavior you desired with the card-based language?* We recorded and transcribed all interviews.

Two researchers employed a grounded theory [73] approach, and individually coded the audio recordings to find emerging themes through an inductive coding process. They then compared codes and identified three overarching themes among the participants, specifically: increased support for personalization (see Section 5.4.1), means to longitudinally vary the robot's operating mode and interaction style (see Section 5.4.2), and collaborative goal setting (see Section 5.4.3).

5.4 Results

We recruited six clinical researcher participants through word of mouth, all of whom work with people with MCI. These included four neuropsychologists, a psychiatry professor, and a research coordinator. Five were female and one was male; their ages were 28-49 years old (mean = 34 years, SD. = 7.67 years). They had between 14 months to 23 years of experience working with people with cognitive impairments (mean = 6.53 years, SD = 8.31 years), had little to no general programming experience, and none had ever programmed robots.

All participants were able to successfully program at least one interactive session for a person with MCI, each of which could run to completion on Kuri. Four participants each created one program, and two participants each created two programs, yielding a total of eight programs. These programs can be found in the supplementary materials. On average, participants spent 2:15m (SD = 1:40m) creating a program. They spent an average of 12:35m (SD = 7:45m) viewing their programs. They used an average of 8.25 cards (SD = 4.37) with an average of 7.38 activity cards (SD = 3.78) and 0.88 sensor cards (SD = 0.83) in each program. *Greeting* (8) and *Congratulate* (8) cards were used most often, and *Tell a joke* (1) and *Sneeze* (0) the least.

On SUS, participants scored JESSIE an average of 90.83 (SD = 9.31) which is above average compared to other systems [21]. Participants described using the system as, "easy," "simple," and "straightforward". One participant commented: *"I've never interacted with a robot before, so it's brand new for me, but it's easy to use. I thought it was fairly engaging."* Overall, no participants explicitly expressed frustration or confusion using the system, though they suggested improvements, discussed below. While several of these suggestions can be easily incorporated into the JESSIE system by creating more ROS nodes, other articulate future research directions.

5.4.1 Increased Support for Personalization

Personalized sessions are critical for people with MCI because their needs and goals can change as their condition progresses [79]. Participants described a range of different people with MCI for whom they imagined using the system, such as people managing comorbidities (e.g. heart disease) interfering with their planning abilities, and people living alone who often forget to bring important objects when they went out. Participants suggested three main ways JESSIE could be extended to enable increased personalization: feedback customization, communication modalities, and adaptation.

5.4.1.1 Feedback Customization

The frequency and type of feedback the robot provides can greatly impact people's engagement and perception of it [79], so providing personalized feedback and encouragement is imperative. Participants stated that feedback style can significantly impact the person with MCI's recollection of different cognitive strategies and how they apply them outside of training. For example, the robot could vary its feedback depending on the activity type and person's performance. One participant explained: *"In the word game... if the robot could give [the person with MCI] feedback... 'When you use this strategy, you really benefited and your recall is better.'... For the number game, ... [therapists] will give more trial-by-trial feedback, [so the robot could give] some indication that [the person with MCI] had gotten one wrong and [needs] to get back on track."*

In contrast, clinicians may not always want the person to receive immediate feedback. For instance, a participant who primarily conducts research assessments stated, *“We don’t normally tell [people with MCI] how they perform, ...during the research tests, [we] don’t want them to know how they’re doing, because it could discourage [or encourage] them on the next test. ”*

5.4.1.2 Communication Modalities

Depending on the person’s sensory abilities and personal preferences, they may require the robot use and respond to different communication modalities. Participants wanted to be able to specify which modalities the robot use at a given time or for certain populations. One participant expressed, *“For older participants, it might be nice to have some more verbal cues, in case they don’t keep up with the robot.”* However, they also mentioned that during certain activities, such as mindfulness where Kuri asks the person to close their eyes, visual output on the tablet may be distracting. Thus, more control over each modality, such as speech, the tablet, and movement, would help clinicians tailor each session to individual needs and preferences.

In addition to the tablet, participants discussed other ways people with MCI could communicate with the robot, both explicitly and implicitly. One commonly requested modality was speech, especially as an alternative for people with tremors or difficulty spelling. They also suggested that the robot sense different behaviors about the people with MCI to infer their state, such as sedentary time, social activity, and mood.

5.4.1.3 Adaptation

It is important for the robot to be able to adapt to the person with MCI, especially as their preferences, cognitive abilities, and moods may change over time, in order to keep them engaged and support consistent interaction with the robot. As one participant suggested, *“Depending on a particular person and what they like, their strengths and weaknesses, the robot might say different things or suggest different strategies.”* And another said: *“If the participant seems frustrated, [it could] give them encouragement... if they scored low [it could say], ‘Don’t worry. Not everyone gets them all right.’ ”*

Another important aspect of cognitive training is forming habits to routinize tasks [202], so participants wanted the ability to specify the frequency and schedule of activities. Then, either the clinician and person with MCI could work together to define a schedule, or the robot could facilitate scheduling. Participants also wanted to tailor the length and difficulty of activities to help them better integrate with a person's schedule, and thus better support adherence.

5.4.2 Varying Robot Status

All participants indicated that being able to change the state of the robot at various points would be useful. Since MCI can be progressive, people's needs, goals, and abilities can change over time. Thus, participants identified three categories for which they might want the robot to differ its interaction style, discussed below.

5.4.2.1 Staged Robot Deployment Support

Depending on the MCI stage, clinicians may have different goals for the robot, such as monitoring, education, or intervention delivery. One participant mentioned, *"The first work we do [with people with MCI] is getting their patterns down. Sometimes they can provide you with what a typical day looks like, but they might be over or underestimating... The first step would be to use Kuri to play more of an observational role in their home environments."* This can also help clinicians identify the ideal intervention strategy. *"Part of us identifying interventions is, how can we help individuals remain independent?"* Thus initially, the robot could observe the person with MCI to help clinicians understand their behavioral patterns and establish a baseline for usual behavior.

Once a baseline is established, the robot could transition to educating the person with MCI on how to navigate their life with MCI, and support independence. For instance, it can help people with MCI form habits and stick to a schedule, which our participants noted is an important step to living with MCI. *"Perhaps they're beginning to form those habits. That's done by pairing it with day-to-day activities that have become habitual, so [these] things don't rely on* *memory as much."* During this stage, it may also be more explicit when communicating the reason behind each activity. One participant noted that, *"I liked when it gave a break, that it also explained the benefits of taking breaks, because I know that's part of the [cognitive training]."*

As the MCI progresses, the clinician may want to use the robot for further intervention, and allow the person wiwth MCI to rely on it more. For instance, *" If this can help someone retain some level of efficiency and functioning, I think that'd be really important. I'm definitely thinking of those who are on the extreme end of the impairment spectrum."* To help facilitate these stage transitions, clinicians wanted affordances to manage different programs and settings on the robot.

5.4.2.2 Active vs. Passive Robot Interaction Style

An open problem in HRI is how active or passive a robot should be during interaction [193, 316]. Our participants also raised this concern, particularly when the robot is interacting with the person with MCI. Participants noted that at first, the person with MCI may be more independent, so a passive approach would probably be preferred. They suggested the robot conduct observations, and inform the person with MCI during their normal interactions if any different behaviors were observed.

In other cases, the clinician may want the robot to take on a more active role and give the person with MCI suggestions about how to handle their condition. For instance, a participant suggested having *"moments where we're checking in and saying, 'Well, how stressed are you feeling?' Or, 'How is your mood right now and how much have you exercised so far?' Those could be moments where we tell them it's time to go on a walk rather than just monitoring their behavior."*

Participants also discussed initiative - should the robot initiate interaction, or wait for the person with MCI to do so? They imagined being able to leverage Kuri's physical embodiment to have it prompt people when it is time to begin the session. *"But the benefit potentially of having this kind of thing is that... it could remind the patient to do the [activity]."* Another participant mentioned that at set times each day, *"It would present an option of 'Would you like to play the word game now? Yes or no.' Then provide those word game options."*

Other times, it might make sense for the person to initiate engagement with the robot. Participants wondered how this might occur given the varying ability levels of people with MCI. For instance, *"I'm wondering [if] somebody who might be not as mobile would maybe need to wave their hands to get its attention. Or if they're not even able to do that well, are there instructions such as saying, 'Kuri', or a specific codeword that activates the robot."*

5.4.2.3 Research vs. Intervention Mode Switching

Many of our participants work with people with MCI across both clinical and research contexts, which each have different goals, and the role of the robot in them may change significantly. Thus, clinicians wanted a way to easily create and switch between *"modes"* on the robot.

The first main context for which participants imagined using the system was for clinical intervention. In this context, *"We are interested in what sorts of problems [people with MCI] are having in their daily life. And then the intervention, we use it as sort of like a crutch to help people who already have some impairment. We can't cure their impairment. We can teach them strategies to get by."* In intervention mode, people with MCI would regularly interact with the robot in their home, as prescribed by the clinician.

5.4.3 Collaborative Goal Setting Support

Participants wanted ways to collaboratively set goals with people with MCI. This is an important aspect of cognitive training, where clinicians and people with MCI work closely to identify goals in training, and set actions to address them [17]. Participants identified three types of relationships where this may occur: the clinician and people with MCI, the robot and people with MCI, and between clinicians. These activities might occur in clinic or at home, and may be clinician-led or person with MCI-led.

5.4.3.1 Clinician - People with MCI

Participants expressed interest in a way of working with people with MCI to create sessions that support their goals by specifying aspects such as schedules, activities, and reminders. For instance, one participant mentioned that during a session, they *"work with the patient in developing the [session]. 'Based on your routine and the time you get up, what time do you think we should have this thing remind you to take your medications? Or check the mail?"* Similarly, *"A clinician and the patient can collaboratively work to decide, 'We are noticing these are your patterns. We've identified these patterns are certain risk factors or protective factors. Let's work towards helping Kuri to be that point of contact when you're at home. How can we set up these cards to then help nip certain behaviors in the bud before they turn a little bit more worrisome?'"*

Alternatively, the clinicians could also specify higher-level goals for or with people with MCI, then allow them more freedom to choose specific activities. One participant suggested, *"They could pick, 'Today I want to do a [mindfulness exercise].' Or I could pick, 'Today I want them to [practice mindfulness].' Or focus, attention, exercise, [etc.] "* Another participant stated, *"I think there should be several standard things that could be informed by what we know of the patient population that this is being targeted towards. Then certain customizable options that talk about how certain instructions can be changed or activities can be changed but the underlying programming wouldn't change."* Then, the person could choose a specific activity that exercises the broader area each time they interact with the robot.

5.4.3.2 People with MCI - Robot

Participants discussed how the person with MCI might work with the robot to develop their goals and cater to their preferences. As the clinician will usually not be with the person with MCI when they interact with the robot, people with MCI need ways to work directly with the robot to develop and assess their goals. For instance, one participant mentioned, *"Kuri can [...] recognize those patterns together and intervene in those moments of providing that feedback* *to that person to be able to help them assess points to improve."*

However, they noted that the card-based specification interface might not be the best means of interaction between the person and the robot directly, particularly those who are not familiar with technology. While participants believed they might be able to create an activity using the cards, they also mentioned that they might have trouble taking a picture of the program for the robot to process and execute. Instead, they suggested allowing the person to interact with the robot primarily directly through the tablet or verbally.

5.4.3.3 Clinician - Clinician

People with MCI may be working with multiple healthcare providers in addition to a neuropsychologist, such as their primary care physician. Our participants were mindful of this, and suggested that our system allow for multiple providers to program the robot. *"I'm not a primary care physician, so I don't know what that person might need in terms of exercise, or what their physical limitations might be. I'm not allowed to prescribe an hour of exercise a day. So there might be [...] a way for multiple providers to program [the robot]."*

5.5 Discussion

By making the benefits of control synthesis accessible, JESSIE enabled clinicians, who had no prior experience programming robots, to program cognitive therapy sessions with personalized activities, reactions, and constraints after little time, training, and without errors. Our observations and assessments of participants' experience with JESSIE suggest that our system enables novice programmers to leverage control synthesis techniques to create complex, interactive sessions on a social robot, which would take more time to write and test with procedural programming languages.

Our evaluation using Kuri to execute programs written by clinicians, and the subsequent replication and execution of these programs on a TurtleBot reflects the reproducibility and extensibility of our approach to numerous robot platforms. Researchers can modify our provided

ROS nodes to replicate our behaviors on different platforms, or create entirely new behaviors to leverage our approach for many different applications, such as in manufacturing or entertainment. The approach presented in this chapter will expand the accessibility of control synthesis for social robots for people of all programming skill levels across many domains.

5.5.1 Key HRI Considerations

In our discussions, participants raised some crucial HRI concepts that have yet to be thoroughly explored, which we discuss below.

5.5.1.1 Robot Roles

Since a person's needs and goals may change as the MCI progresses, participants imagined the role of the robot would change accordingly. For instance, they envisioned the robot would take a passive role during the beginning stages of the condition, such as monitoring the person's baseline behavior. As their condition progresses and they need to rely more on the robot, it could take a more active role in educating them about different cognitive strategies, completing interactive sessions, and serving as a virtual assistant. The ability to fulfill different roles is a fundamental aspect of adapting to the individual's needs and preferences. This capability to shift between the foreground and background when interacting with the person with MCI aligns with other HRI research.

Participants also discussed how people with MCI may see the robot as a "companion" as they complete the cognitive training activities. This raises the question of the robot's role in the relationship between the clinician and person with MCI. Whether the robot should be a companion, serve as a point of connection between them, or act as a personal assistant, programming languages and robotic systems need a way for programmers to specify and explore this concept of robot role.

Participants suggested ways the person with MCI might initiate the interaction with the robot as well as how the robot could initiate the interaction. As suggested by other HRI research [3, 316], the initiating party and methodology depends heavily on factors such as the robot's role. This work helps to inform the problem of initiative, particularly in longitudinal HRI where users interact with the robot over long periods of time. Additionally, it is currently unclear how we might design a language to reflect this sort of robot behavior.

5.5.1.2 Timing

The concept of timing is an important aspect of social interaction and robotics research. Participants identified multiple levels of timing to specify for different people and purposes, such as scheduling trial-by-trial feedback, feedback after numerous sessions, and setting the duration of different activities. Thus, our system may need to integrate complex representations of timing to give programmers more control over the timing of activities. However, the specifics of how these details can be both implemented within LTLStack and reflected in the tangible specification interface requires further research, the results of which will improve the accessibility and expressivity of end-to-end systems for social robots.

5.5.1.3 Multi-party programming and longitudinal HRI

In addition to supporting a single novice user programming a robot to perform a task in longitudinal HRI settings, our study illustrated that multiple stakeholders with different goals and backgrounds may need to program the robot at various points throughout its deployment, including neuropsychologsts, people with MCI, family members, and other clinicians. This raises a series of interesting questions about how to support these differing needs within a system like JESSIE, particularly with users (people with MCI) who may be experiencing rapid changes to their brains in ways where it is difficult for others to keep up.

5.5.1.4 Cultural Considerations

Cultural background plays a key role in determining an individual's preferences, such as the robot's communication style [268, 477]. For instance, in Western culture, the robot may adopt a more direct, proscriptive communication style. Contrastly in Finland, where people tend to have more reserved communication styles [296], people may prefer a more passive robot. Even non-verbal aspects of communication (e.g. eye contact) may impact a person's interaction with a robot. This can significantly impact adherence to treatment plans [186] and robot adoption. More research is needed to explore how to support this variablity.

5.5.1.5 Ethical Considerations

As we designed this system to support people with MCI, a vulnerable population, there were several ethical considerations that arose in our discussions with participants. Many participants wanted the robot to monitor people with MCI and send reports back to the clinician. They imagined the robot could monitor daily patterns to establish baselines and identify abnormal behavior, as well as to produce compliance reports about treatment adherence. While this may have clinical benefits, it raises privacy concerns, particularly for people whose MCI is more advanced or who may have lower levels of technological literacy, which impacts informed consent [177, 316, 375, 467, 479]. This requires thoughtful consideration and additional research to identify how to best balance these potentially conflicting constraints both with JESSIE and more broadly.

5.5.2 Limitations and Future Work

There are some limitations of this work that must be considered researchers build on our system. First, we only tested with our expected end-user, neuropsychologists. While their input was invaluable for our particular system and context, other end-users may want other features implemented for their applications, and constraints unique to their domain. Additionally, we pre-programmed activity module and sensor nodes to represent behavior specific to cognitive training. To alter existing behaviors or create additional ones, one needs some familiarity with ROS and Python or C++. Nevertheless, JESSIE is a simple and accessible means for novice programmers to specify high-level robot behavior for people with MCI.

As we continue to research this area, we plan to continue an iterative design process with stakeholders, including usability improvements, longitudinal deployments, and evaluations with people with MCI.

5.6 Chapter Summary

In this chapter, we presented JESSIE, an end-to-end system that affords control synthesis techniques to enable novice programmers to generate high-level behaviors for a social robot. Robots have shown great potential to support people with MCI [98, 350], and this system will extend the scalability, accessibility, and personalization of social robots. Additionally, this chapter presents the first evaluation by possible end-users of a system whose back-end employs control synthesis layered with a tangible front-end. The evaluation and feedback from participants shows that the system is easy to use and articulates future research challenges the community should address. As an open-source, intuitive way of utilizing control synthesis, and artifact to support reproducibility, this work will enable the robotics community to leverage our approach to customize robot behavior, adapt to end-user preferences, and promote longitudinal HRI within their own application domains. We hope that this work inspires researchers to make robot programming more accessible and collaborative, expanding the potential for robots to support people throughout the HRI community. This work served as a platform for my later work, which explores how a home robot can deliver and support a longitudinal cognitive intervention in the home.

5.7 Acknowledgements

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International Conference on Human-Robot Interaction (HRI) [256]. The dissertation author was the primary investigator and author of this work.

Chapter 6

HRI Design Patterns for Translational Science

The COVID-19 pandemic has illustrated great health disparities worldwide, particularly for minoritized populations, who lack access to quality healthcare services [187, 195, 295, 367, 461]. While telemedical interventions have proliferated, they still require one-on-one clinician time (which has become even further reduced during the pandemic) and technology knowhow on the part of the clinician and user. Thus, many robotics researchers are motivated to explore how to extend clinic delivered interventions longitudinally into the home.

Researchers have explored long-term robot-delivered interventions at home for children to support social and academic learning [83, 221, 276, 312, 378, 394, 429], and young adults to support mental health [38, 43, 224]. Others have explored longitudinal, clinic or nursing-home based interventions for adults with social robots, e.g., to provide upper limb rehabilitation [128], music [439, 463] and behavioral therapy [75, 387], and assistance to clinicians [242]. These interventions illustrate the promise of using robots long term in real world contexts. However, for older adults with cognitive impairments (such as MCI) undergoing neurorehabilitation, there is less guidance on translating provider-delivered interventions in clinic to robot-delivered ones at home.

There are considerable barriers to developing robots for this purpose. First, roboticists typically lack the clinical expertise to safely and effectively translate interventions to a robot, and it can be challenging to locate clinical collaborators to ensure an intervention's success. Similarly, clinicians typically lack technology expertise to fully understand a robot's capabilities and limitations, and are rarely trained in interaction design, limiting their ability to co-design robot behaviors, roles, and functionalities. There are also well-known research-to-practice gaps when clinicians attempt to implement digital technology interventions without deep understanding of their contextualization in a user's life [160, 275]. These barriers can result in interventions ineffective on an intended population, and for some vulnerable individuals, such as people with dementia, they can be harmful [37, 244]. Thus, both HRI researchers and clinicians would benefit greatly from practical methods and examples on how to design robot-delivered home interventions.

Our work focuses on designing home-based, robot-delivered interventions for people with MCI. These interventions strengthen the memory and attention skills of people with MCI via cognitive stimulation and training [202]. Many researchers have delivered these interventions via computer programs [26, 132, 411], and explored how to improve engagement and motivation [111, 158, 294, 317, 392].

Physically embodied robots offer great potential to support engagement [106]. However, there is a lack of common techniques to support users and sustain engagement in longitudinal interventions delivered by a CAR, particularly without supervision from a clinician or researcher.

Another key challenge is *transfer* - can the person with MCI apply these skills broadly to their real life, outside the context of the computer-delivered intervention [163, 237]. Variation in how different populations (e.g. children vs. adults, people with cognitive vs. physical impairments) and individual users might engage with their respective interventions can make it difficult to ensure that they are effective when delivered by a CAR [127, 394]. Thus, establishing strategies for translating these interventions to a robot is crucial to ensuring that they are adopted by both clinicians and users, and the HRI community needs more systematic approaches to support this process.

In this chapter, we report on how neuropsychologists envision translating CCT to a CAR, and features the robot intervention needs to be successful, such as supporting goal setting, content personalization, encouragement for real-world transfer, and ways to longitudinally maintain engagement. We also conducted interviews with people with MCI, the end users of the robot-delivered intervention, which revealed how they envision using the CAR long term at home. This work establishes the foundations of translating neuropsychologist-delivered, clinic-based cognitive interventions to robot-delivered, home-based interventions, and provides a framework to researchers to support this process.

The contributions of this work are as follows. First, we provide insights for translating neurorehabilitation interventions to CARs in order to contextualize them to the lives of people with MCI. Second, we present new interaction design patterns for robot-delivered neurorehabilitation interventions to maintain longitudinal engagement and intervention efficacy. Finally, we propose design considerations for developing robots for people with MCI, a population with unique needs and abilities distinct from those of people with dementia and older adults. This work will guide roboticists through translating clinical interventions to robots, support their longitudinal efficacy and engagement, and ultimately extend the accessibility of longitudinal health interventions for people with cognitive impairments.

6.1 Background

6.1.1 Design patterns in HRI

Design patterns are repeatable, general solutions for a specific design problem [351]. Software design patterns have been created for clinical contexts, such as to support system explainability [328, 399] or personalized care [472]. In HRI, design patterns describe social and physical interactions between humans and robots which can be used for interaction design. These patterns may be designed by observing human-human interactions or exploring how people expect robots to behave.

Prior work has defined patterns for various HRI applications, including modeling interactions and interactive storytelling [232, 279, 345, 351, 391]. For instance, Ligthart et al. [279] proposed design patterns to encourage engagement and agency of children in interactive storytelling (e.g. Co-reenactment: the robot animates the story and invites the child to join). These patterns are tools the robot can use to support engagement.

To our knowledge, there are no HRI design patterns for translational science, particularly to support adults with cognitive impairments during clinical interventions at home. Methods and examples based in current clinical practice are essential to translating these interventions to CARs effectively. We propose design patterns to address this in Section 6.4.

6.2 Methodology

Given our robot prototypes (see Chapter 4), our research has reached the point where we can shift our focus from functionality to an in-depth understanding of how to contextualize the CCT intervention into the homes and lives of people with MCI. We engaged in a collaborative design research process [42] with neuropsychologists and people with MCI to explore how to best translate clinician-delivered CCT into a robot-delivered intervention at home.

Using our prototypes as a design probe, we conducted interviews with our two key stakeholders: clinical researchers and people with MCI. We explored how clinical participants deliver CCT and how they envision a CAR doing so. They were familiar with CCT, and could thus share key considerations for delivering it. For people with MCI, we focused on their use of technology, how they envision using a robot for support in an intervention, and initial impressions of our robot prototypes. Our study was approved by the UC San Diego IRB, under protocol number 800004. All participants gave informed consent to participate in the study, and agreed to be recorded.

6.2.1 Participants

Clinical participants: We recruited six clinical participants via word of mouth, all of whom work closely with and deliver CCT to people with MCI. They included four neuropsychologists, a psychiatry faculty member, and a research coordinator. All were female and work at the same location. Their ages ranged from 24-51 years (mean = 34.83, SD = 9.20). They had between 18 months and 25 years of experience working with people with cognitive impairments (mean = 6.50, SD = 9.18).

People with MCI: We recruited three people with MCI via word of mouth. All completed CCT in a clinic-based setting. All were male[1], and their ages were 73 - 77 years old (mean = 74.33, SD = 2.31). They reported moderate familiarity with technology.

6.2.2 Procedure

Clinical participants: We explored participants' experiences with CCT and their perception of using CARs to deliver it at home. We used the same interview script to guide conversation with each participant, but adjusted the order and questions based on their responses. We conducted all interviews virtually to minimize risk from the pandemic.

First, we conducted individual semi-structured interviews to explore their experiences delivering CCT to people with MCI. We first gave participants an overview of the study, and asked about how they interact with people with MCI in clinic. We also explored the unique space of designing for people with MCI, population-specific considerations, and ethical considerations. We did not show participants our robot prototypes during this phase to avoid biasing their responses, as the focus was on clinicians' general experiences working with people with MCI.

Following this, we conducted focus groups to understand how robots can longitudinally support people with MCI during CCT at home. Each consisted of two clinical participants and three members of our team. We explored how people with MCI and a robot might interact during training, how to implement intervention strategies on a CAR, and obtained feedback on our prototypes.

[1]While we ideally would have more gender diversity in both participant groups, our recruitment strategy was limited due to gender skews in our local population of CCT practitioners and recipients of CCT interventions. We recruited people with MCI from a larger study testing MCI treatments, whose population is all veterans. In the US, veterans are approximately 90% male.

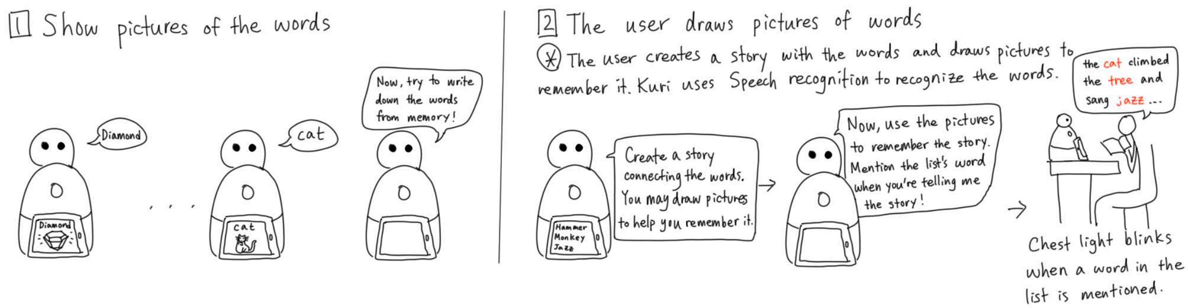

Figure 6.1. Storyboards which demonstrate potential interactions with a robot during CCT. These activities were drawn from an existing CCT intervention [204] and aim to help users practice *using visual imagery* to improve memory. We showed these to clinicians to obtain feedback on their translation to the robot.

We showed video demonstrations of our existing CCT activities on our robot prototypes, and storyboards of potential new activities to practice the strategies (see Figure 6.1). We discussed roles a robot might play while longitudinally delivering CCT at home and explored how people with MCI might integrate a CAR into their lives, such as for people with low technology literacy.

People with MCI: We conducted individual, semi-structured interviews with people with MCI. We used a script to guide conversation, but adjusted the questions and their order based on the responses.

These interviews aimed to understand the context in which people with MCI might use a robot to support CCT. We asked about their daily lives, including their routines, challenges, and current use of technology to understand their context. Before moving on to the rest of the interview, we offered a short break as people with MCI may have difficulty focusing for extended periods.

We then explored how they imagine using a CAR for support in an intervention. As people with MCI may not be familiar with robots, we showed examples of social robots in the healthcare space, including Jibo, Mabu, and Pepper, and a demonstration of our prototypes leading CCT activities. These videos helped participants imagine how social robots could support their daily life and health. Then, we asked how they imagined incorporating the robot into their lives (e.g. when and where they would interact with it), how they envisioned using it to support CCT (e.g. cognitive areas to focus on), and additional capabilities they might want (e.g. reminders).

6.2.3 Analysis

We recorded and transcribed all interviews and focus groups. Three researchers each analyzed all the data using a grounded theory approach [73], enabling us to analyze for considerations that participants found important, rather than potentially interpreting them through preconceived ideas of what we thought was important. We individually coded the transcripts through an inductive coding process [449] to identify emerging themes before discussing the final themes together. Any inconsistencies were resolved through discussion.

6.3 Findings

6.3.1 Insights for translating a clinical intervention to a robot

Participants discussed several themes regarding how to implement CCT on a CAR. These themes included working together with people with MCI to identify their intervention goals, personalizing intervention content, encouraging the use of intervention concepts in the real world, providing feedback to people with MCI, and recognizing and maintaining engagement.

6.3.1.1 Help people with MCI identify intervention goals

Working with people to establish goals is essential for improving motivation to engage in an intervention and increasing its efficacy [17]. People with MCI may not explicitly report impairment, yet may show awareness of dysfunction when confronted with difficult tasks [473]. The people with MCI in our study may have anosognosia, or imperception of disease [308]. As one person with MCI expressed, *"I don't have [cognitive] issues. I don't need [reminders] at this stage in my life. Because my life is simple, the methods I'm using now fully compensate [for my memory]."* Thus, helping people with MCI set goals that reflect their needs can ensure they benefit from the intervention. Clinicians may help people with MCI identify initial goals, and during the intervention, the robot can suggest areas of improvement or update goals with people with MCI.

The robot can prompt people with guiding questions to help them form and evaluate their solution. One clinician suggested asking questions such as, *" 'Do you think that the [cognitive] skill would be helpful to you? How likely is it that the skill will help you meet your goals?' "* These questions allow people to consider why the goal is appropriate, which can increase long-term motivation, commitment, and belief that it is achievable.

A robot can then validate the solution and/or offer alternatives. Validating a person's ideas can improve motivation and self-confidence, but sometimes people may propose unrealistic goals. One clinician explained, *"It might be something like, 'I want to remember all my appointments for next week,' but [the person is] cognitively not able to do that. In which case, we might try to modify the goal."* The robot can help guide people to an attainable goal, thus uniting clinical expertise with the person's own knowledge of what is realistic for them.

Participants with MCI imagined that using the robot could be an interesting way to achieve goals they are unmotivated to work on. One person with MCI explained, *"I've been trying to learn Spanish for a long time, so [practicing with the robot] could definitely help."* Another stated, *"I need to take on more challenges. That's where I could see a robot being beneficial."*

6.3.1.2 Personalization of intervention content

CARs can personalize the intervention to a person's goals, which is crucial, as a person's needs may vary with the severity of their impairment, progress in the intervention, or other circumstances [79].

People with MCI have existing routines a robot should consider to improve adoption and engagement. One person with MCI stated, *"I don't need more creative avenues because I usually find a way to eat up my day. I could make room for [a robot] in some capacity, but how much? I'm not sure."* Thus, finding opportunities to incorporate the robot in their routine is essential to increasing its use. Another person with MCI imagined having *"the robot sit in as another person in a [multiplayer] game."*

Robots can also ask about their concerns to personalize intervention content. One clinician suggested, *"[A robot] might ask if sleep is a problem. And if it is, then [it] launches that content. That might help them work on it if it needs to be fixed, or not stress about it if it's fine."* People may have different needs and goals, so asking them what content they want to review can help them focus on activities that suit them.

Clinicians also emphasized letting users choose the content they focus on. As one clinician explained, *"The robot can say, 'You indicated that you want to try [these strategies]. Which one do you want to try today?' "*

In longitudinal interventions, a person's cognitive abilities can change over time. The goals and content of CCT, as well as the robot's behavior and role, must also adapt to sustain engagement. Over time, a robot may need to modify CCT content to avoid monotonous and predictable sessions. As one participant with MCI said about a 6-week mindfulness intervention, *"At least 30 - 45 minutes, [the breathing exercise goes] through your whole body, over and over every week. That got boring."*

6.3.1.3 Encouraging real-world use of intervention concepts

One major benefit to using robots to deliver clinical interventions in the home is their potential to encourage and facilitate intervention practice in a person's daily life. As one clinician explained, *"If [people] don't practice [the skills] in the real world, they're probably not going to get much better at them."* Clinicians suggested that a CAR can help people learn and practice the intervention content with examples from their lives, such as with their grocery list. *"[The robot could] say, 'How might you remember your grocery list for this week?' They're practicing their skills, but this is also the list they need to remember when they're going to the store."*

Furthermore, a CAR can help people practice content by relating it to a person's personal life, making it more actionable and concrete. Clinicians suggested that people with MCI identify opportunities to apply cognitive strategies to events outside of the home. *"Having [people] identify an opportunity to [practice], like, 'I'm going to church and am going to be meeting new people. What strategies am I going to use [to remember their names]?' "* Clinicians also proposed that a robot can help people recognize steps they can take in their daily life to support their goals, such as to improve sleep.

Clinicians also mentioned the importance of checking in and asking people to reflect on their experiences. *"If [people with MCI] identify a time and setting to try [a strategy], the robot can ask how it went so there's some accountability. Like, 'Hey, did you try learning some new names at this event you went to? Do you feel like you should practice that [strategy] again? Do you feel like you have it?' "* Asking people with MCI to reflect on their experience can help motivate them to continue applying the content in the future, while identifying what works best.

Using the intervention content in the real world may also give people the opportunity to involve family and/or care partners which can improve motivation. Participants with MCI expressed interest in using the robot with friends and family, such as by practicing the intervention together. One participant stated, *"I like to get [my wife] involved [with training]. I think [I could] engage better with the [robot] and we can learn together."*

6.3.1.4 Providing feedback to people with MCI

Clinicians identified feedback as important for increasing engagement and understanding of content. Thus, they provided a few suggestions for how a robot can give feedback to people, including focusing on effort over performance and showing progress over time.

Clinicians emphasized that robots should reward people with MCI for the effort they give, rather than their performance on a task. *"I might give rewards for consistent practice, like the amount of time they engage with the robot or complete exercises."* They expressed that rewarding people for interacting with the robot consistently can help improve their motivation to engage with the intervention. In addition, this behavior may be more attainable and fair, as *"it wouldn't be fair to those who are more cognitively impaired that they are not doing well."*

Table 6.1. Design considerations for cognitively assistive robots for people with MCI.

	Consideration	Description
Cognitive	Simplicity of content	Information should be presented in a clear and concise manner to help people with MCI maintain focus.
	Visual aids	Visual aids may convey information more effectively and can help people with MCI focus on important points.
	Organization	Organizing important information in a logical manner can help people with MCI focus on those points.
	Repetition	Repeating information can help people with MCI review it if they do not remember or understand it the first time.
	Minimize distractions	Minimizing distractions from the robot and the environment can help people with MCI focus.
	Take breaks	Taking breaks can give people with MCI an opportunity to process the information or clear their minds.
Physical	Adjustable physical settings	Adjusting these attributes can improve communication with people with physical or sensory impairment.
	Physical size	The robot should be small enough to move between rooms easily, but large enough to not get lost.
	Straightforward physical setup	Minimizing the area that a person with MCI is expected to pay attention to can help reduce distraction.

Clinicians also wanted to track a person's progress over time to show progress toward goals. This could be a relatively short-term comparison, such as informing people with MCI of improvement from their last session, or long term, such as throughout the intervention. These longitudinal statistics can help both people with MCI and clinicians keep track of their progress.

6.3.1.5 Strategies for recognizing and maintaining engagement

Maintaining engagement throughout an intervention is vital to improving its efficacy and retention of material [202]. Some clinical assessments can be long and tedious, so people may become frustrated or bored. Thus, clinicians shared ways they recognize and maintain engagement with people with MCI, as well as suggestions for how a robot can do so in an intervention.

For example, clinicians observe a person with MCI's speech and eye contact to identify engagement and disengagement. Active participation such as *"asking clarifying questions,"* or *"coming up with ideas or goals"* indicates engagement. In addition, clinicians suggested that a robot could identify engagement based on how long and often a person interacts with it. In contrast, people with MCI *"will vocalize that they don't want to do [a task] anymore,"* or *"close or roll their eyes"* when disengaged.

Taking breaks was a common way to maintain engagement, as it *"works for most people."* Breaks allow people to rest and potentially address the cause of distraction (e.g. taking a bathroom break, answering a call). Thus, it is important that a person *"can take their own breaks and initiate their own breaks if they want to"* during a session with a robot, and that the robot *"checks in and sees when they need a break."*

Clinicians also use physical cues to draw attention and convey information. One clinician gave the example of raising her hand in a "stop" sign to convey that a person should slow down and focus on what she is saying. They suggest robots could similarly use cues to communicate with users.

Clinicians also use verbal cues, such as reminders or encouragement. For instance, a robot could cue people to continue if they get distracted. They also suggested providing encouragement, particularly if users get frustrated. Encouraging phrases they suggested included, *"Give it your best guess," "Thank you for hanging in there," "You're almost done."* Reminding people of intervention benefits can also motivate people with MCI to continue, even if they do not yet see improvement. One clinician recommended *"making [people] cognizant of why they're seeking treatment and what benefits they hope to see."*

6.3.2 Design considerations for people with MCI

Clinical participants and people with MCI discussed key considerations to improve accessibility and usability of CARs for people with MCI. These included ways to improve both the physical and cognitive accessibility of robots for this population.

6.3.2.1 Making robots physically accessible to people with MCI

Clinicians were mindful that most people with MCI are older adults who may also have physical or sensory disabilities. Thus, they suggested spacing tablet buttons apart to avoid *"tapping the wrong [one],"* such as if someone has tremors. In addition, *"Visuals must be big, high contrast, clear, and not too busy,"* and *"speech must be clear and understandable."* They also warned, *"[loud, slow speech] might seem demeaning to someone without hearing loss or impaired mobility,"* so they proposed that people could adjust these attributes to their needs.

People with MCI may have low technology literacy, so a robot using familiar communication modalities, such as speech, can improve its usability [166]. These are easier to learn and may be more reliable. One person with MCI expressed, *"I definitely have a hesitancy about [my] ability to learn [new technology], getting it to work correctly, and figuring out why it's not working."*

The physical size of a robot is also important to consider. People may need to move it between rooms (e.g. if one room is too distracting because of a TV). Thus, clinicians suggested it be relatively small and lightweight *"to make it easier... to transfer it"* if necessary. However, people with MCI often misplace personal items, and *"[too small a device] could get lost."*

The physical setup of a robot can also help people with MCI focus. Narrowing the area of interest, such as by *"having [the robot and tablet] in one straight shot"* can promote a focused presentation. Additionally, as people with MCI cited technology as a challenge they face, a simple setup with few components can help reduce risk of error and increase usability [267].

6.3.2.2 Making robots cognitively accessible to people with MCI

Minimizing cognitive demand can help reduce cognitive fatigue.

Simple and succinct content is more digestible so people do not need to remember as much at once. *"If [the material] is too complicated, [the intervention] is going to be difficult because they'll feel like they're not able to master it."* Thus, a robot needs to be concise to help people with MCI maintain focus. *"The longer [people with MCI] are expected to follow along,*

Table 6.2. Interaction design patterns for translational science to support clinical interventions delivered via a CAR at home.

Design Pattern	Examples
Promote engagement	Robots can offer breaks after long tasks, or use physical or verbal cues to sustain engagement.
Connect the intervention to the real world	Robots can use features from the real world (e.g. grocery lists), and encourage users to practice intervention content in their lives and with other people.
Relate the intervention to a user's interests	Robots can be incorporated into a person's existing routines, or use books or games that a person is familiar with to practice intervention strategies.
Reward perseverance over performance	A robot can reward users for engaging with it a certain number of times, maintaining a "streak," or for trying new intervention content.
Obtain feedback from users	Robots can obtain implicit feedback (e.g. performance), or ask for explicit feedback on preferences, etc.
Goal setting	Robots can ask users about any concerns and help identify solutions.
Reminders	Robots can verbally cue users to engage, or remind them of intervention goals.
Personalization	Robots can adjust activity difficulty based on performance, or communication modality to suit user abilities.

the easier it is to lose their attention." In addition, grouping important points together makes them easier to keep track of.

Visual aids can also help convey information without overwhelming people with MCI. In general, *"icons are more accessible than text"* if people have difficulty reading the font or understanding the text itself. Clinicians also explained, *"the visual component really clues you in to the main points."* As such, a robot might use gestures or facial cues to help emphasize important ideas.

Repetition can help people with MCI review material if they do not remember or understand it at first. Clinicians suggested asking if people would like anything repeated, such as after giving instructions, or reiterating important points during a session.

Furthermore, minimizing distractions from the robot and the environment can help people with MCI focus. Clinicians suggested that a robot's behavior could be minimal while providing information, *"because that might break their train of thought,"* but it could be more engaging at other points. In addition, a robot could encourage people with MCI to engage in a *"quiet environment where they can pay attention."* One person with MCI envisioned using the robot *"in* *my computer room. That would be a quiet place [where I] can close the door and separate the noise."*

Breaks can also improve focus and engagement, such as by giving people time to process information or clear their minds, making the interaction more enjoyable and manageable.

6.4 Design patterns for translational science to support robot-delivered clinical interventions

We propose interaction design patterns for translating clinical interventions to CARs to maintain longitudinal engagement and maximize efficacy (see Table 6.2). They are intentionally broad so they can be applied to other contexts. They can be combined to be more complex, e.g. adjusting goals based on user feedback. For each pattern, we describe what it is, how human clinicians use it, and example robot implementations.

Promoting engagement is essential to improving adherence to an intervention over weeks or months. Clinicians use strategies including humor, showing empathy for a person's situation, redirecting conversation back to the intervention, or taking a break to help keep people motivated. A CAR can employ similar strategies, such as taking a break after long or challenging tasks, to help reduce cognitive load and minimize frustration. CARs can also use physical (e.g. gestures) or verbal cues (e.g. encouragement, sounds) to sustain engagement.

Generally, an intervention aims to enact change in a person's life. **Connecting the intervention to the real world** is essential to improving a person's ability to transfer the content. A clinician might ask a person to reflect on opportunities where they can practice a cognitive strategy. Similarly, a CAR could help users practice strategies with real world examples, such as asking them to recall their grocery list, or helping users identify opportunities to practice strategies in their life.

Relatedly, **relating an intervention to a person's interests** can make it more enjoyable. Clinicians might encourage people to consider scenarios that are meaningful to them during an intervention, such as family or music. A CAR might adjust the activities themselves, such as asking users to recall details about a book they are reading, or using games like chess to help users practice intervention skills. There may also be opportunities to incorporate the robot in their existing routines, such as engaging in conversation while they watch the news.

A person's progress in an intervention may not be linear, and it may be demotivating if they are not progressing as much as they would like. Thus, it is important to **reward perseverance over performance**. When delivering cognitive assessments, clinicians may not tell people their performance to avoid influencing future performance. A CAR may reward users for engaging with the intervention a certain number of times, or for trying new strategies to keep them motivated.

To ensure the intervention is interesting, effective, and applicable to a person's life, it is important to **obtain feedback from users**. For instance, a clinician might ask people whether they would like to take a break to keep them focused on the intervention, or which cognitive strategies work best for them in order to evaluate their use of the strategies in their lives. Similarly, a CAR can ask users for feedback in order to personalize the intervention to their goals or preferences, or ask users to reflect on their experiences using a strategy.

Encouraging users to **set intervention goals** can sustain motivation and help them be more aware of its impacts. Clinicians often work closely with people with MCI to set achievable goals. CARs can also facilitate this by asking users to reflect on their concerns and helping them identify potential solutions.

Reminding people to engage in an intervention can also improve engagement. Clinicians might remind their clients of upcoming appointments. Similarly, a CAR could verbally ask people to complete a session together or cue users to continue a session. It might also remind people with MCI of their goals and benefits they hope to see to help keep them motivated.

Personalization can help ensure the intervention and robot behavior are appropriate for a person's preferences, goals, and abilities. A clinician might adjust the intervention based on a person's abilities. A CAR could also adjust the difficulty of activities based on their performance, or modify its communication modalities to suit a person's abilities.

6.5 Discussion

6.5.1 Translating clinical interventions to robots

6.5.1.1 Opportunities to explore design patterns in other HRI contexts

While developed for home-based CCT for people with MCI, our proposed design patterns are also relevant to other HRI applications. Many robotic interventions emphasize *connecting skills to the real world*, e.g., including care partners in interventions with autistic children [378, 394], encouraging students to identify personal strengths to support mental health [224], or conducting physical rehabilitation with everyday items [126]. This can help improve transfer of skills to a user's real life.

To our knowledge, no robots that deliver longitudinal interventions *reward perseverance over performance*. Users may become discouraged and stop using the robot if they perform poorly [83], whereas they may stay engaged if rewarded perseverance, e.g. maintaining a "streak" [310]. Rewarding effort, rather than objective performance, may improve motivation and engagement, especially in longitudinal applications.

More research is also needed on collaborative *goal setting* with robots, which clinicians cited as vital to increasing motivation in interventions. Identifying goals can also help focus an intervention, such as by focusing on strength vs. flexibility exercises in post-stroke rehabilitation. Clinicians or care partners could also help with goal setting, such as for children who might not understand what goals are realistic.

6.5.1.2 Challenges to translating clinical interventions to robots

Design tensions arose from our discussions with clinicians and people with MCI. For instance, participants with MCI thought a CAR would be most useful for people with severe cognitive impairment and were therefore unsure of how often they would use it. In contrast, clinicians envisioned people with MCI engaging with it regularly, perhaps multiple times a week.

Clinicians also envisioned the robot primarily delivering CCT, whereas people with MCI were excited by other potential functions (e.g. game partner). Clinicians were concerned that robot behaviors (e.g. lights, movement) could distract people with MCI, but no participant with MCI indicated this. Continued research on balancing these tensions is essential to improving the efficacy of these interventions.

Clinicians emphasized the importance of people with MCI using the intervention content in real life, but a person's progress in a cognitive intervention is often more ambiguous to measure than in contexts such as physical rehabilitation. A robot cannot necessarily observe a person's everyday behavior to measure progress. Instead, it may need to infer progress from activities completed together, or feedback from the user or family members [394, 429]. Other sensors could be used to observe a person and gauge progress, but this may infringe on privacy.

Despite reporting low technology literacy, people with MCI viewed robots as an opportunity to improve their understanding of technology. In contrast to children who may be more curious about new technologies [443], older adults may be hesitant to adopt new technology, as evidenced by two participants with MCI who did not own a computer. While others have suggested adapting the robot's role during an intervention [256], our findings suggest that a period before the intervention, where users can become familiar with the robot as a companion, may help improve adoption and acceptability.

Our discussions also touched on ethical concerns for robots for people with cognitive impairments such as MCI or dementia, aligning with recent work [207, 209, 257, 407] (also see Chapter 8). For instance, people with MCI imagined the robot as a companion, which could increase trust, but also lead to overreliance or social isolation. A robot may also influence (i.e. "nudge") users to support their goals, but this may be seen as manipulation [383]. Furthermore, users with anosognosia may not understand why they should use a CAR. If a clinician or care partner requires that they use it, this could limit their decision-making ability and infringe on their autonomy. Further exploration is required to support ethical robot design for people with MCI.

6.5.1.3 Challenges co-designing with stakeholders

While people with MCI in our study showed interest in the robot, they stated they do not need assistance for their level of cognitive impairment. They believed a CAR would be most beneficial for people with severe impairment, either later in life or others in their age group. Thus, they had difficulty imagining how such a robot could fit in their lives. Researchers may need to rethink how they propose CARs to users, considering the possibility of anosognosia to improve adoption. E.g., a CAR may be introduced as a companion rather than cognitive support.

In addition, the pandemic highlighted the importance of remote solutions to collaborate with all stakeholders, such as clinicians and people with MCI with low technology literacy [168]. Others have explored co-designing with end-users remotely [124, 290], but more research is needed.

6.5.2 Limitations and Future Work

There are limitations we will address in future work. First, our sample size was small. Recruiting people with cognitive impairments can be challenging [290, 448], exacerbated by the pandemic. Additionally, our participants did not physically interact with the robot. While this may impact their perception of some physical attributes (e.g. size, volume), we believe the majority of our findings would not be impacted (e.g. translating clinician behaviors to robots). This was our first step to robot-deployed CCT, and we have a longitudinal in-home study planned with people with MCI to further explore using robots to transition interventions from clinic to home. We will implement our design patterns on robots to validate with users.

6.6 Chapter Summary

We presented interaction design patterns for translational science to support longitudinal clinical interventions deployed via CARs. We introduced design considerations for people with MCI, unique from those of older adults and people with dementia. These contributions will reduce barriers to robot-delivered clinical interventions, and enhance the potential for robots to expand telemedical solutions, which are invaluable during the pandemic. This work is a basis for supporting longitudinal interaction at home for intervention contexts and beyond. The next chapter dives deeper into how robots can facilitate collaborative goal setting, which is a key component of clinician-led cognitive interventions.

6.7 Acknowledgements

I thank Dagoberto Cruz-Sandoval and Soyon Kim for their assistance with data collection and analysis. I also thank Elizabeth Twamley for providing her expertise on cognitive interventions for people with cognitive impairments. This chapter contains material from "Cognitively Assistive Robots at Home: HRI Design Patterns for Translational Science," by A. Kubota, D. Cruz-Sandoval, S. Kim, E. Twamley, and L. D. Riek, which appears in Proceedings of the ACM/IEEE International Conference on Human-Robot Interaction (HRI) [253]. I was honored that this work won a Best Paper Honorable Mention. The dissertation author was the primary investigator and author of this work.

Chapter 7

Robot-Facilitated Collaborative Goal Setting

When translating clinician-led interventions to robot-delivered ones, one key aspect to consider is collaborative goal setting. Collaborative goal setting is the process in which people receiving a cognitive intervention work closely with a clinician to identify and modify their goals [306]. Collaborative goal setting can increase motivation, confidence, and self-efficacy among patients, and lead to more concrete and achievable expectations of an intervention's impact [122, 372, 458]. Thus, CARs should support collaborative goal setting to ensure their efficacy. This may also enable these systems to tailor intervention content for a more personalized experience that focuses on a person's most pertinent needs and goals.

Clinicians usually help people develop goals using the SMART framework (specific, measurable, achievable, relevant, and time-based), which is essential to establishing appropriate and realistic goals for an intervention [52, 475]. However, clinicians may not be available to help people using a robot at home. Even if a robot supports goal setting, people may set goals that are unrealistic for their current abilities without clinician guidance. This can lead to decreased motivation and engagement with the intervention if people do not see the therapeutic outcomes they expect [266].

There are many digital health technologies that autonomously deliver health interventions, many of which enable users to set goals. For instance, many cognitive training games incorporate

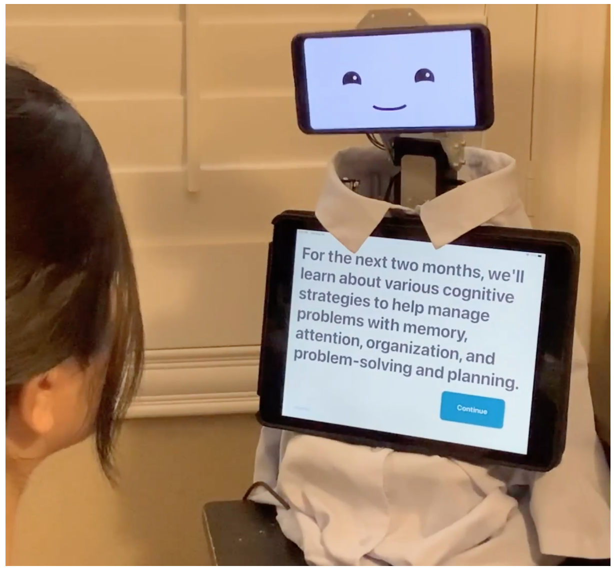

Figure 7.1. CARMEN teaches people cognitive strategies to support their goals and minimize the impact of MCI on their daily life.

in-game reward systems which may serve as goals for users [40, 161, 344].

While this work illustrates the importance of integrating goals with technology-delivered health interventions, there are still many open questions with regard to designing CARs that can autonomously support collaborative goal setting. First, measuring goal progress can be challenging due to a wide variety of possible rehabilitation goals, and variation in what progress might look like for each person. This is particularly difficult for cognitive interventions, as performance on robot-led activities does not necessarily correlate with ability to transfer intervention skills to real life. Robots need to be able to help a person set, measure, and manage goals, as this is vital to improving efficacy of and adherence to the intervention, and possibly supplement what a human clinician is able to observe in an intervention.

In addition, with many existing systems, users must choose from a set of goals pre-defined by clinicians or developers, limiting applicability to their context and abilities. Allowing users to set their own real world goals can also help improve motivation and adherence to an intervention, particularly over long periods of time. One open question is how robots can help users develop their own SMART goals and adapt an intervention to support those goals.

In this chapter, we address these challenges in the context of delivering CCT to people with MCI via CARMEN (see Figure 7.1, Chapter 4). We interviewed neuropsychologists to explore how robots can support collaborative goal setting. We also conducted co-design workshops with people with MCI to explore robot behaviors in an intervention, including how users can convey goals to a robot, how to measure goal progress, and how to adapt intervention content to support goals. We prototyped several of these behaviors on our robot CARMEN, and obtained additional feedback from people with MCI.

The contributions of this work are four-fold. First, we report insights, grounded in current clinical practice, on how robots can support collaborative goal setting during longitudinal interventions at home. Second, we present a framework which will support HRI researchers to develop robot-delivered health interventions which can help users set and meet their goals. Third, we present concrete examples of how robots can interact with people during the goal setting process, which were co-designed with clinicians and people with MCI. Fourth, to support reproducibility within HRI, we have submitted these interactions as supplementary materials. This work will help researchers design CARs which can support collaborative goal setting with clinicians, users, and a robot to improve the efficacy of robot-delivered health interventions.

7.1 Background

7.1.1 Goal Setting with People with MCI

As MCI may impact each person differently, people with MCI often have unique goals they wish to achieve. *Rehabilitation goals* refer to the real-world outcomes a person wishes to see from the intervention [291]. For instance, people may wish to remember to attend their doctor's appointments, get a job, or improve their relationship with their family. This is in contrast to *cognitive training goals*, such as practicing a certain strategy some number of times. While cognitive training goals typically aim to help a person reach their larger rehabilitation goals, this is not guaranteed. In this work, we focus on enabling technology to help people achieve their rehabilitation goals, as these are the most relevant to their everyday life.

7.1.2 Goal Setting in Technology-Delivered Health Interventions

Many existing cognitive training systems for older adults incorporate gamification features to improve and sustain engagement, motivation, and intervention effects [161, 288, 344]. In-game reward systems can increase intrinsic motivation and encourage users to continue using the system [297, 452]. The benefits of applying gamification to cognitive training systems are varied. Gamified interventions can challenge and support various overarching goals, such as challenging and exercising different cognitive and motor functions (e.g. attention, memory, perceptuomotor skills) [464]. Although gamification efforts can be a strong motivator for people to achieve their self-set goals, achieving in-game rewards does not necessarily translate to real world changes, which can reduce the efficacy of these interventions [318].

In addition, there are a multitude of technology-delivered health interventions [59], many of which include goal-setting as a key component and strategy [89, 422, 484]. For example, UbiFit [89] is a mobile, persuasive technology meant to encourage individuals to incorporate physical activity into their lives. They found that participants were more motivated to work towards goals they set for themselves or in collaboration with a domain expert. [422], who created a patient-center tablet app, noted collaborative goal setting is a key aspect of the rehabilitation process between healthcare professionals and patients, and that it is important patients feel in control of their healthcare decisions during the rehabilitation process.

Longitudinal robot interventions are becoming more widespread, including helping autistic children learn neurotypical social cues, supporting mental health, or delivering physical rehabilitation [38, 94, 226, 240, 253, 312, 378]. Kidd and Breazeal [240] introduced Autom, a robot that interacts with people to support their weight management goals over time. Autom facilitates goal setting by enabling users to input and update their daily exercise and calorie goals in accordance with their weight management goals. While Autom does support goal setting and participant motivation toward goals, it was specific to the context of weight loss (e.g., daily exercise, calorie intake). In contrast, we aim to enable robots to support broader, real-world goals in order to help improve intervention efficacy and motivation.

Thus, while there exist robots which can deliver longitudinal interventions, it is still unclear how these systems can support people with identifying, measuring, and achieving their real world goals throughout an intervention. Users should be able to effectively interact with the robot in order to progress towards and assess the goals they set. In this work, we explore how robots can support the collaborative goal setting process for longitudinal health interventions.

7.2 Methodology

We explored how to support collaborative goal setting with a robot-delivered intervention at home. We employed a collaborative design research process with clinical neuropsychologists and people with MCI. We conducted interviews with neuropsychologists to explore how they facilitate collaborative goal setting in clinic and how they envision a CAR doing so. With people with MCI, we explored the goals that they might have for a cognitive intervention and co-designed robot interactions for supporting collaborative goal setting at home. Our study was approved by the UC San Diego IRB, under protocol number 800004. All participants gave informed consent to participate.

7.2.1 Participants

Clinical neuropsychologists: We recruited two clinical neuropsychologists who deliver CCT to people with MCI. They include a psychiatry faculty member and a neuropsychologist, and both work in the same location. Both were female, with a mean age of 45 years (SD=9.9). They had on average 16 years (SD=14.1) of experience working with people with cognitive impairments.

People with MCI: We recruited 5 people with MCI via word of mouth. 4 were male and 1 was female[1], aged 65-80 years (mean=73.4, SD=5.5). All previously completed CCT in

[1]We recruited people with MCI from a larger study exploring MCI treatments with veterans. In our country,

clinic, and most (n=4) reported moderate to high technology familiarity, e.g. computers and smartphones.

7.2.2 Procedure

Clinical Neuropsychologists: We virtually conducted individual semi-structured interviews to explore neuropsychologists' experiences with collaborative goal setting during a longitudinal intervention and how they envision CARs can support this process. We used an interview script to guide conversation with each participant, but adjusted the order and questions based on their responses.

We asked neuropsychologists about how they conduct collaborative goal setting in clinic, including how they determine what goals are achievable for each person, how they measure goal progress, and how they modify goals during the intervention. Following this, we explored how a robot can help people achieve their goals during an intervention, and co-designed appropriate robot interactions with participants. We presented a hypothetical scenario about a person with MCI following CCT with a robot at home. This helped contextualize the robot and its interactions during the intervention, which was important because clinicians may be unfamiliar with robotic technology and may therefore have difficulty imagining how people might interact with it [442]. For these scenarios, we intentionally chose a name that is considered gender neutral in our country, "Sam," as the name for the person with MCI.

We conducted live sketching sessions with participants, where we presented a scenario, and a member of our research team sketched storyboards and designs based on ideas the participant discussed. Then, we showed them the sketch and iterated based on their feedback. In this way, we collaboratively explored how a robot can interact with users to set up their goals, adapt its behavior to support user goals and encourage engagement throughout the intervention.

People with MCI: We performed a two-phase study with people with MCI. First, we conducted individual semi-structured interviews to explore goals that participants may have had

veterans are about 90% male, leading to a gender skew in our local population of CCT practitioners and recipients.

during their in-person intervention and how they envision a robot supporting those goals during a longitudinal intervention at home. We used a script to guide the conversation, but adjusted the questions and order based on their responses. Throughout the interview, we periodically offered breaks as people with MCI may have difficulty focusing for extended periods of time. In the second phase, we showed video demonstrations of these behaviors and got feedback from participants.

In our interviews with participants, we asked about their intervention goals in clinic, including their motivation for beginning the intervention, goals during the intervention, and what progress towards those goals looked like. Then, we showed examples of home-deployed social robots (e.g. Jibo, Kuri), and a video demonstration of CARMEN delivering CCT to help them imagine the capabilities of these robots. We then conducted live sketching sessions with participants, where we explored how they would collaboratively set goals with a robot, and how a robot could provide motivation during an intervention. A member of our research team sketched storyboards and designs based on the participants' responses, showed them the sketch, and then iterated based on their feedback. To co-design longitudinal interactions, we focused on participants' experiences setting and managing goals during the 8 week ME-CCT intervention. We asked them to recall when they felt unmotivated to work on their goal, and how they managed that situation. Thus, we captured how a robot can support CGS across an intervention.

We selected six robot behaviors that people with MCI designed which were common across multiple participants with MCI and/or aligned with our discussions with neuropsychologists, and implemented them on CARMEN (see Figure 7.2). These included how a robot can: a) help people identify intervention goals, b) suggest goals if people do not have a specific goal in mind, c) respond if people complete a (sub)goal, d) support people if they do not complete a (sub)goal, e) connect a goal to the intervention content, and f) show goal progress visually. We have submitted videos of these behaviors as supplementary material.

We recorded videos of these interactions and showed them to the same people with MCI[2].

[2]Due to scheduling constraints, we met with three of the original five participants with MCI.

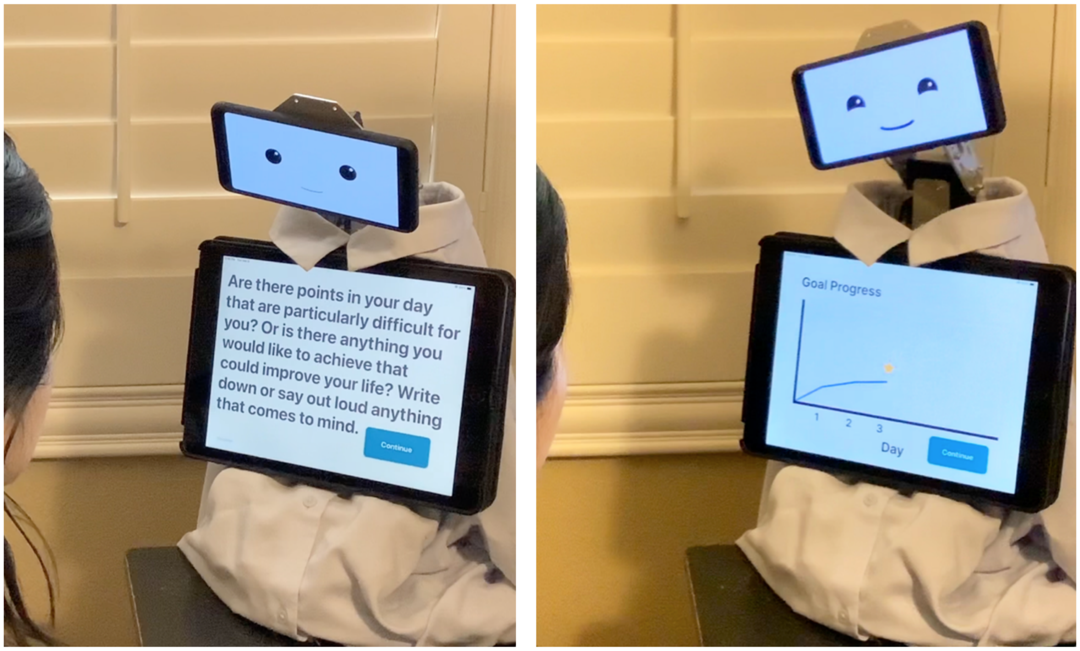

Figure 7.2. *Left:* CARMEN helping a user identify their intervention goals. *Right:* CARMEN showing the user a mock graph of their progress toward their goal.

We virtually conducted individual, semi-structured interviews to get feedback, including whether these interactions could support their goals and motivation during an intervention.

7.2.3 Analysis

We recorded and transcribed all interviews. We analyzed all the data using a reflexive thematic analysis (RTA) approach [54, 55]. This enabled us to center the perspectives of our participants, and helped limit interpretation of the data through preconceived ideas of what we may have thought was important. We coded the transcripts through an inductive coding process [449] individually, then discussed the final themes as a group. Inconsistencies were resolved via discussion. As we aimed to generate recurring themes and salient concepts, we did not calculate inter-rater reliability, as per current best practices in the RTA literature [56, 307].

As the focus was different for each participant group (leading collaborative goal setting with neuropsychologists, and designing these interactions with participants with MCI), we analyzed each set of interviews separately. Two researchers analyzed each interview, and one researcher analyzed both sets.

7.3 Insights for Collaborative Goal Setting with Robots

7.3.1 Robot Behaviors to Support Users

Robot Roles: Passive and Active. People with MCI imagined a robot could play both passive and active roles in setting and supporting goals. For instance, people with MCI imagined a more passive robot to offer suggestions to help them identify their own tasks and goals. *"I'd like to maybe start out having the robot suggest some [strategies or goals] and then I can, as I get more comfortable, [...] start coming up with my own ideas" (Person with MCI-2). "If it could suggest some strategies, that would be good. Like, 'Would it work if you were to do such and such?' " (Person with MCI-3).*

People with MCI also imagined a robot could take a more active role, such as by providing solutions to questions a person might have about their goals. For instance, in response to a video where a robot asked guiding questions to a user, one participant noted, *"The robot was asking questions that should have been answered by the robot, like [...], 'Okay, how do I get organized?' " (Person with MCI-5).* They later emphasized, *"Just keep it light and try to give answers, because that's what [the user is] there for. They're looking for answers to their issues." (Person with MCI-5).*

In most CAR scenarios though, the robot will be in a person's life temporarily [44]. *"We want to train people to be their own [neuropsychologist], so we want to have them take on all the skills themselves and not be dependent on the robot for anything really" (Clinical Neuropsychologist-1).*

People with MCI expressed that a robot could serve as a companion throughout the intervention to encourage them to achieve their goals. *"It's like having some support to help you reach your goals, you know. You're not all alone trying to do it." (Person with MCI-3).* They imagined the robot could be like a friend, *"I think that it would be good for me and be like, 'My* *friend the robot is going to check up on me and I've done a really good job and I can't wait to tell it.' [...] When the robot checks in and asks me, 'How'd it go? Did you get it done?' Then I could say, 'Yes, I did.' I rarely finish things, so if I'm with someone who would check up on me, maybe it would be motivating." (Person with MCI-3).*

Robot Having a Positive Personality: Participants expressed the importance of a robot providing encouragement and motivation. *"It's encouraging. The interaction makes me feel like I could actually do things, you know?" (Person with MCI-3).* It was also important that a robot is not judgmental if they do not accomplish their goals. *"I think the biggest thing for me was, there isn't a big stress on accomplishing everything right now. More laid back. 'Okay, we'll try again tomorrow. Maybe look at some different ways to do it.' " (Person with MCI-2).* Another Person with MCI stated, *" Even if I didn't complete my goal for the day, the robot's not gonna say, 'Well you screwed up,' you know?" (Person with MCI-3).*

In addition, people with MCI suggested ways that a robot could be more humanized in its interactions. *"Might put some laughter in there. A scoff or a giggle." (Person with MCI-5).* Participants also pointed out its appearance. *"He's as cute as he can be all dressed up" (Person with MCI-3).*

They also suggested adding humor and more expressions. *"There might be some things that you could pull in that seem funny to people, just to keep them on a bit of a light side. Wise cracks or something. [...] Like, 'Good morning, Sam. I can't be much help today. I'm a little hungover' " (Person with MCI-5). "Actually it'd be funny if when you're going through, 'Here's the progress you've made on your goal,' for the next screen, the robot's eyes get really big. 'Whoaa' " (Person with MCI-5).*

Privacy Considerations: Participants discussed privacy, particularly when collecting data from participants. For instance, they wanted it to be more clear when a robot was recording a user. *"When [the user] is talking, is it being recorded on [the tablet display] or is it just what the robot is saying?' " (Person with MCI-5).* Furthermore, neuropsychologists believed that maintaining privacy could help reduce bias in user responses. *"If [goal progress is] just saying* *internal to themselves, I think it's a lot less prone to that bias of trying to look good." (Clinical Neuropsychologist-2).*

7.3.2 Identifying Goals

Set Priorities: Due to the variety of ways that MCI can impact a person's cognitive abilities and life, people with MCI may have many goals they would like to accomplish. *"There's a whole list of things I want to do, but I just don't know where to start" (Person with MCI-5).* Throughout the course of an intervention, neuropsychologists emphasized the importance of working towards a few goals at a time. When it comes to identifying goals with a robot, *"You want to limit it. You don't want people to be working on a dozen different goals at the same time, so they should select probably their top [...] four would be the maximum. Two or three is probably best [...], so you'd have them rank their most prioritized goals" (Clinical Neuropsychologist-1).* Then once people have learned the skills to accomplish their goals with the robot, *"they can hopefully take this education and then apply it to their next round of goals" (Clinical Neuropsychologist-2).*

Enable Users to Identify Their Own Goals: To ensure that a goal is relevant and useful to a person's life, it is important for a robot to let users identify goals that matter for them. *"Setting a goal that is important to [the person] is probably a good idea" (Person with MCI-5).* This can help improve a person's motivation to achieve those goals.

If users are unsure what goals they might want to work towards, participants proposed that the robot could provide possible goal suggestions. One neuropsychologist stated, *"We could probably give them a list of examples, like example goals, and have them select" (Clinical Neuropsychologist-1).* One participant with MCI imagines a robot leading such an interaction as follows: *" 'What are your goals?' Input my goals and hopefully it can come [up] with a strategy to help me reinforce those. Maybe come up with some suggestions for other things that I haven't tried" (Person with MCI-2).*

However, neuropsychologists were aware of the limitations of supporting such open-ended goals on robots. *"I think the problem might arise that if the person lists a goal that the robot doesn't have [in its knowledge base], the robot's not going to understand that" (Clinical Neuropsychologist-1).*

Create Specific and Achievable Goals: Enabling a robot to support users with fitting their goals to the SMART framework is an essential part of collaborative goal setting. *"In terms of measuring the goals or figuring out some outcomes, [...] the goal should be specific, measurable, achievable, relevant, and time based. [...] Having those goals be specific and measurable can help create a system that's better" (Clinical Neuropsychologist-2).*

Robots can ask questions to help users reflect and step through fitting their goals to this framework. *"What's your goal? All right, is it measurable? How are you going to measure [it]? Is it achievable? Is it relevant? Is it time-based? What is your timeframe?" (Clinical Neuropsychologist-2).*

People with MCI also thought setting a time limit on goals could be helpful. *"As long as I know I've got a time limit, I can dedicate myself more to accomplish it (Person with MCI-2).* Another noted, *"My desire [is] to actually accomplish the goal, even if it's a small thing like cleaning off my desk. It might take me two times, but I'll get it done, you know? (Person with MCI-3).*

Set Subgoals: To help ensure that goals are achievable, participants suggested setting subgoals. *"If you want to get a job, for example, you're going to have to get yourself organized, you're going to have to do some job searching, you're going to have to create a resume, you're going to have to apply for a job, and so on. So there are all these subgoals" (Clinical Neuropsychologist-1).* A participant with MCI noted, *"I need to look at things connecting to the big picture. Take things a step at a time [...]. I like that better than, I have to do all of this today." (Person with MCI-3).*

Several participants with MCI imagined setting daily subgoals that align with their overarching goals with a robot. *"That way, [the goals] are broken down into smaller steps that can be done in a short period" (Person with MCI-5).* One participant imagined a robot *"to* *just start out in the morning saying, 'Okay, today is the 1st of September. What are your goals today?' " (Person with MCI-2).* This can help people identify concrete and achievable tasks to work on during the day. *"If they had a suggestion and concrete path to take toward [achieving their goal], [...] that would definitely be helpful, I think. And then you start narrowing it down from 'get organized' to 'store your screwdrivers' " (Person with MCI-5).*

Set Goals Based On Existing Behavior: To help identify goals that are realistic, robots can encourage people to base their goals around existing behavior. *"Achievable might be taking what they're doing now and expanding it by 10-20%" (Clinical Neuropsychologist-2).* They stepped through an example of helping someone remember to check their calendar. *"How are you going to remember to check your calendar? And so we might set up some systems around that. Maybe he checks it during meals, maybe it's checked in the morning and then in the evening, maybe it's checked when he has [his] morning coffee" (Clinical Neuropsychologist-2).*

7.3.3 Goal Progress Measurement

Scaling Goals for an Individual: Goal progress can be difficult to measure as it can vary widely based on individual goals. Thus, neuropsychologists expressed how HRI researchers might use goal scaling techniques to measure and set appropriate goals for people with MCI. *"[Asking] 'How far are you toward your goal now?' at the start and end of the training can be a way of 'goal attainment scaling,' allowing for a better understanding of what strategies work" (Clinical Neuropsychologist-1).* They also expressed how a standard self rating measurement would allow for easier data collection, which can lead to better understanding of which strategies work for each goal. *"If you keep it simple and you just measure self rated progress toward a goal on a one to ten scale, it puts every goal on the same metric which is really useful for data analysis later on, because they're all going to be on the same scale" (Clinical Neuropsychologist-1).*

Highlight the Wins: People with MCI feel more encouraged to incorporate strategies presented by the robot when they feel like they are improving. One participant discussed how it felt *"reward[ing] if you do something" (Person with MCI-3).* During the intervention, neuropsychologists suggested giving positive feedback on a person's improvement to encourage people with MCI to try strategies in their lives. *"In an ideal world, they're going to do better when they use more strategies and so you'd be able to give feedback to them that their performance improved when they categorize the information, when they wrote it down, when they use visual imagery, and so on. Then you would encourage them to try the strategies that just helped them" (Clinical Neuropsychologist-1).*

Visualize Progress: People with MCI stated that seeing progress and feedback can help them advance towards their goals. *"The feedback is good. And I can see how it would help me progress" (Person with MCI-3).* Visualization of progress can positively reinforce working towards goals. *"If the person is motivated to do the goal, it would be a handy thing to have a motivational point. You do something and you go, wow, I didn't know that I got that far. It was kind of like, yay" (Person with MCI-5).*

7.3.4 Intervention Delivery

Highlight Goals Throughout Intervention: Participants expressed how reminders about their goals can keep them on track to complete their goals. People with MCI discussed how reminders about their goals (both overarching and subgoals) at the start and end of sessions could help them focus. *"I think if you're working towards the goals, then it's a good idea to keep indicating, here's a small goal or here's a larger goal, whatever. You emphasize the goal thing because it's where it seems to be going" (Person with MCI-5).*

Participants found repetition to be a key part of retaining memory and focus on their goals. *"If I go over something more than one time, it helps my memory. If I say my goal is to do that this afternoon [...] to myself, it goes right in and right out of my brain, you know? And I forget that I was going to do that this afternoon. So a reminder is good" (Person with MCI-3).* A neuropsychologist also suggested using repetition in terms of having users, *"do some writing about using [. . .] strategies to improve this domain is going to help with the real world goal" (Clinical Neuropsychologist-1).*

Reflecting on their goals can also help keep people with MCI focused. *"[Reflecting can] make me think about progressing toward getting my life more organized, rather just drifting, not actually accomplishing anything" (Person with MCI-3).* Another participant suggested the robot could ask, *" 'Were you able to use this strategy anywhere else?' [...] That way it would be a daily thing to get that new task embedded" (Person with MCI-5).*

Cover All Intervention Content: It is important for people with MCI to try all strategies presented by the robot to determine the most applicable strategies for them. *"With these cognitive [interventions], I've taken the approach that we want to offer everything. So we want to at least expose them to all the strategies and then see what they find helpful, even if they don't initially report a problem in that domain [...] There's usually a few things that at first blush, it doesn't feel natural to the person, or it doesn't feel like something that they would use, but we really want to encourage them to try it anyway" (Clinical Neuropsychologist-1).*

7.3.5 Transfer to the Real World

Build Good Routines: Participants stated how the robot could help them practice cognitive strategies that incorporate into their daily routines. *"Once I get something attached in my morning routine and I keep working on it, hopefully it will become more ingrained. And then I can add something else" (Person with MCI-2).* A neuropsychologist gave an example of connecting strategies to a daily routine. *"Attaching this calendar planning to something you do everyday. And then you have a little note on your coffee pot say[ing], 'So let's check your calendar.' And so, Sam looks at it, [they go] to get the coffee in the morning and it says to check your calendar. And that's [their] cue to review [their] calendar that day" (Clinical Neuropsychologist-2).* People with MCI also expressed interest in having flexibility when practicing with the robot and completing goals on their own time. *"I like the idea that [...] you're busy this morning but you have time this afternoon to organize your desk" (Person with MCI-3).*

Check In and Reflect: Participants imagined that the robot can check in with their goals and help people with MCI reflect on the strategies they have been using. This provides direction with goals, understanding which strategies work, and strengthening the investment levels of people with MCI. *"Having Sam be a part of the solution and having Sam generate some of those solutions can be really helpful to support that investment level and that level of interaction and kind of bolster it a little bit" (Clinical Neuropsychologist-2). "Every once in a while the robot can check in. 'Now you've finished this module on prospective memory. How do you think this list of strategies is going to help you with your goals over here? Take some time, think about it, jot down some notes. Which strategies do you need to practice more?' " (Clinical Neuropsychologist-1).*

Connecting With Other People: People with MCI articulated how practicing strategies with others would be helpful. A participant with MCI expressed, *"if it's a home task? It might be a good idea to have the other person in the house working on it with you" (Person with MCI-5).* The same participant also stated, *"if it is something somebody wants to do, it would be motivational" (Person with MCI-5)* and how goals can be *"embed[ed] [...] especially if you're in a group situation working on a common task" (Person with MCI-5).*

7.3.6 Providing Motivation

Be Empathetic: Enabling a robot to exhibit empathy can be motivating for users to achieve their goals regardless of any discouragement they may experience. For instance, people with MCI stated that reinforcement and guidance from the robot can be encouraging if they did not complete the goal they set for the day. *"It's like saying, you know, to me, 'It's OK if you didn't quite make your goal. We'll try again tomorrow.' " And maybe, you know, 'Just rethink how we want to accomplish it."' (Person with MCI-2).* Neuropsychologists also stated that empathetic phrasing from the robot can prevent people with MCI from feeling a sense of failure if they do not accomplish their goals. *"Normalizing the likelihood that they won't have achieved [their goals] 100% right off the bat can be a good way to phrase it" (Clinical Neuropsychologist-2).*

Show Goal Progress: Participants expressed that being able to see their goal progress can also increase their motivation. For example, a participant with MCI stated that seeing their progress can inspire them to strive for more, and *"[it would feel like] now you can move on to something more challenging" (Person with MCI-2).* Similarly, a neuropsychologist suggested having dialogue that can encourage participants to keep working towards their cognitive goals. *"Just kind of being like, 'Look, these are all the things you've done so far. Let's try one more' " (Clinical Neuropsychologist-2).* Additionally, a participant felt as if seeing progress is a form of positive feedback that shows the impactful progress they have made. *"Especially seeing [a] chart that shows what my accomplishments were will [make me] more likely to want to do more" (Person with MCI-2).*

Provide Check-Ins: Participants suggested having the robot check on them at some point during the day to increase their motivation. *"I think that it would be good for me and be like sort of, my friend the robot is going to check up on me and I've done a really good job and I can't wait to tell it, you know?" (Person with MCI-3).*

7.4 Discussion

7.4.1 Proposed Framework for Collaborative Goal Setting in HRI

We propose a framework for developing longitudinal, robot-delivered health interventions with collaborative goal setting capabilities. We provide key considerations for each step of the collaborative goal setting process to support goal achievement and motivation. While we discuss this framework with respect to our population and intervention context (People with MCI, ME-CCT), our conversations with neuropsychologists suggest that it could be helpful for other health conditions of interest to the HRI community.

Support Self-Identified Goals: When helping people identify goals for an intervention, it is important to allow space for self-identified goals. For some people, this may be straightforward (they may already have a goal in mind), but others might be unsure about what they want to achieve. Thus, robots can ask open-ended questions to help people reflect on particular challenges they face, or changes they might want to see in their life. If people are still unsure, robots may

Table 7.1. Our proposed framework for supporting collaborative goal setting in HRI.

Goal Setting Component	**Robot Considerations**
Support Self-Identified Goals	Robots should allow people to self-identify intervention goals, and provide goal suggestions if needed. They can help users set SMART goals with preset questions, or ask users to set daily goals.
Goal Progress Measurement	Robots can scale goals and progress to an individual using the Goal Attainment Scale. People can then track their own progress, and this will also simplify progress visualization. Robots might use sensors to observe user behavior, or use visual aids (e.g. facial expressions, gestures) to highlight wins.
Intervention Delivery	Robots can remind people of their goals and encourage them to connect their goals to the intervention content via multiple communication modalities (e.g. speech, tablet, gestures). Roboticists may explore additional modalities to support different goals and abilities, e.g. a memory game where users speak aloud vs. touch the robot.
Transfer to the Real World	Robots should let people identify their own“homework” that is specific to their lives and goals, possibly based on their existing behaviors or involving other people. Robots might cue users to build routines verbally or nonverbally. And as a social presence, they may facilitate the inclusion of family with intervention activities or discussion of goal progress.
Provide Motivation	Robots can adjust facial expressions, movements, or tone of voice to convey empathy or excitement, remind them of the “bigger picture”, or provide positive reinforcement.

suggest goals to start with, such as recommendations from professionals. Either way, robots should encourage people to focus on just a few goals for the duration of the intervention so they do not get too overwhelmed. In particular, asking users to identify a daily task that is in service of their larger goals can help them set achievable and time-based subgoals.

Goal Progress Measurement: Due to the highly individualized nature of goals and what success might look like for each person, it is important that robots measure and scale goals based on the individual. Neuropsychologists suggested using the Goal Attainment Scale (GAS) [457] which allows for each person to set their own goals and what success means for them, set around their current and expected levels of performance. Then, robots can ask people to track their own behaviors that may correspond to their progress between sessions, such as how many times they took their medication or whether they completed their daily goal. Robots can check in periodically and record progress, enabling people to view their progress over time, which can also help with motivation. Or depending on a robot's capabilities, it might observe a person's behaviors relevant to that activity and possibly give feedback (e.g. as one particpant with MCI suggested, giving specific instructions for how to organize a desk).

Intervention Delivery: Robots can also support goals in how they deliver intervention content. For instance, they can remind or ask users to reflect on their goals throughout the intervention, including at the beginning and end of a session. In doing so, they can encourage users to connect the intervention content to their goals and promote motivation to follow through with the intervention. This is especially important for contexts such as ME-CCT where it is beneficial to expose people to all of the content from the intervention, and they can choose for themselves which strategies to integrate into their lives. On the other hand, it is important to not overload people so robots could focus on content that may be most relevant or interesting to the individual. This could help maintain adherence, especially at the beginning of an intervention.

Transfer to the Real World: Providing people with opportunities to consider how they can put the ideas they learn with a robot into practice is key to enabling them to transfer those skills to the real world. This may come in the form of assigning or helping them identify "homework" where they can try out the skills. These homework assignments should be specific and fit into a person's existing life so it is easy to achieve and can become a new habit over time if they see fit. If applicable, robots might also encourage them to engage other people in their lives as they complete their goal. Then, in the following session, robots can ask open-ended questions to help people reflect on how it went, including identifying any challenges they faced and possible solutions for the future.

Provide Motivation: Motivating people to achieve their goals is key to maintaining adherence to an intervention and improving its efficacy. Robots can leverage many strategies that neuropsychologists use, including showing empathy if people do not show progress towards their goals, reminding people of "big picture" goals and changes they want to see in their life, and providing positive feedback such as by highlighting any progress or celebrating when people show progress (e.g. dancing, playing music, telling a family member). It may also be beneficial to modify goals if the original goal turns out to be unattainable, or if their priorities change over time.

7.4.2 Connection with Other HRI Contexts

We developed this goal setting framework in the context of a robot delivering CCT to people with MCI, but we hope that researchers can apply it to other populations and applications. Our population very much wanted to be able to set goals in collaboration with a robot, and we expect this to be true more broadly as well. Collaborative goal setting can help people determine what real world behaviors will help achieve those goals, and likely will be more inclined to follow a robot's suggestions for reaching those goals. This is particularly important for HRI applications where interactions with a robot do not necessarily correspond to goal progress or how well a person can transfer the skills to their real life. In these cases, it is important for people to be truthful with themselves and the robot about goal progress, and decide for themselves what is useful for their lives.

For example, consider a scenario proposed by Jeong et al. [224, 226], where a robot aims to support the mental health of students. If a student aims to improve their social relationships, identifying personal strengths might improve their confidence and indirectly help their social life. Applying the collaborative goal setting framework, the robot can further help a student identify and scale their goals to their behaviors to ensure those goals are achievable and relevant (e.g. joining a club or messaging an old friend). Letting individuals define and scale their goals around their existing life and priorities can help improve motivation and confidence that they can achieve those goals.

Furthermore, collaborative goal setting with robots may need to support input from other stakeholders, including domain experts (e.g. clinicians) who may have intervention goals, or family members who can provide support if someone cannot set achievable goals for themselves. Supporting all stakeholders in the collaborative goal setting process will be crucial to improving the efficacy of these interventions in numerous contexts, such as for academic and social learning for children [378, 394], or interventions for people with cognitive impairments [253, 387].

7.4.3 Robot Implementation Considerations

People with MCI suggested additional robot implementation considerations that would help support goal achievement and motivation. For instance, they suggested the robot ask open ended questions to help people reflect on their day. In this case, the robot does not need to necessarily understand what the person says in response. For example, the robot can ask people if they accomplished their goal(s) for the day, and if there were any challenges they faced. Providing an opportunity for them to reflect can help them contextualize their goals and increase motivation in working towards their goals regardless of whether or not they accomplished it for the day.

Roboticists can also simplify implementation of robot behaviors through goal scaling and similar self-report measures. Since goal progress varies based on an individual, this can enable the robot to easily help people assess progress without implementing a system that can handle all permutations of robot content and goals.

Participants also suggested that the robot record audio and play it back to the person. For example, people could record themselves saying their goals and the robot would store that audio recording to play back to the person later. This feature can help people keep accountability to their goals and provide an additional motivational push to reach their goals. As technology advances, robots could use many abilities to enhance collaborative goal setting, such as open-ended discussion to lead motivational interviews and personalized conversation.

In addition to the goals people with MCI have for the intervention, other stakeholders, including clinicians and family, may have different, possibly conflicting goals [256]. Some challenges that may arise include implementing a system which can consider and balance these differing goals and priorities. For example, clinicians expressed how people with MCI should try all of the strategies to gain a sense of which strategies work the best for them. However, this may be demotivating for people with MCI who may not see success with strategies they do not think are applicable or can be integrated into their life. More research needs to be done in order to determine methods that can be used to support the multiple, differing goals of each stakeholder.

Design tensions also emerged from discussions with neuropsychologists and participants with MCI. For instance, they differed in how integrated the robot would be in their lives. Neuropsychologists recommended more independence from the robot through shorter, more user-led interactions. In contrast, people with MCI seemed to prefer if the robot provided daily support in their lives indefinitely, e.g., an alarm clock, daily reminders, or answering questions and giving recommendations on how to do tasks.

Another tension was how to use the intervention to achieve goals. Neuropsychologists imagined concrete "homework" where people can directly apply and practice the strategies in their lives. However, people with MCI imagined tasks that were not necessarily related to the strategies. For example, participants with MCI focused on goals such as making their bed or doing dishes, where their main barriers were motivation rather than cognitive abilities. Practicing the strategies would not necessarily contribute to achieving these goals, so the question arises whether a robot should still encourage the use of the strategies.

Ethical considerations also arose in our discussions, which HRI researchers will need to thoroughly explore before deploying collaborative goal setting on robots longitudinally in the real world, particularly for people with cognitive impairments. For instance, people with MCI had high expectations for the support a robot could provide, such as holding full conversations, knowing details about their lives and abilities, and providing support with various tasks throughout the day. Realistically, clinicians and possibly robot developers will be in-the-loop while robots complement care, so more research is needed on how to set appropriate expectations while considering user privacy and technical limitations [201, 208]. Furthermore, most robot-delivered interventions will only be in a person's life for the duration of the intervention. While neuropsychologists envisioned people with MCI learning the skills but ultimately being independent of the robot, participants with MCI envisioned the robot integrated in their lives indefinitely. This raises questions regarding how to design robot behaviors to promote independence from the robot, especially if people begin to see it as a companion that motivates them to achieve their goals [44, 257, 370].

7.4.4 Limitations and Future Work

There are some limitations we will address in future work. First, we kept our sample size small to avoid burdening the community, following recommendations from participatory health research [20]. As MCI affects people differently, participants had a diversity of behavioral and motivational factors which arose in the challenges and goals they shared (e.g. improved organization vs. prospective memory). While we were mindful of these differences in our analysis, people with MCI expressed commonalities in how they set and manage goals over time (e.g. daily subgoals), and how robots can provide support (e.g. reminders). In this work, we aimed to establish generalizable collaborative goal setting concepts and approaches for robotic technologies, and we will explore how CARMEN can support personalized goal setting in future work. In addition, due to the pandemic, participants viewed video demonstrations of robot interactions rather than physically interacting with it. While participants would ideally interact with CARMEN to understand its abilities, we aimed to design robot interactions and explore their potential to support collaborative goal setting. Thus, we do not believe video demonstrations impacted our findings significantly.

7.5 Chapter Summary

In this chapter, we presented our findings from co-designing robot behaviors with people with MCI and clinical neuropsychologists on how CARs can support collaborative goal setting in the context of supporting a home-deployed cognitive intervention. Based on these insights, we introduced a collaborative goal setting framework, which we hope other HRI researchers can use within their application domains. We demonstrated concrete examples of goal setting interactions with CARMEN, co-designed with stakeholders, to support reproducibility and extensibility in HRI. These contributions lay the foundation for enabling robots to support motivation and goal achievement throughout a longitudinal intervention at home, which will ultimately extend their efficacy, support accessibility, and improve care for countless people.

7.6 Acknowledgements

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Chapter 8

Ethical Considerations for Personalizing Care Robots

Imagine the following scenario: A person with dementia lives at home with a full-time care partner. That care partner is overburdened, stressed, and is an older adult with their own health problems. This scenario is experienced by over 16 million informal dementia care partners in the US, and this number will only continue to grow, representing a global health emergency [13].

Over the past 20 years, many researchers have explored the use of assistive robots that can aid both people with dementia and their care partners with a range of daily living tasks, including to provide companionship, deliver cognitive stimulation, and support household chores (see Figure 8.1) [94, 154, 166, 256, 316, 323, 474, 478]. For example, PARO (see Figure 8.1.3) is a robotic seal which has been shown to provide companionship to people with dementia and reduce stress, anxiety, and pain among people with dementia and their care partners [148, 324, 474]. In addition, researchers have used CARs with the goal of slowing the progression of cognitive impairment and/or reducing the severity of its impact [27, 94, 256, 439, 466]. For instance, JESSIE (see Figure 8.1.1, Chapter 5) teaches people metacognitive strategies to reduce the impact of cognitive impairment on their daily lives [256].

For these assistive robots, a key concept discussed in the health technology community is personalization, which reflects how well a system can adapt to a person longitudinally.

Figure 8.1. Three exemplar robots used to support people with cognitive impairments and their care partners. From left to right: 1) **JESSIE** is a tabletop robot developed by our lab, and is used to support people with mild cognitive impairment and early-stage dementia. It provides personalized, adaptive cognitive training to help teach users metacognitive strategies to minimize the impact of cognitive impairment on their daily lives [256]. 2) **Spoonbot** is a tabletop robot radio developed by our lab, and is used to support people with late-stage dementia who have trouble eating. It leverages embodied cueing, mimicry, and music to encourage eating [166]. 3) **PARO** is a robotic seal and is used to stimulate social interaction and support therapy for people with dementia, including robot-assisted therapy and sensory therapy [387, 474].

Personalization offers many benefits, such as improving adherence to cognitive interventions, increasing engagement with intervention content, and enabling goal-oriented health management [258, 381, 445].

Personalizing assistive robots for people with cognitive impairments is especially important due to the progressive and unpredictable nature of conditions such as dementia, as one's individual needs and preferences will evolve over time [166, 262]. For example, for people with early stage dementia, a robot can interact verbally with someone (e.g., provide medication reminders) [264], whereas for those with late stage dementia verbal prompts will not work, and physical and nonverbal aural cues are more appropriate [166, 191]. Spoonbot (see Figure 8.1.2) is an example of a robot our team built for people with late-stage dementia - it uses mimicry cues and a person's favorite music to assist with eating. Therefore, it is important to adapt to a person's physical and cognitive abilities, personal preferences, care setting, and other life circumstances [262].

Roboticists have made great strides in developing personalized systems for people with cognitive impairments and their care partners. However, a large body of this work has been either primarily technology-focused or health-outcomes focused, yet there's a growing need for further investigation into the potential negative consequences assistive robots could have on this population. For example, researchers have raised concerns about some robots used in dementia caregiving, such as PARO use being associated with irritability, hallucinations, and disinhibition among people with severe dementia, or overstimulation of people with dementia in group settings [231, 463]. People with cognitive impairments are a vulnerable population who are already at high risk of manipulation and abuse [305], so one must think critically about how these robots could cause harm, and possible means for mitigation.

We are currently at an inflection point, where it is becoming relatively easy and inexpensive to develop and deploy CARs to deliver personalized interventions to people with cognitive impairments, and many companies are vying to capitalize on this trend. However, it is important to carefully consider the ramifications: What are the potential consequences of introducing underdeveloped personalized CARs to care for people with cognitive impairments? Furthermore, what are some unintended consequences of a highly personalized CAR for people with cognitive impairments?

In this chapter, we draw upon empirical data from our own work, as well as from the literature, to explore these questions. We contextualize concerns regarding inaccurate personalization of CARs for people with cognitive impairments, and the potential unintended consequences of personalizing robot behavior accurately. We also propose key technical and policy concepts to enable robot designers, law-makers, and others to develop CARs that protect users from unintended consequences, particularly those designed for people with cognitive impairments. We hope that our work will inspire roboticists to consider the potential risks and benefits of robot personalization, and support future ethically-focused robot design.

8.1 Background

8.1.1 Person-Centered Care for People with Cognitive Impairments

Person-centered care is one predominant care approach that can help maintain the relationship between a person with cognitive impairments and their care partners by encouraging care partners to recognize the personhood and individuality of a person with cognitive impairments. As a strengths-based approach, person-centered care recognizes an individual's goals, abilities, and preferences, such as by understanding their culture or building on their strengths and current abilities, rather than trying to replace the abilities they have lost, to promote their well-being [123, 131, 262].

One important aspect of person-centered care is supporting the autonomy of people with cognitive impairments. Being active in daily decision making can help a person preserve their dignity and identity, which can help them lead more full and rewarding lives [131, 262]. These decisions may be major, such as deciding which health interventions to receive, or relatively minor, such as choosing what food to eat. It is generally agreed that people should be able to make and act on their own decisions whenever possible, and care partners should structure interactions to support the autonomy of people with cognitive impairments.

However, as conditions such as dementia progress, people often begin to lose their capacity to make or communicate decisions. Thus, they may not know or be able to reason about what is best for their health. Care partners may be forced to choose between supporting a person's autonomy vs. ensuring their health or safety. For example, if a person with cognitive impairments refuses to maintain basic personal hygiene (e.g. bathing), should a care partner respect their desire to not do so and risk causing harm (e.g. a urinary tract infection, social ostracism), or should they override the person's wishes and force them to complete these activities [414]? Neither scenario is ideal for satisfying both the person's autonomy and health, so there is much debate surrounding whether to prioritize respecting a person's autonomy or abiding by the principle of non-maleficence (i.e. preventing harm). The care partner's decision may change based on culture, situation, and personal preference, but a person's independence and privacy are often considered secondary to harm prevention [131,169].

8.1.2 Critical Dementia in Technology Design

The majority of assistive technologies have been designed and developed without thorough consideration or understanding of the needs and perspectives of people with cognitive impairments, particularly those in the later stages of their disease. In addition, many commercial technologies center themselves around a person with dementia's cognitive limitations, rather than their strengths which can lead to them being stigmatized and disempowered [166,210].

Fortunately, researchers are increasingly adopting more inclusive approaches when designing robots for people with dementia through a *critical dementia* lens [166,265]. Critical dementia encapsulates person-centered dementia care, and focuses on understanding and supporting the strengths and personhood of people with dementia in technology design. It explores how embodiment, context, and emotional and sensorial experience impact how people with dementia interact with the world around them [265]. It draws from approaches including participatory design, which aims to involve all stakeholders (e.g. people with cognitive impairments, care partners, clinicians) throughout the design/development process in order to ensure that the end product is usable and valuable to them [281,400]. It also includes user-centered design, which prioritizes the interests and needs of users and entails gathering iterative feedback at each stage of the development process [1,113]. These approaches enable technology creators to move away from a deficit model of aging, which focuses on a person's potential disabilities and loss of ability, and instead incorporate a social model of aging, which better captures the preferences and contexts of users [267]. This framing can help promote the dignity and personhood of people with cognitive impairments when designing assistive robots.

While it is vital to include the perspectives of people with cognitive impairments and care partners in the development of robots, their respective values may not always align, particularly in relation to the autonomy of a person with cognitive impairments. For example, care partners may use cameras to surveil a person with cognitive impairments to ensure their safety (e.g. see if they are wandering or have fallen) which can infringe upon the person's privacy. Care partners may also imagine using robots to encourage people with cognitive impairments to do something that they do not want to do (e.g. eat, bathe), or prevent them from doing something unsafe that they want to do (e.g. go out alone, eat unhealthy food) which can limit their autonomy [316, 336, 414]. Thus, it is important to also consider these design tensions and how they might impact the autonomy of a person with cognitive impairments and their relationship with their care partners. We further explore this in Section 8.2.2.

8.1.3 Personalization of CARs that Deliver Health Interventions

To ensure assistive robots are usable and acceptable for individuals living with cognitive impairments, it is critical that the robots are personalized. Personalization is tailoring a health intervention or system to suit an individual's factors such as their preferences, abilities, and goals, and it reflects how well a system can adapt an intervention to a person longitudinally. Personalization is essential in this space because there is no singular experience shared by everyone living with or caring for someone with cognitive impairments. Personalization can maximize the utility and efficacy of interventions for each person's individual situation by enabling assistive robots to address the heterogeneity of people with cognitive impairments including cultural and personal backgrounds, living situations (e.g. at home, in a long-term care facility), how conditions progress in different people, and individual preferences. For instance, an assistive robot can be personalized to a user physically (e.g. adjusting movement speed, proxemics), cognitively (e.g. adjusting the difficulty level of cognitive training tasks), and socially (e.g. referring to a person by name) [258, 386]. In this chapter, we primarily focus on the personalization of CARs that deliver health interventions [466].

Personalized CARs offer many benefits, including improving adherence to and adoption of an intervention, as well as adoption of and engagement with the technology. For example, cognitive stimulation is most effective and enjoyable if it meets a person where they are in terms of their cognitive abilities [133, 138]. Tapus et al. [439] demonstrated that adjusting the difficulty of a robot-delivered cognitive stimulation game to the performance of a person with dementia improved their overall task performance, engagement with the intervention, and enjoyment during the task. In contrast, if a health intervention is not personalized, it can provoke frustration and depression in a person with cognitive impairments and their care partners [17, 412].

Research also demonstrates that adapting robot behavior to an individual can help improve its adoption and engagement with users. For example, a robot can adapt its behavior in real time to a user to maintain engagement, such as changing its tone of voice to draw their attention back if they are distracted during an interaction. This can help maintain engagement with users for longer periods of time, and thus improve retention of material (such as in a therapeutic intervention) [430]. A robot may also adapt its behavior to be more acceptable to a user, such as adjusting its communication style to be more passive or assertive depending on a user's cultural background or which they respond better to [386].

There are also health applications for which personalization to people with cognitive impairments is necessary. For instance, reminiscence therapy encourages people with dementia to recall memories from their past. So, robots that provide this intervention must have some knowledge of a user's history in order to ask relevant questions and guide the therapy. The MARIO robot is one such example, which could store and retrieve user-specific knowledge provided by family members and care partners in order to facilitate reminiscence therapy [12].

Robots that can autonomously personalize their behavior are particularly important in this space to fulfill the needs of people with cognitive impairments. The ability to adapt with little to no input from users is especially important when users have low technology literacy and do not have the time or resources to learn how to use the system, as is often the case for clinicians, informal care partners, and people with cognitive impairments [168, 256].

8.1.4 Key Technical Concepts for Personalization

From a technical perspective, developers often use machine learning algorithms to enable robots to autonomously personalize their behavior to users (see Chapter 2). This can be decomposed into two main phases: preference learning and behavior adaptation. In this section, we will provide a brief overview of these topics and why existing computational approaches may not be appropriate for use with people with cognitive impairments.

One technique for personalizing robots to an individual is to learn and understand what that person's likes and dislikes are, i.e., learning their preferences. **Preference learning** aims to predict what a person will prefer based on their known preferences, often inferred from previous behavior [140]. For instance, in the context of assistive robots for people with dementia, a robot might take note of songs that elicited a positive response in order to play new music for a person. Common computational approaches to preference learning include classification algorithms such as k-nearest neighbors and decision trees [140]. While most work in preference learning is limited to only ranking a specific set of items, more recent work aims to infer a user's underlying preferences so that learned preferences can be generalized across contexts [480, 481, 488].

Once a system has an understanding of a person's preferences, it can adapt its behavior to suit those preferences. **Behavior adaptation** refers to how a robot adjusts its behavior, usually in response to external stimuli. This adaptation can occur over short periods of time (e.g. making a noise to draw attention to itself if a user is distracted), or longer periods of time (e.g. adopting an encouraging personality if a user responds better to that during a therapy). Reinforcement learning (RL) approaches are among the most common for autonomous behavior adaptation, though researchers are also exploring other methods such as neural networks and Gaussian processes [258]. Inverse RL is another approach which enables systems to learn from human experts; for instance, a therapeutic robot might observe how a human therapist interacts with a user in order to learn how it should behave.

While existing approaches to preference learning and behavior adaptation have proven effective for applications such as post-stroke rehabilitation and teaching social skills to children [33, 376], most may not be appropriate for longitudinally personalizing robots to people with cognitive impairments for a few reasons.

First, the majority of approaches assume people's preferences and abilities stay constant. However, learning the preferences of people with cognitive impairments can be difficult due to the complex and fluctuating nature of these conditions. For example, many people with dementia experience "sundowning," or increased confusion, anxiety, and agitation later in the day [236], as well as fluctuating levels of lucidity, which may make it challenging for robots to learn what types behaviors to communicate when. Furthermore, one cannot assume that a person will have the same preferences over time or in different contexts. This concern is especially true for people with cognitive impairments whose cognitive abilities may change dramatically as their condition progresses, so a personalized assistive robot must be able to keep up with these changes. For instance, the roles of an assistive robot may transition from delivering a one-on-one cognitive intervention, to observing and sharing information with a care partner as a person needs more support from care partners as their condition progresses.

Next, many approaches suffer from the "cold start" problem, where a system must begin interacting with a user with no prior knowledge about them [395]. In order to learn more about a user, many approaches rely on exploration of possible actions. However, depending on the possible actions and the context, acting without knowing the preferences or abilities of a person with cognitive impairments may have the potential to harm them. For instance, a robot may need to know a person's level of dementia, tolerance for sensory input, or emotional state to avoid overstimulating them or causing distress during an interaction.

Finally, there are existing computational approaches that learn from human experts (e.g. inverse RL). These approaches require stakeholders to commit much time and effort to use them effectively. However, in the context of assistive robots for people with cognitive impairments, these experts are often care partners and clinicians who are already overburdened, and may lack the time and technical literacy to communicate their expertise to a robot. Thus, these robots may not interact with a person with cognitive impairments to their full potential or in the way that these experts intend.

8.2 Risks to Personalizing Robots for People with Cognitive Impairments

While personalizing robots offers many benefits, there are also risks associated with doing so, even for people without cognitive impairments. Inherently, personalization requires the collection of personal information, including health-related information, which raises privacy concerns. Furthermore, these data are often collected longitudinally, fused with other data, and then used by other machine learning systems to infer and predict behavioral patterns of individuals. This not only raises the risks of bias and proxy discrimination [361], but also violates users' ability to provide informed consent as they are unwitting recipients of these opaque systems [228].

Personalizing technology to users has led to a rise in concerns such as privacy violations, over attachment to the technology, "echo chambers" (i.e. only conveying content that reinforces a user's existing beliefs), and manipulation of users [178, 201, 370]. For instance, social media platforms have become adept at presenting users personalized content in order to maintain engagement with the platform. They can even use a person's personal information to show them targeted advertisements in order to maximize advertisement revenue, sometimes at the cost of a user's well-being, through the dissemination of inaccurate information or falsely advertised products [35]. In addition, researchers have identified content personalization as a mechanism that has amplified extreme behavior among radicalist groups, including violent extremists, by enabling large-scale personal expression and collective action with little moderation [34, 450, 476].

The physical embodiment of robots introduces additional concerns that are not present in virtual systems. Research shows that a robot's physical embodiment affords it many advantages that can increase engagement and trustworthiness in social interactions (e.g. richer communication channels, physical presence) [106]. However, these characteristics can be problematic if used in a careless or manipulative manner. For instance, perceived trustworthiness of a robot based on its appearance can significantly influence a user's intention to purchase the device [415] or cause them to find a robot more authoritative [176]. Thus, a robot could exploit a user's trust and manipulate them to behave in ways they might not otherwise (e.g. share personal information, purchase products). Researchers predict that robots will be used to surveil users and market products to them, but with access to far richer and more intimate data than can be gathered by a web-based system, resulting in more persuasive advertisement [114].

Personalizing robots could further exacerbate these risks by leading to the development of "Spybot" robots which gather personal information and can lead to more effective deception by "Scambot" robots or manipulation by "Nudgebot" robots [178]. For instance, a CAR might be perceived as more trustworthy by a person with cognitive impairments if it resembles a family member or clinician, which could inadvertently deceive users and give the robot more authority [316].

Lying and deception are widely discussed concerns in both the dementia caregiving and personalized technology communities [36, 116, 178, 304, 338]. In HRI, deception can occur if a robot leads someone to believe something that is not true. This deception may happen intentionally or unintentionally, and there are many ways it might occur when interacting with people with cognitive impairments, including Turing Deceptions and misconceptions of a robot's capabilities.

Turing Deceptions: People with cognitive impairments may experience Turing Deceptions when interacting with a robot, i.e. believe they are interacting with a human when in fact they are interacting with a robot, and assume the robots have their own motives, goals, beliefs, and feelings [349, 376]. For instance, if a robot visually or aurally resembles a trusted care partner or clinician, people with cognitive impairments may be more willing to cooperate with the robot, share personal information with it, or otherwise act in a way that they would not otherwise [316, 374]. While this may be desirable in some cases (e.g. using a care partner's face or voice to encourage people with cognitive impairments to return to bed, take medication, or eat [316, 336]), this is also a form of deception.

Misconceptions of a robot's capabilities. Another major source of unintentional deception is a disconnect between the actual capabilities of a robot and the capabilities that users think it is capable of. This disconnect is problematic because over- or underestimation of a robot's capabilities can impede users from making informed decisions regarding how robots are involved in their care [470]. This can also affect the level of trust that a user has in a robot, which may lead users to overtrust it and attribute it too much authority during an interaction, or undertrust it and not follow the guidance it provides. Either scenario may result in negative health outcomes, or misuse of the robot [19, 491].

Vandemeulebroucke et al. [470] suggest that increased use and familiarity of robots earlier in life can moderate such deception. However, the memory challenges of people with cognitive impairments may prohibit them from becoming familiar with a robot in this way once the condition has progressed. To proactively help circumvent this, an increasing number of older adults integrate assistive technology into their lives in preparation for the potential development of future memory challenges [112]. In addition, dementia community health workers and family care partners suggest incorporating features that people with cognitive impairments may already be familiar with (e.g. touch screens, common objects) into robot design in order to increase their usability and acceptability among people with cognitive impairments [166, 316].

Furthermore, Moharana et al. [316] found that people with dementia have greater trust in robots that resemble people they are already comfortable and familiar with. Integrating familiar features into robot design can help convey its capabilities to a person with cognitive impairments and build trust between a robot and a person.

Personalizing CARs to people with cognitive impairments amplifies these concerns and introduces many others. In this chapter, we identify and discuss four major risks of personalizing CARs to people with cognitive impairments (see Figure 8.2), which include: 1) Safety risks that arise from inaccurate personalization, 2) (Human) autonomy infringement risks, 3) Social

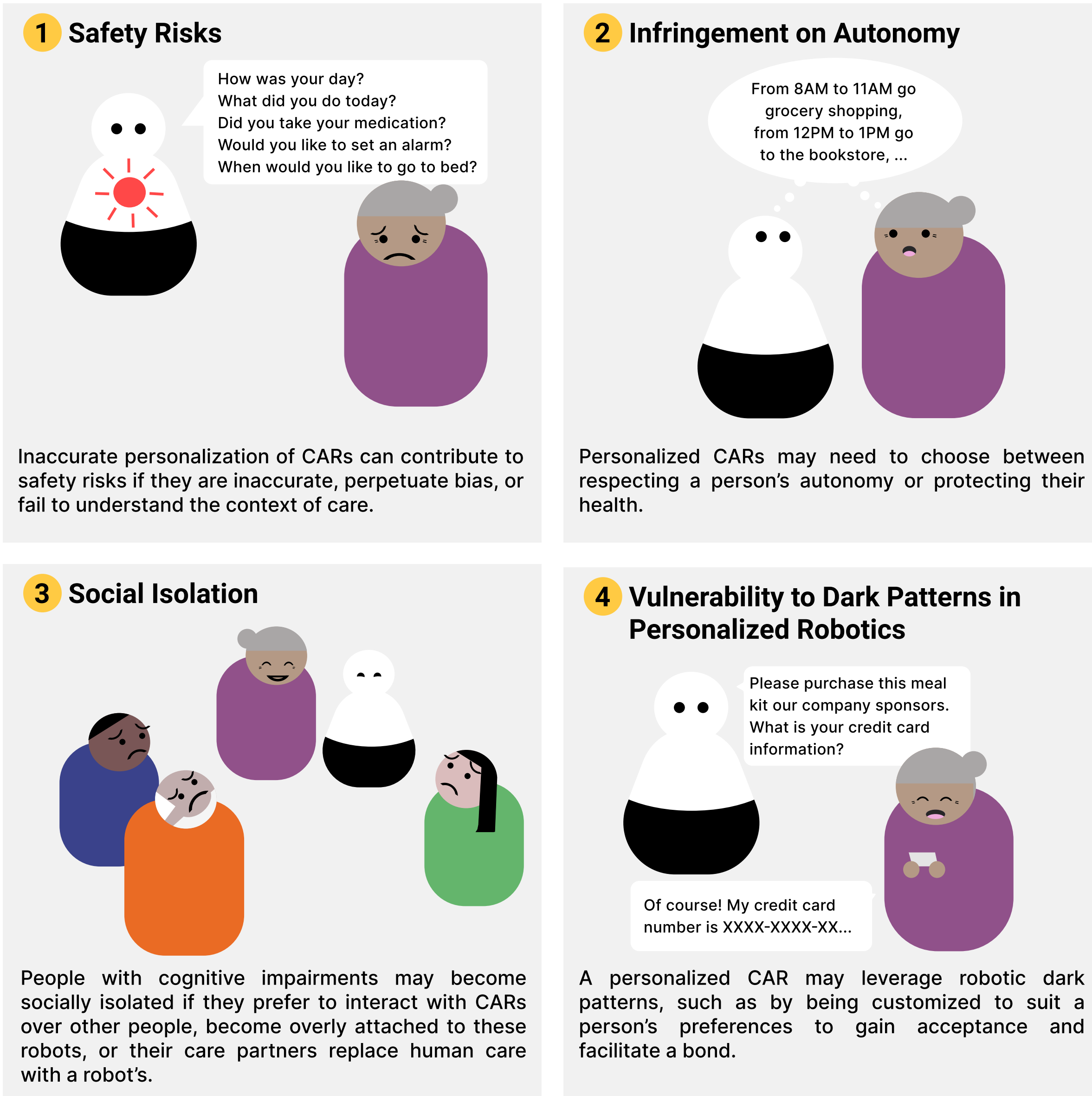

Figure 8.2. Personalizing CARs to people with cognitive impairments introduces many ethical concerns, including 1) Safety risks that arise from inaccurate personalization, 2) (Human) autonomy infringement risks, 3) Social isolation risks, and 4) Risks of being taken advantage of due to dark patterns in robot design.

isolation risks, and 4) Risks of being taken advantage of due to dark patterns in robot design. To support discussion of these risks, we introduce three exemplar robots representative of those currently in use in dementia care, as shown in Figure 8.1.

8.2.1 Risk 1: Inaccurate Personalization can Lead to Safety Risks

While carrying benefits such as autonomy, machine learning approaches have the potential to cause physical or mental harm when they are not adequately personalized to people with cognitive impairments, such as not understanding the context of care, perpetuating bias, or simply being inaccurate. One of the most significant risks of inaccurately personalized CARs is providing a person with cognitive impairments with inadequate care or care that is misaligned with the stage of their condition. A robot may not necessarily understand the complexities of care, so there is a rising concern that automating these decisions without human supervision will cause them to be ineffective or harmful. For example, the automation of a medical diagnosis system may cause physical harm without supervision of a human medical professional [41], demonstrating the challenges of health automation technology even before introducing the additional complexity levels of physical embodiment, home settings, or cognitive impairments. Also, the robot may provide self-care instructions that do not account for a person's comorbidities, which may contribute to harm.

As a person's condition progresses, they may require different levels of support to use or understand a CAR effectively. However, if a robot fails to adequately understand or adapt to a person's conditions, this can limit their ability to fully utilize an assistive robot. This failure may be considered an error of omission (if the robot did not adapt its behavior at all) or commission (if the robot adapted its behavior incorrectly) [384]. In either case, these errors may have negative effects including reducing the usability of the robot, which can reduce a person's use of the robot, lower their self-confidence in their cognitive abilities, and possibly lead to depression and anxiety [17, 147]. People with cognitive impairments may also be unable to communicate what they want or need to the robot if it fails to account for their physical or cognitive considerations, which can leave people feeling as though they have lost their autonomy and dignity [147]. Although this problem could be avoided through care partner supervision, care partners are often already overburdened by existing caregiving responsibilities, and having to monitor an adaptive robot would simply add further cognitive load.

ML algorithms for therapeutic interventions could demonstrate biases that unintentionally exclude or harm people with cognitive impairments. In the case of robots for people with dementia, most existing work frames dementia and aging as a series of losses, rather than acknowledging the full life and identity of the person with dementia. This narrow understanding of people with dementia may perpetuate existing biases about this population, limit an algorithm's performance, and ultimately place the mental and physical health of users at risk [432]. Thus, it is vital to develop concrete guidelines for assessing the potential mental and physical impact of inaccurate personalization on people with cognitive impairments and ways to avoid harm.

While researchers will ideally test ML algorithms extensively before using them in real world applications, there are still limitations to what these algorithms can achieve, such as for uncommon scenarios (i.e. "edge cases") or populations not reflected in test data (e.g. people with cognitive impairments). Developers may be tempted to naively apply an algorithm to the context of personalizing robots to people with cognitive impairments. However, if that algorithm was not tested or validated with this population and possible scenarios were not considered in the design while personalizing the algorithm, it may lead to inaccurate physical and mental health assessments of these people (e.g. depression, detection of pain in non-verbal individuals) which can cause serious harm to their mental and physical health. For instance, pre-trained models of facial analysis technology such as Facial Alignment Network (FAN) achieve relatively high accuracy for older adults without dementia, but the accuracy drops significantly for people with dementia [432].

Care partners may rely on such algorithms to automatically identify and alert them of agitation and aggression in people with cognitive impairments so they can reliably intervene in a timely and appropriate manner. However, if the algorithm was not developed with or trained on data from these people, a system may not alert a care partner of agitation or aggression until the harm has already occurred (e.g. causing distress, emotional withdrawal, physical harm) [239]. On the other hand, a system may give the care partner false alarms, which may cause them unnecessary stress and cause them to become desensitized to alarms, so they are unprepared to react in the case of a true agitated or aggressive episode.

8.2.2 Risk 2: Infringement on the Autonomy of People with Cognitive Impairments

As discussed in Section 8.1.2, respecting the autonomy of people with cognitive impairments empowers them to construct their lives based on their values and personality. This entails supporting their freedom, independence, and privacy. Although people with cognitive impairments may not be able to execute all their decisions (i.e., *agent autonomy*), they often can express their interests (i.e., *choice autonomy*), which care partners or assistive robots can consider in order to make choices that support their values [414]. The choices a person makes reflect their unique identity, personality, and lifestyle (i.e., *actual autonomy*). It is important for family members, care partners, and technology developers to support a person's choice autonomy and respect their actual autonomy longitudinally [414]. Studies suggest using personalized assistive robots can promote the autonomy of people with cognitive impairments and support person-centered care [209].

However, just as care partners may be forced to choose between respecting the autonomy or protecting the health and safety of a person with cognitive impairments, personalized assistive robots may also be forced to make this decision. This places personalized robots for people with cognitive impairments in a peculiar position where their actions (or lack thereof) may depend on how autonomy and control are distributed between themselves and the person.

Consider a scenario encountered in our prior work, told to us by a dementia care partner [316]. A person with dementia, who also has diabetes and cancer, was feeling ill, and only wanted to eat popsicles, to the point where she wanted to have more than ten each day. Even though the popsicles brought her joy, consuming too many popsicles upset her stomach and detrimentally affected her blood sugar. Care partner participants in our study suggested an assistive robot could "be the bad guy," denying the frequent popsicle requests, so that the care partner did not have to. On the one hand, offloading emotional labor from an overwhelmed care partner may be beneficent; however, the scenario raises questions regarding the autonomy of the person with dementia. A fully autonomous robot may, indeed, be configured to limit the consumption of sweets and keep the person on a strict diet to promote their wellbeing. However, situations like this can also create conflicts between the autonomy of the person with dementia and the beneficence of the care partner [414].

One approach to sharing autonomy is to always give users ultimate control of assistive robots. In the context of supporting older adults, Sharkey and Sharkey suggest this will have positive effects on a user's sense of autonomy and can reduce the risks of infringing on their privacy [407]. However, people with cognitive impairments may have impaired judgment, so respecting their autonomy may be at the cost of their own health. Furthermore, personalized robots that must wait for approval from a person with cognitive impairments before acting may be limited in their ability to protect users, such as if the robot recognizes a dangerous situation but cannot autonomously take steps to prevent it (e.g. if a person tries to reach a tall cupboard by climbing on a precarious chair [407]). Thus, it is infeasible and potentially harmful to give people with cognitive impairments full control over assistive robots.

On the other hand, assistive robots may act in opposition to or without user feedback. Sharkey and Sharkey [407] suggested that assistive robots might help people with cognitive impairments as "autonomous supervisors" to help protect their safety. This can happen by designing robots such that they autonomously take steps to prevent the dangerous situation, or restraining people with cognitive impairments from performing a potentially dangerous action. In the case of the person with dementia who loves popsicles, a personalized robot might recognize her dietary restrictions and choose to protect her health by limiting her popsicle consumption, even if doing so defies her wishes. As people with cognitive impairments often have impaired judgment abilities, a robot may be unable to obtain accurate (or any) feedback when trying to make decisions, which further raises the risk of autonomy infringement [188, 287]. However, the ethical problem here is that restraining a person with cognitive impairments to prevent potential harm could be “a slippery slope towards authoritarian robotics” [407].

Another alternative to sharing the autonomy between assistive robots and people with cognitive impairments suggests developing robot technology with the aim of having robots provide care to the older adults while considering their autonomy. This means that instead of overriding the person, the system should allow them to make decisions about their daily activities, and warn them to stop a potentially dangerous activity, if needed [207]. Including people with cognitive impairments in decision making can decrease infantilization and improve their independence [207]. So rather than just outright refusing to give the person with dementia a popsicle, the robot might try to explain why it cannot give her a popsicle right now or distract her from the topic altogether [166]. While a downside to this is that the person with dementia may not pay attention to the robot, understand the suggestions the robot is making, or simply not trust the capabilities of the robot to make reliable suggestions, a personalized CAR may be able to more effectively understand and coordinate with a person with cognitive impairments to reach a satisfactory outcome.

How a personalized robot should behave in these situations is still an open question, as each of these approaches requires considering the tradeoffs between a person’s autonomy and safety. While a personalized assistive robot will likely be forced to decide which tradeoffs to make, the ideal solution will be much more nuanced than simply adapting to a user’s preferences. However, as with human care partners, a robot will likely be expected to prioritize a person’s health and safety over their autonomy. Personalized robots may be particularly adept at distracting or redirecting a person from their potentially unsafe desire (e.g. to eat a popsicle), such as by knowing what alternatives they might like or how to change the topic of conversation. This can preserve the health of people with cognitive impairments, but it effectively restricts their autonomy. Thus, roboticists need to consider developing personalized assistive robots that suit a person’s individual personality to support their actual autonomy as well as their needs and choices to support their choice autonomy. However, when designing CARs, roboticists should be mindful of the fact that the cognitive limitations that restrict a person’s agent autonomy may also limit how they can interact with these robots.

8.2.3 Risk 3: Social Isolation

Social isolation has significant effects on the physical and mental health of people with cognitive impairments. Anxiety, boredom, depression, and lack of meaningful activities are prevalent among people with cognitive impairments living in assisted living facilities [9, 63, 174]. Given that having strong social connections has been shown to protect against various adverse health outcomes, including depression [389], it is important that the social support needs of people with cognitive impairments are considered when designing assistive technology.

In an effort to encourage social connectedness for people with cognitive impairments, care partners use technology such as robots to connect people to family members [323] and to provide companionship [231]. To better address the social support needs of a person with cognitive impairments and encourage social interactions, many researchers are exploring how to personalize these systems and tailor them to an individual's interests and capabilities. However, while personalized robots are intended to be more effective, using them in the context of cognitive impairments care may pose more risks than benefits, including preferring to interact with robots over other people, over-attachment to these robots, and the supplanting of human interaction by a robot.

A personalized assistive robot that aims to combat social isolation among people with cognitive impairments may have the unintended consequence of over-attachment. For instance, it might emulate the "perfect companion" by learning the likes and dislikes of a person. A person with cognitive impairments might find the companionship of such a robot to be preferable to another person's, so they might choose the company of these robots over other people. This problem becomes even more pronounced as people with cognitive impairments may believe they are interacting with another person when they are actually interacting with a robot (i.e., a Turing deception) [374]. While some people believe that robots can help mitigate feelings of isolation and help improve social connectedness (e.g. serving as a social facilitator, establishing virtual visits with family and friends) [407], many scholars question whether the relationship between a person with cognitive impairments and a robot can be considered meaningful or moral [338, 407, 470].

If people with cognitive impairments prefer the companionship of a robot to that of another person, there is also the risk of becoming overly attached to the robots. A personalized CAR could understand how and when a person would be receptive to social cues such as touch and eye contact in order to establish and maintain a bond with the them [467]. Over attachment can lead to distress and loss of therapeutic benefits when robots are taken away, and further exacerbate social isolation [470].

As CARs become more adept at providing care and more personalized to suit a person's individual needs, they can help relieve some care responsibilities of human care partners [470]. However, some researchers are concerned that robots that are adept at providing care to people with cognitive impairments could lead to reduced interaction between a person and care partners [470]. Furthermore, a robot that is highly personalized to a person with cognitive impairments may be able to provide comprehensive care, potentially replacing human care partners entirely [407, 470]. Care partners may also trust a personalized robot to be more proficient at providing care than a robot that is not personalized, leading them to leave the person with cognitive impairments under the care of a robot for longer periods of time, further reducing human interaction and exacerbating the potential for social isolation.

In addition to the aforementioned risks of highly personalized care robots, non-personalized (or poorly personalized) robots may also lead to social isolation, such as by causing confusion or lowering the confidence of people with cognitive impairments. For instance, a CAR that fails to appropriately adapt to a person's capabilities could cause them to lose confidence in their communicative or cognitive abilities. This can lead to anxiety or depression, and cause them to withdraw from their friends and family [17].

8.2.4 Risk 4: Vulnerability to Dark Patterns in Personalized Robotics

Conditions such as dementia gradually diminishes an individual's communication abilities and judgment, making it more difficult for them to avoid, prevent, and report deception. While some researchers believe that introducing assistive robots for care can reduce the abuse that many people with cognitive impairments experience [338], it is not a stretch to imagine a scenario where a robot could take advantage of a person, particularly if these robots follow a model similar to existing adaptive technologies (e.g. maximizing engagement, prioritizing advertising revenue over user well-being) [178].

In the field of user interface design, dark patterns are user experience (UX) and user interface (UI) interactions designed to mislead or trick users to make them do something they do not want to do. In existing technologies such as online social media, designers have been known to leverage dark patterns, or use their knowledge of human behavior and the desires of end users, to implement deceptive functionality that is not in the user's best interest [60, 162]. For instance, on social media platforms, dark patterns may be used to increase engagement with the platform, increase ad revenue, or get users to share personal information. While these behaviors are beneficial for the platform, they can be detrimental to users, as over-engagement with these media can lead to addiction, social isolation, anxiety, and depression [104, 251].

In the context of CARs that personalize their interactions based on the data collected from a person with cognitive impairments, there may be dark patterns that designers could use to take advantage of these users. Thus, as robots become more sophisticated and autonomous, it is important to research how personalized robots that collect personal information from users may be designed to leverage or exploit this data to facilitate deceptive interactions with people with cognitive impairments.

Dark patterns in robotics is a largely unexplored area. Lacey et al. [259] discuss how cuteness of robots can be a deceptive tactic that roboticists use to gather information from users. For example, Blue Frog's Buddy is an emotional robot whose marketing website states: "How not to resist to his cuteness and not want to adopt him?". Prior research has found that "cute" technology is "lovable" and fosters an affectionate relationship [153, 259]. Among people with cognitive impairments, a personalized CAR may be customized to suit a user's preferences (e.g. have a "cute" appearance or friendly personality) to gain acceptance and facilitate a bond.

However, a person with cognitive impairments may therefore more readily share sensitive information with a personalized robot, unwittingly give them access to private accounts, or be manipulated into purchasing other products from the robot's developer. Additionally, because a personalized robot could have information on the wants and needs of a person with cognitive impairments, and these users and care partners often have low technology familiarity, developers may have the power to intentionally make turning off the robot or disengaging from the robot difficult. It is important that dark patterns in the context of personalized CARs among people with cognitive impairments are further explored to avoid negative consequences for people with cognitive impairments and to hold technology creators accountable.

8.3 Additional Ethical Considerations

In addition to the risks discussed in Section 8.2, there are some additional ethical considerations when developing personalized CARs for people with cognitive impairments. These include: a) how a robot can practice beneficence to people with cognitive impairments, b) where responsibility falls should harm to a person with cognitive impairments occur because of a robot, and c) how a robot can acquire informed consent from a person with cognitive impairments. While these considerations are not necessarily unique to personalized CARs for people with cognitive impairments, it is important that roboticists keep them in mind in order to understand how these robots may impact users in real world environments. Thus, we explore each of these considerations in this section.

8.3.1 How can a robot practice beneficence toward people with cognitive impairments?

Human care partners are often very intentional with their language and actions in order to set a person with cognitive impairments up for success and practice beneficence to these people (e.g. minimizing confusion or agitation). For instance, they will purposefully phrase their sentences to be short and simple, and ask closed questions such as those that can be answered with a "yes" or "no" response. In addition, care partners will use non-verbal cues such as gestures or visual aids to help communicate with people with cognitive impairments, particularly as a person's verbal communication abilities deteriorate with the progression of the disease. This can help improve comprehension, increase their ability to respond successfully, and reduce the chances of causing frustration or confusion [103, 166].

Even so, frustrating or confusing interactions are largely inevitable, especially for people with advanced dementia. These individuals may have difficulty processing abstract language or not even recognize they have dementia (i.e., anosognosia), which can lead to reduced confidence or perceiving themselves as being "faulty". In addition, as the disease progresses and prospective memory becomes weaker, technologies that were previously helpful (e.g., reminder technologies) may become less effective and can cause tensions and frustration between a person with cognitive impairments and care partners [166]. Therefore, it is not a stretch to imagine that even the most accurately personalized CARs are likely to inadvertently cause confusing or frustrating feelings in interactions with people with cognitive impairments.

It is not uncommon for human care partners to deceive people with cognitive impairments, often coming from a place of compassion with the goal of minimizing disorientation or distress that might come along with correcting a person's perception of the world [116]. In fact, human care partners may deceive people with cognitive impairments to help improve their sense of self-agency and autonomy [49, 86, 88, 402, 470]. For instance, in our prior work [166], a professional dementia care partner told us about a person with dementia who used to be an accountant.

The professional care partner allowed her to think that she was the current accountant of their dementia caregiving organization, thereby respecting and acknowledging her domain expertise. On the other hand, many researchers argue that deceiving people in such a way is a "moral failure" because this alters the person's perception of reality and may lead them to believe a different reality than those around them [116, 396, 416, 470].

However, these experiences beg the question of whether it is appropriate for assistive robots to actively deceive people with cognitive impairments, as a human care partner might. Thus, while these robots could leverage the knowledge, background, and expertise of a person in order to respect their autonomy, whether or to what extent they (or human care partners) should deceive a person with cognitive impairments is still an open question. Some scholars argue that this deception is benign and permissible as long as it is in the best interest of a person [164, 496]. In addition, regardless of whether a person with cognitive impairments can tell if a robot's empathic response is real or not, users may still experience real feelings of comfort and companionship [97] which many argue is acceptable [87, 408]. On the other hand, some people express discomfort with the idea that people with cognitive impairments might perceive and engage with robots (even non-personalized ones) as living agents [53].

It is generally agreed that assistive robots should, whenever possible, practice nonmaleficence and not bring harm to people [125, 246, 471]. Indeed, under the beneficence principle, assistive robots should actively behave in a person's best interest. This might entail telling white lies to promote a person's dignity, provide comfort, or avoid confusion or distress [402]. But while it is possible that a personalized CAR may be more effective at practicing beneficence, they cannot necessarily avoid frustrating or confusing interactions with people with cognitive impairments. It can be difficult to avoid frustrating or confusing interactions even for human care partners, so we propose that these robots can practice beneficence by: a) taking appropriate precautions to mitigate frustrating or confusing interactions before they occur, b) taking steps to alleviate feelings of frustration or confusion should they occur (even if that means notifying a human care partner), and c) striving to ensure that these feelings are no worse than that which the person might experience with a human care partner.

8.3.2 Responsibility for harm

There has been much debate around who or what should be held responsible if a machine causes harm to a person, particularly in healthcare contexts [235, 469]. Traditionally, care providers are required to assume responsibility for the outcome of a medical intervention [468]. Historically, if a machine causes harm to a person, there is a clear entity at fault. For instance, an operator controlling a machine may be blamed if they make a mistake, or a manufacturer may take responsibility for defective hardware.

However, when considering personalized CARs for people with cognitive impairments, there are many gray areas that arise due to impaired reasoning abilities and the "responsibility gap" (i.e., the inability to trace responsibility to any particular entity due to the unpredictable nature of an autonomous robot's future behavior) [303]. With the introduction of personalized robots into caregiving, there needs to be a sense of moral, legal, and/or fiscal responsibility in order to ensure that people with cognitive impairments and other users of personalized assistive robots are safe.

There is much discussion about who should be held responsible for the actions of an autonomous robot. Some researchers suggest that the autonomous systems themselves should be held responsible [199]. However, others argue that machines cannot understand the consequences of their actions and thus hold the concept of responsibility meaningless [280]. Others argue that the manufacturers (e.g. researchers, developers, designers) should take responsibility for the robots they created, since they have a professional responsibility to follow proper ethical and professional design protocols before getting into the hands of users [280, 469].

Alternatively, others adopt antiquated views of user blaming [206], suggesting users are responsible, as they supervise and manage the robots, and they are the ones that the system is learning from [31, 469]. Elish [119] coined the term "moral crumple zone" to describe such scenarios, in which responsibility for harm caused by an autonomous agent may be misattributed to a human who in fact had little control over the agent's actions.

The responsibility gap can make it difficult to attribute responsibility for harm caused by autonomous systems [303]. Inherently, personalized assistive robots must learn to behave in ways that were not explicitly defined by a human programmer. This can lead to unpredictable robot behavior, so nobody, from the programming team to the end user, can be seen as clearly responsible for a robot's behavior. As a personalized robot learns from more people and must base its decisions on potentially conflicting information (e.g. if a person with cognitive impairments enjoys baking, but a care partner does not want them to use an oven, and a clinician suggests avoiding desserts), this can add an additional layer of complexity and uncertainty when trying to attribute responsibility for harm, should it occur.

So, how does one determine who should be held responsible in the case that a personalized robot harms a person with cognitive impairments? It is imperative that the field of autonomous systems protect users from misattributed responsibility and avoid moral crumple zones [119]. Instead, there is an increasing emphasis on "responsible robotics" which places the responsibility on the researchers and developers [469]. This requires that an organization determines ethical issues that arise from use of the robot, as well as to assign people to resolve those issues [469]. Furthermore, some researchers suggest that determining how to regulate the responsible use of these robots will require more thorough exploration and testing across populations and cultures with multidisciplinary studies and collaborations [125, 470].

8.3.3 Acquiring consent from people with cognitive impairments

Informed consent is a person's adequate comprehension and subsequent voluntary choice to participate in some event, such as a medical intervention [96]. It is important for both human and artificial agents providing healthcare services to obtain consent (or assent) from people with cognitive impairments to protect a person's wellbeing and agency. However, in the context of dementia, the problem of acquiring informed consent is difficult because it is challenging to determine whether their condition affected their capacity of giving informed consent [207], and their capacity to provide consent may change as their dementia progresses. Difficulty obtaining consent can be especially problematic for personalized health interventions such as assistive robots personalized to people with cognitive impairments, as data collection and processing are essential for a robot to learn a person's preferences.

To help address this challenge in the medical and research spaces, organizations have developed various recommendations for acquiring informed consent from people with cognitive impairments. In general, there are three ways to acquire informed consent from or on behalf of a person with cognitive impairments: (i) direct consent from a person with acceptable level of competence and cognitive capacity, (ii) proactive consent through advanced directives (i.e. externalizations of a person's wishes, decisions, and choices about future actions), or (iii) through proxy decision making (e.g. assent from a third party) [207]. Ienca et al. [207] suggest that the combination of the three may better protect the autonomy of a person with cognitive impairments. In the context of personalized robots for people with cognitive impairments, third parties (e.g. children, spouses) can help identify the aspects of an assistive robot that they would like to adjust [207].

However, there are no standard protocols for obtaining consent from people with cognitive impairments across institutions, sectors, or countries, including in the context of personalized robots for these users [189, 355]. Even the question of who is responsible for providing informed consent (the person with cognitive impairments, care partners, researchers, or another party) has no clear answer [147]. Researchers and developers across numerous communities (e.g. dementia caregiving, robotics, gerontechnology) have proposed recommendations for obtaining consent from people with cognitive impairments and have called for regulatory frameworks to standardize this process [207, 451].

In the case of personalized CARs for people with cognitive impairments, researchers recommend using an iterative model known as "ongoing consent" [208]. For instance, a robot learning to personalize its behavior to fit an individual's personality and goals should obtain consent at multiple intervals during an intervention. It should be able to answer questions or provide additional information in a clear and transparent manner (e.g. employing visual aids). A robot should also communicate with people with cognitive impairments using well-designed communication modalities suitable to the person's stage of their condition (e.g. non-verbal embodied cueing, mimicry, and music) to better convey meaning, improve self-agency, and reduce care partner burden [166]. The specific points at which a robot might provide this information and ask for consent might vary depending on the context, but it is generally agreed that a person may withdraw consent at any time, whether verbally or by expressing signs of distress [208].

In addition, as a personalized CAR further learns from a person's choices and decisions, it may be able to help clinicians with more in-depth competency assessments, by being able to provide insights into longitudinally observed behaviors. Care partners and clinicians would then have a better understanding to reprogram the robot (or remove it) as needed [256].

8.4 Key Policy Concepts

There are some key policy concepts that robot designers, law-makers, and others should keep in mind to develop safe and ethically-informed approaches for longitudinal robot-delivered health interventions, particularly those designed for people with cognitive impairments. These include a) Community care approaches to design, b) Justice and accessibility, c) Educating care partners and clinicians, and d) Promoting the agency of people with cognitive impairments (see Table 8.1). In this section, we provide a brief overview of each of these concepts and how they relate to personalized CARs for people with cognitive impairments.

8.4.1 Community care approaches to design

In order to ensure CARs will accurately address and personalize their behavior to the needs of people with cognitive impairments, robot developers should adopt community-centered care approaches to design and closely involve key stakeholders such as people with cognitive impairments, their care partners, and clinicians throughout the development process. In particular,

Table 8.1. Key policy concepts to help guide the creation of safe and ethically-informed robot-delivered health interventions, and help protect people with cognitive impairments from unintended consequences.

Policy Concept	**Description**	**Example**
Community-centered care approaches to design	In order to ensure robots can accurately address and adapt to the needs of people with cognitive impairments, robot developers must closely involve key stakeholders, including people with cognitive impairments, care partners, and clinicians throughout the development process.	User-centered design approaches and offering "whole person care."
Justice and accessibility	Roboticists should support and encourage accessibility of care robots in order to ensure that they are affordable and usable for people with cognitive impairments and their care partners.	Curb the cost of production, use affordable materials, and leverage open-source solutions. Partner with health systems to understand local community needs and barriers with regard to technology adoption.
Educating care partners and clinicians	It is important for care partners and clinicians to be educated on the potential risks of using a personalized care root in order to mitigate its potential for harm.	Provide care partners the knowledge, resources, and skills to be able to use robots to best support people with cognitive impairments through in-person education sessions and resources they can refer back to later.
Promoting the agency of people with cognitive impairments	A robot's morphology and behaviors should support the autonomy of people with cognitive impairments when possible in order to support their dignity and individuality.	Practice user-centered design, make systems intuitive and easy to control, and establish systems through which people with cognitive impairments (and/or care partners) can express their preferences.

adopting user-centered design approaches and offering "whole person care" (i.e. care that aims to improve a person's situation as a whole by addressing their social and/or behavioral needs in addition to their physical health) is essential to recognizing a user as a person and addressing their well-being as individuals beyond simply someone living with cognitive impairments [262].

Our earlier work suggests several design guidelines to contextualize new roles and behaviors for assistive robots within the person's family caregiving paradigm, including: a) relieving a care partner's emotional burden by communicating facts and information people with cognitive impairments may not want to hear or make them do things they may not want to do, b) redirect people with cognitive impairments to more positive interactions during emotionally difficult times, and c) accentuating positive shared moments [316]. Furthermore, our recent work on community-centered design for people with dementia suggests that using non-verbal, embodied action prompts as a health intervention for caregiving technology can help convey meaning, improve the sense of self of a person with dementia, and reduce the burden of care partners [166].

As researchers continue this avenue of exploration, it will be important to consider the needs and goals of the community in addition to those of individual end users, which may require closer collaborations between ethicists, engineers, and other stakeholders [166, 209]. This will help empower people with cognitive impairments and their care partners by supporting their independence and promoting their agency, as well as mitigate the risks of social isolation, objectification, and deception that personalization might cause [470].

Both Dixon et al. [113] and Guan et al. [166] suggest several methods for engaging in these research practices, such as conducting interviews, community design workshops, and family meetings. Robotics researchers have used tools including low fidelity design probes, sketches, and foam blocks to help stakeholders communicate their ideas and envision interactions with a robot during these design sessions [166, 316]. In addition, employing these methods remotely is particularly important because people with cognitive impairments and their care partners are primarily older adults, and thus at a higher risk for severe illness and death from COVID-19. Furthermore, remote studies provide the opportunity of having people in their normal home environment rather than controlled environments during the study [113], which can help provide better contextualization to researchers.

8.4.2 Justice and accessibility

There is a growing movement among the robotics and caregiving communities to support fair distribution and universal access to technologies for care [166, 207]. Nonetheless, robots that can adapt their behavior to be personalized to people with cognitive impairments may be more expensive to develop and produce than their non-personalized counterparts due to more complex hardware or software. However, due to the limited low-cost and open-source technologies currently available or in development, the adoption of personalized care technologies is likely to be limited by socio-economic factors, or even exacerbate a growing socio-economic divide [209]. This concern underlies the fact that many people with cognitive impairments may live in poverty, may not have access to broadband internet, and care partners often have low technology literacy [166]. Thus, it is crucial that those developing and deploying personalized assistive robots for caregiving consider the unique needs of this population to prioritize access.

There are many steps roboticists can take to support accessibility of these robots, which may traditionally be prohibitively expensive for people with cognitive impairments and care partners to adopt into their homes. These include curbing the cost of production, using affordable materials, and utilizing and developing open-source solutions [207]. These steps can help reduce the cost of a product for end users, or potentially make it possible for them to create their own (e.g. 3D printing hardware and downloading software). Decommodification of assistive technology for people with cognitive impairments is an alternative solution to lowering cost for users and improving the accessibility of these products (e.g. offering robots through a rental service or long-term care insurance system) [80].

In addition, roboticists across industry and academia can partner with health systems to learn more about the cost-related barriers to technology adoption and sustainment unique to the populations they serve. Such partnerships can help roboticists create robots that are more likely to be purchased by healthcare systems, rather than patients. Most healthcare systems are incentivized by payers to improve health outcomes (e.g., reducing unplanned hospital visits among home health patients [359]), which in turn incentivizes them to adopt new interventions in support of those goals.

Increasing accessibility to technology also entails ensuring it is intuitive and usable by the intended end users: people with cognitive impairments and their care partners. However, this population tends to be older adults with low technology literacy. One approach to improving usability for this population is to integrate familiar features into the design of a device, such as touch screens or verbal communication. Developers can also design technologies that are based off of or extend the functionality of existing items in a person's home, such as a smart photo frame. Leveraging aspects of objects and technologies that people may already be familiar with can improve the acceptability and usability of new technologies for people with cognitive impairments and care partners.

8.4.3 Educating care partners and clinicians

As the number and quality of robots to support people with cognitive impairments increase, so too will the number of care partners who will adopt personalized assistive robots into their caregiving routine. While these robots will ideally help alleviate their caregiving responsibilities and enable them to have more productive interactions with people with cognitive impairments, it is essential that care partners and clinicians understand how to use these robots, as well as the potential risks associated with using them. This will help ensure that stakeholders have realistic expectations of the robot's capabilities and expected impacts, as well as help them understand how to regulate responsible use of these robots. For example, it is important that care partners are aware of the possibility that the personalized behavior of these robots can lead a person to form stronger attachments with them, so care partners can recognize signs of over-attachment and know what steps to take to prevent escalation to social isolation.

To help facilitate this education, there are several approaches the robotics and caregiving communities can take, including face-to-face content delivery and providing easily accessible information that stakeholders can refer back to. Research shows that the majority of education about dementia caregiving in general is delivered in face-to-face interactions [371], so this is a natural way to teach care partners about personalized CARs as well. In fact, in our conversations with clinicians who work with people with cognitive impairments and their care partners, they recommended having an individual in-person session with stakeholders to teach them about technology before they use it. This enables roboticists to immediately answer any questions a care partner might have, show them demonstrations of the robot in a controlled environment, and help lower technical barriers to use. Berridge et al. [36] similarly recommends including people with cognitive impairments in the installation and onboarding processes of new technologies.

In addition to an in-person education session, our conversations with clinicians revealed that it is beneficial to provide important information in a form that stakeholders can easily refer back to later. For instance, developers might give stakeholders a manual that covers the main points that they should know, or print a QR code on the robot itself that links to a digital version of the information. Regardless of the form, the information should be written in common language, preferably accompanied by icons or images to improve its accessibility, as care partners often have low technology literacy [168]. Thus, they can easily find and refer back to the information if they have questions.

In addition to the many opportunities for personalized CARs to support people with cognitive impairments, robots can also be a powerful tool that support training and education for care partners and other stakeholders. Neither formal nor informal care partners receive adequate training and support to provide effective care for people with cognitive impairments [371, 379]. However, studies have shown that having this knowledge can help improve both the quality of care they can provide [7], as well as health outcomes for care partners themselves [7, 425]. Thus, it is crucial that care partners are provided the knowledge, resources, and skills to be able to use personalized CARs to best support people with cognitive impairments, while also maintaining their own health and well-being [262].

8.4.4 Promoting the agency of people with cognitive impairments

As discussed in Section 8.2.2, it is extremely important to encourage the autonomy of people with cognitive impairments when designing personalized assistive robots in order to support their dignity and individuality. There are multiple steps developers can take to help promote a person's agency, including practicing user-centered design to make systems intuitive and easy to control and establishing systems through which people with cognitive impairments (or care partners, in their place) can express their preferences.

Developing robots that are intuitive for people with cognitive impairments will help ensure that they can easily communicate their needs to the robot. This can improve their ability to modify the robot's behavior, thus promoting their agency [117]. As discussed in Section 8.4.2, intuitive interaction can be achieved by leveraging familiar features such as voice commands or touch screens, and using or alluding to common objects such as a radio as shown in Figure 8.1.2 [166]. Applying a critical dementia lens to the design of personalized robots (and care technology in general) is essential to ensuring that robots can best support stakeholder needs and interests while also preserving their agency and personhood.

In addition, developers can also promote the agency of people with cognitive impairments by establishing systems through which they can express their preferences. For example, people with cognitive impairments may provide advanced directives (i.e. specifying their desires before the onset of their condition) or consent by proxies (i.e. delegating decisions to a trusted individual such as a family member) [207]. Moreover, developers can design robotic systems that require people with cognitive impairments to be active participants in decision making. For instance, the robot can offer a variety of stimulating activities for a person and prompt them to choose. While these are not foolproof methods to understanding the wishes of a person with cognitive impairments, these approaches may be the closest that an assistive robot can get to understanding the desires of a person when they are not necessarily in a state of mind to communicate or fully reason about a decision.

8.5 Chapter Summary

Personalized robots have the potential to vastly improve whole person care for people with cognitive impairments, but it is also important to minimize the risks they might pose. The risks raised in this work are but a few potential challenges that accompany these technologies, demonstrating the need for continued and critical exploration into the potential consequences of personalizing CARs, particularly for people cognitive impairments.

Weighing the benefits and risks of behavior adaptation in this domain can help guide robot developers, policy makers, and other stakeholders as they help shape a world where robots can assist with care in homes, hospitals, and other community care settings. Moving forward, it will be essential for these stakeholders to acknowledge and address the potential risks of these technologies when developing technology, policy, and other advancements in this space. Promoting this culture of ethical awareness will be more likely to produce safe and ethically-informed personalized technologies which mitigate their risks while augmenting their benefits. We hope that our work will inspire roboticists to consider the potential risks and benefits of robot personalization, and support future ethically-focused robot design.

8.6 Acknowledgements

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Chapter 9

Conclusion

This chapter discusses the main contributions of my research to the the fields of HRI, robotics, and pervasive health. I then briefly introduce future research avenues which follow from my work, and broader open questions which will need to be addressed to enable personalized robot interactions in real-world settings. Finally, this chapter concludes with closing remarks.

9.1 Contributions

9.1.1 Identified how non-visual sensor modalities can be combined in a complementary fashion to detect human activity.

When robots are deployed to dynamic, real-world environments such as a person's home, they need to be able to perceive their surroundings. A robot must be able to reliably understand what a person is doing, how to react to it, and observe the person's response to its actions.

Many existing activity recognition systems rely on visual cameras, sometimes in conjunction with audio sensors. But in real-world environments, visual sensors are often impractical due to occlusion caused by poor lighting or dynamic objects. In addition, these sensors introduce privacy vulnerabilities when placed in spaces such as a person's home [78].

In order to enable robots to understand human activity in these privacy-sensitive environments, I identified how non-visual sensors can be combined to recognize human activity automatically (see Chapter 3). I explored the relative efficacies of two prevalent sensor modalities, motion capture camera and wearable sensors, for recognizing gross and fine motion. While both sensor modalities have proved effective for activity recognition, I aimed to discern how they might be combined in a complementary fashion to more accurately detect a wider variety of activity.

Thus, I collected a new dataset of people performing two tasks predominantly characterized by each motion type. Using this data, I employed standard classification algorithms for HAR, and found that motion capture yielded higher accuracy than wearable sensors for gross motion recognition, while the wearable sensor yielded higher accuracy for fine motion.

These findings suggest that the motion capture and wearable sensors offer complementary strengths which can be leveraged to recognize complex activities and help robots better understand human intention. Thus, depending on the types of relevant activities in the space, robots may need different kinds of sensor data, or even a combination of sensor modalities, to accurately recognize the intentions of their human counterparts.

9.1.2 Developed a new deep learning algorithm for recognizing fine-grained activity for dynamic, real world settings.

Robots can quite accurately recognize activity consisting of full-body movements such as walking or bending down. However, recognizing fine-grained motion, like hand or finger movements, is much more difficult, but imperative for accurately understanding human intention in the real world.

Thus, I explored the use of multimodal, deep learning approaches and non-visual wearable sensors to recognize fine hand and finger movements (see Chapter 3). In this work, I designed a hybrid Convolutional Neural Network Long-Short-Term Memory classifier (CNN-LSTM) which captures both convolutional and temporal features from a wearable sensor which captures both inertial and muscle activity data.

I compared this classifier to other common approaches and found that my hybrid CNN-LSTM architecture outperformed existing state-of-the-art approaches, likely due to its ability to automatically extract relevant features from raw data and leverage the temporal nature of activity data. I also found that augmenting inertial data with muscle activity yielded higher accuracy than inertial data alone, suggesting that it assisted most classifiers in categorizing tasks that involved targeted hand movements and helped discern between tasks with similar broad arm movements. However, it had a detrimental effect on the recognition of other activities, which suggests that additional modalities may confound classification on smaller or more intricate datasets.

These results underline the importance of evaluating all robotic systems on realistic data for their target environment, as it cannot be assumed that previously successful classifiers will perform well in all settings. Researchers must also carefully test the use of additional modalities to select the ones that are most effective for their tasks.

9.1.3 Developed CARMEN, a robot which delivers a cognitive intervention autonomously and longitudinally.

Home-deployed robots have great potential to fill care gaps to support the independence of people with disabilities, and extend the accessibility of health interventions to the home. However, a robot's behaviors may need to vary widely depending on the user and context in order to maximize engagement and intervention efficacy. Roboticists can leverage expertise from stakeholders who have experience working with these populations in order to build algorithms to enable robots to learn and adapt to users longitudinally.

I developed CARMEN in collaboration with neuropsychologists and people with MCI (see Chapter 4). CARMEN is a robot which delivers cognitive interventions autonomously and longitudinally to people with cognitive impairments at home. CARMEN sets the stage to extend the accessibility of healthcare interventions to the home and ultimately improve health equity.

9.1.4 Developed JESSIE, a new robotic system which enables novice programmers to program social robots.

Particularly in healthcare contexts, integrating expert and personal knowledge into a robot's behavior is essential to maintaining engagement and adherence over long periods of time, and ensuring that it is safe and appropriate for these populations. Robots can leverage domain knowledge from stakeholders such as clinicians or family members to inform what actions are most effective or appropriate.

Thus, it is critical that end users (e.g., people with disabilities), clinicians, and family members can program robots without advanced skills in robotics or programming. However, existing frameworks to support novice programmers are entirely procedural, require understanding code structure, or do not allow high-level specification of desired behavior. This can lead to unusable code or unexpected robot behavior, and must be extensively tested.

To address this problem, I developed JESSIE, a robotic system which enables novice programmers to program social robots by expressing high-level specifications and leveraging control synthesis approaches (see Chapter 5). JESSIE enables users to specify and synthesize personalized activities, reactions, and behavioral constraints. Users can therefore focus on their overarching goals, such as the training goals of a session, rather than specific implementation details.

Overall, we found that by improving the accessibility of control synthesis, our system enabled neuropsychologists to successfully program at least one interactive session for a person with MCI. My analyses also revealed additional considerations robotic systems will need to support stakeholders throughout longitudinal health interventions at home. Thus, this system enables stakeholders to imbue robots with their domain knowledge and extend the reach of their work by making control synthesis more accessible to novice programmers.

9.1.5 Proposed interaction design patterns for translating an existing clinical intervention to a robot.

Existing robot-delivered interventions illustrate the promise of using robots long-term in real-world contexts. For instance, there are numerous robot interventions to support social and academic learning, mental health, and physical rehabilitation. For people with cognitive impairments though, robots are just beginning to enter the space of delivering neurorehabilitation in the home, and they may increasingly be seen as an intervention themselves.

I explored how robots can longitudinally deliver an existing clinical intervention to people with cognitive impairments at home. Using CARMEN as a design probe, I engaged in a collaborative design research process with key stakeholders, including clinicians and people with cognitive impairments (see Chapter 6). I identified design considerations to make robots both physically and cognitively accessible to people with cognitive impairments. In addition, my analysis revealed interaction design patterns for translating clinical interventions to robots in order to maintain longitudinal engagement and maximize efficacy.

This work will guide roboticists through translating clinical interventions to robots, support their longitudinal efficacy and engagement, and ultimately extend the accessibility of longitudinal health interventions for people with cognitive impairments.

9.1.6 Defined a framework for robot-delivered health interventions with collaborative goal setting capabilities.

Collaborative goal setting can help users be more aware of the impacts they see from the intervention, and increase motivation, confidence, and self-efficacy. However, people may set unrealistic goals for their current abilities without the guidance of a clinician, which can lead to decreased motivation and engagement with the intervention if they do not see the therapeutic outcomes they expect.

Thus, I explored how robots can support collaborative goal setting at home in collaboration with clinical participants and people with MCI. I co-designed how they envision a robot supporting collaborative goal setting longitudinally at home. I implemented select robot behaviors on CARMEN, and showed these interactions to participants with MCI.

I developed a new framework for roboticists creating longitudinal, robot-delivered health interventions with collaborative goal setting capabilities (see Chapter 7). This framework comprised design considerations and concrete examples of robot behaviors for the major components of collaborative goal setting which were co-designed with clinicians and people with cognitive impairments. This includes how robots can help users set goals, measure goal progress, deliver intervention content to support transfer to the real world, and motivate people to achieve their goals.

My work lays the foundation for enabling robots to support motivation and goal achievement throughout a longitudinal intervention at home.

9.1.7 Identified ethical considerations of personalized robots for people with cognitive impairments.

CARs have great potential to support people with cognitive impairments and their care partner. Personalizing these robots to an individual's abilities and preferences can help enhance the quality of support they provide, increase usability and acceptability, and alleviate care partner burden [7, 166, 316]. However, personalization can also introduce many risks, which I explored in Chapter 8.

These risks include risks to a person's safety and autonomy, the potential to exacerbate social isolation, and risks of being taken advantage of due to dark patterns in robot design. I weighed the risks and benefits of personalization by drawing on empirical data garnered from the existing ecosystem of robots used for dementia caregiving.

I also explored ethical considerations for developing personalized CARs for people with cognitive impairments, including how a robot can practice beneficence, where responsibility falls if harm occurs to a person because of a robot, and how a robot can acquire informed consent from people with cognitive impairments. I proposed key technical and policy concepts to help robot designers, lawmakers, and others to develop personalized robots that protect users from unintended consequences, particularly for people with cognitive impairments. We hope that by promoting a culture of ethical awareness, technologists will produce safe and ethically-informed personalized systems which mitigate their risks while augmenting their benefits.

9.2 Future work

9.2.1 Learning from multiple data sources

Chapter 4 introduced CARMEN, which utilizes information such as interaction frequency and activity performance in order to learn about a person and their goals and goal progress. However, this work only scratched the surface of what robots can learn in order to safely and appropriately adapt their behavior to users, particularly people with disabilities. There are other kinds of data that robots can leverage to understand a person's state, preferences, and abilities. For example, in Chapter 3, I introduced new methods that enable robots to automatically recognize human activity using non-visual wearable sensors. This work was essential for automatically recognizing a person's physical movements and responses in privacy-sensitive environments. Robots can also leverage data communicated directly from users and other stakeholders, such as through systems like JESSIE which I introduced in Chapter 5.

In my future work, I will explore how a robot can automatically infer a person's state and appropriately adapt its behavior by leveraging data from interactions between the person and robot, external sensors, and explicit feedback from stakeholders. There are many exciting questions I plan to explore in this space to support human-centered AI and design. For instance, what data are representative of different goals and goal progress, and how can robots collect that information while respecting user privacy? How can a robot balance these different, possibly conflicting, streams of data to develop an interaction that can support a person's personal needs and health goals? These investigations are critical to developing systems that can safely and accurately support people longitudinally in privacy-sensitive environments.

9.2.2 Quantification of goals and goal progress

In Chapter 7, I introduced the first framework for enabling robots to facilitate collaborative goal setting with users during a longitudinal clinical intervention. This framework was drawn from existing clinical practice and co-designed with clinicians and people with MCI. However, measuring intervention goals and goal progress can be challenging due to the broad nature of these goals, as well as the fact that goal progress may vary widely depending on the individual person and current context.

To address this problem, clinicians recommended using self-report measures such as the Goal Attainment Scale to measure progress, motivation, and confidence in achieving goals over time [457]. This scale allows each person to set their own goals and what success means for them, based on their current and expected levels of performance. However, this approach relies on users to self-report their progress, which may not always be accurate due to bias in reporting, or misremembering past behavior.

Thus in my future work, I plan to develop quantitative representations of goals and goal progress in order to enable robots to automatically measure a person's progress using other types of data. For instance, a robot could leverage explicit data from users such as survey responses, and implicit data such as their performance on activities and interaction frequency or duration. I will explore how to combine existing clinical measures with the behaviors that a robot observes in order to provide a more accurate understanding of goal progress and enable robots to better understand their human counterparts.

9.2.3 Learning from and adapting to groups of people

The work discussed in this dissertation assumes dyadic interactions, where the robot learns from and delivers a cognitive intervention to one person. However, there are many situations where a home-deployed robot may have to interact with many people at once, such as facilitating a group activity among family members, or conveying a person's intervention goal progress to clinicians and family.

Thus, I will explore how robots can learn and interact with groups of people. Interacting with a group of people may also help a robot understand how to translate preferences shared by the group (e.g., cultural preferences, intervention goals) to individual interactions. This work will enable robots to learn and adapt to multiple people, extending their utility and acceptance, and opening their feasibility for additional applications and settings, such as senior living communities.

9.3 Open questions

9.3.1 How can robots leverage knowledge from limited previous interactions to adapt to new scenarios?

In real-world environments, robots will undoubtedly encounter scenarios they were not trained to handle, and robots may respond with unpredictable behavior that may be inappropriate for the given context. This can lead to disastrous consequences, particularly in potentially risky situations such as when interacting with people with disabilities. For example, a robot might need to provide different types of support to a person with dementia than to a person with both dementia and diabetes.

Many existing systems rely on large amounts of data (i.e. "big data") gathered from a variety of users to train machine learning algorithms which can help increase the number of previously seen scenarios [229]. However, people with disabilities are often underrepresented in these datasets, and these datasets typically lack context surrounding their conditions, so these models may not fully address the needs of these users [495]. Thus, it will be critical for robots to quickly and accurately adapt to new scenarios from a small number of interactions in order to best support people in new contexts.

In addition to these technical challenges, there are also ethical considerations that arise in the context of home-deployed robots for people with disabilities as discussed in Chapter 8. For example, robots will need to gather an adequate amount of data about a person in order to robustly exhibit personalized behavior, but it is unclear how to accomplish this without infringing on a person's privacy.

Robots may be able to transfer knowledge from interactions with previous users in order to quickly adapt to new users or contexts. However, biases and stereotypes about certain populations may be reflected in the data used to train a robot system. It will be important for robotics researchers to avoid perpetuating harmful stereotypes or causing harm to these people.

9.3.2 How can a robot continually learn and adapt its behavior to best support a person throughout an intervention?

Continuous adaptation is essential for maintaining a person's interest and engagement, which may then translate to increased adherence to and efficacy of a longitudinal intervention. While much existing research in robot learning and adaptation has focused on short-term interactions, researchers are exploring how robots can continually learn and adapt to users over long periods of time [219, 274]. The longitudinal nature of home-deployed health interventions presents unique challenges for robotics, including enabling robots to exhibit personalized behavior that evolves with the user's current context or needs.

For instance, a person's abilities may change as their condition progresses over time. In an ideal world, they will maintain their current abilities or level of independence, or even show improvement as a result of the intervention. However, it is also possible that their abilities will decline over time. A clinician may also have different goals for a robot depending on the individual and their abilities, such as for observation or intervention delivery. Thus, a robot's role may need to change throughout an intervention, for example, by providing more active or passive support.

This is a highly nuanced problem that will need to be explored thoroughly in order for robots to successfully provide appropriate support to users. Some challenges include how a robot can understand what level of support a user needs, when to switch between different roles, and what behavior is appropriate for a user in a given situation.

9.3.3 How can robots be deployed longitudinally to support people in dynamic, privacy-sensitive environments?

As researchers continue to design robots for dynamic, privacy-sensitive environments such as the home, there are many considerations to ensure these systems are safe, effective, and robust. Researchers are increasingly exploring the use of assistive robots to support people, but more work is required to understand the long-term impact of personalized cognitively assistive robots in home settings.

Long term robot deployments are notoriously complex, which reveals many open research questions with regards to developing and deploying these robots longitudinally for real world applications. These include: How can home-deployed robots and embodied AI systems be engineered to support longitudinal system reliability? How can robots be designed to maximize usability for non-technical users?

Roboticists will also need to collaborate with clinical experts and end users to evaluate the efficacy of these systems on human factors such as intervention outcomes, transfer of intervention skills to the real world, and clinician workflow. This will help contextualize these systems to home settings for the target population, and ultimately help researchers understand the technical, ethical, and social implications of these personalized robot systems.

9.4 Closing remarks

My research addresses fundamental challenges in robot design, learning, and adaptation, which are critical to enabling them to support people in dynamic, real-world environments. My work aims to transform how robots longitudinally interact with people, with the ultimate goal of enabling more safe and effective human-robot interaction, particularly for underserved populations.

As robots enter human-centered spaces, they will need to accurately and robustly adapt their behavior in ways that are safe and appropriate for an individual. Robots have great potential to improve the accessibility of key services such as healthcare and make great strides to reducing health disparities, and my work will shape how technology supports and empowers people. Throughout my Ph.D., I designed and developed algorithms and systems which enable robots to continuously learn from people in the real world.

My research opens the door for the development of socially impactful technologies which can autonomously learn from and adapt to people. It is my hope that this work encourages other robotics researchers to critically consider how these systems can safely, effectively, and ethically support people in their everyday lives.

Glossary

adaptation The ability for a system to autonomously modify its behavior to be personalized to an individual. 19

attention and concentration A cognitive domain which focuses on the ability to focus on something for a prolonged period of time. 193

behavioral interventions A health intervention that aims to alter a person's behaviors. 13

CARMEN (Cognitively Assistive Robot for Motivation and Neurorehabilitation) A robot we developed which autonomously and longitudinally delivers ME-CCT to people with MCI at home. 6

cognitive domains Areas of functioning which MCI may affect. The domains targeted by the strategies taught during ME-CCT include organization and prospective memory, attention and concentration, learning and memory, and executive functions. 13

cognitively assistive robot (CAR) Robots designed to support healthy cognitive functioning. 3

collaborative goal setting The process in which clinicians and people receiving an intervention will work together to identify and manage their goals for the intervention. It can help improve motivation, increase engagement, and set realistic expectations for the intervention. 122

compensatory cognitive training (CCT) A type of behavioral treatment that teaches metacognitive strategies to help strengthen a person's cognitive abilities to minimize the impact of

MCI on their daily life. 14

control synthesis A technique to automatically transform high-level specifications into control guaranteed to satisfy the specification. 78

convolutional neural networks (CNN) Deep learning architectures that extract convolutional features from input data. 54

dark patterns A design element that aims to deliberately manipulate users into doing something they would otherwise not do. 158

dementia A syndrome entailing noticeable cognitive decline. It can also lead to significant physical, social, and economic burden for both the person with dementia and their caregivers. There are numerous types and causes of dementia, including degenerative neurological diseases (e.g. Alzheimer's, Parkinson's) and vascular disorders (e.g. stroke). 12

design considerations Factors that may affect the requirements of a system. 104

design patterns In HRI, design patterns describe repeatable, general social and physical interactions between humans and robots which can be used for interaction design. 104

design probe An object used to engage with users and explore its use with regards to a particular question or context. 105

executive functions A cognitive domain which focuses on the ability to perform higher-level thinking tasks, such as decision-making, problem solving, and planning. 193

FLEXI The robot platform on which we based our development of CARMEN. It was originally designed by the Momentary Experience Lab at the University of Washington. 68

Goal Attainment Scale (GAS) An individualized outcome measure that enables clinicians and people receiving an intervention to set their own goals and success measures based on their current and expected levels of performance. 139

grounded theory A qualitative data analysis approach. Researchers analyze the data for codes, and iteratively categorize these codes into themes to reveal the main concepts of the data. 89

human robot interaction (HRI) A field of study focusing on the interaction between people and robots. 1

JESSIE (Just Express Specifications, Synthesize, and Interact) A robotic system we developed to enable novice programmers to program social robots by expressing high-level specifications. 79

Kuri One of the robot platforms on which we prototyped CARMEN. It was developed by Mayfield Robotics. 68

learning and memory A cognitive domain which focuses on the ability to store and retrieve information from memory. 193

linear temporal logic (LTL) A temporal logic formalism which can be used to express tasks and automatically transform them into robot behaviors. In our context, this may include specifying assumptions about the robot's environment (e.g. the state of the PwMCI) and requirements on the robot's behavior (e.g. how to react if the PwMCI is not engaged). 80

long short-term memory (LSTM) A type of recurrent neural network that extracts temporal features over time to learn long-term dependencies from input data. 54

longitudinally Across a long period of time. In the context of delivering CCT, approximately eight weeks. 2

LTLstack A tool for mapping LTL formulas to ROS nodes and executing the synthesized controller. At each time step, LTLstack reads information from the sensor nodes, finds the next state in the controller, and activates behavior nodes. 81

metacognitive strategies Methods which help people understand the way they learn. 14

mild cognitive impairment (MCI) A prodromal, or intermediate, state between normal aging and dementia. It can impact numerous areas of cognitive functioning including memory, attention, and executive functioning. Approximately 10-15% of people who experience MCI convert to some form of dementia. 6

motion capture Technology that records a person's movement. 36

neurorehabilitation Rehabilitation interventions which aim to compensate for challenges experienced due to cognitive impairment. 14

organization and prospective memory A cognitive domain which focuses on the ability to organize one's life in order to help remember to do things in the future. 193

people with MCI People diagnosed with MCI. 6

personalization Tailoring a system to an individual by considering factors such as their needs, goals, or preferences. 1

reflexive thematic analysis (RTA) A qualitative data analysis approach. RTA is a thematic analysis approach which acknowledges that researchers analyze and engage with the data through their own lens. It aims to reveal richer themes and interpretations of the data. 129

Robot Operating System (ROS) A middleware suite of software libraries which abstracts hardware to enable robot programmers to develop platform-agnostic programs. 40

social robots Robots that communicate with people using social cues such as gestures, speech, and facial expressions. 4

stakeholders People with an interest in the developed technology. In our context, these may include people with cognitive impairments, family members, and clinicians. 2

translational science The process of translating fundamental research to the real world. In our work, we explore how to translate a clinician-delivered cognitive intervention to a robot-delivered intervention at home. 105

Acronyms

***k*-NN** *k*-Nearest Neighbors. 37

ADL Activity of Daily Living. 15

ANOVA Analysis of Variance. 45

CAR Cognitively Assistive Robot. 4

CARMEN Cognitively Assistive Robot for Motivation and Neurorehabilitation. 6

CCT Compensatory Cognitive Training. 14

CNN Convolutional Neural Network. 54

FSM Finite State Machine. 29

HAR Human Activity Recognition. 36

HRI Human Robot Interaction. 1

ICC Intraclass Correlation. 43

IMU Inertial Measurement Unit. 39

IRB Institutional Review Board. 10

JESSIE Just Express Specifications, Synthesize, and Interact. 79

LDA Linear Discriminant Analysis. 37

LSTM Long Short-term Memory. 55

LTL Linear Temporal Logic. 80

MCI Mild Cognitive Impairment. 6

MIT-UCSD Massachusetts Institute of Technology - University of California San Diego. 37

RGB Red Green Blue. 24

RL Reinforcement Learning. 30

RNN Recurrent Neural Network. 34

ROS Robot Operating System. 40

RTA Reflexive Thematic Analysis. 129

sEMG Surface Electromyography. 37

SMART Specific Measurable Achievable Relevant Time-based. 122

SUS System Usability Scale. 88

SVM Support Vector Machine. 37

Bibliography

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