Toward Integrating Care Robots into Senior Living Facilities

by

Laura Margaret Stegner

A dissertation submitted in partial fulfillment of
the requirements for the degree of

Doctor of Philosophy

(Computer Sciences)

at the

UNIVERSITY OF WISCONSIN–MADISON

2025

Date of final oral examination: 05/01/2025

The dissertation is approved by the following members of the Final Oral Committee:

Bilge Mutlu, Professor, Computer Sciences
Aws Albarghouthi, Associate Professor, Computer Sciences
Tonya Roberts, Associate Professor, Nursing
Laura M. Hiatt, Research Scientist, Naval Research Laboratory
Emmanuel Senft, Research Scientist, Idiap Research Institute

For Gwenny.

ACKNOWLEDGMENTS

Despite locking myself away for the final few weeks to finish writing my dissertation, the journey I took to reach this last graduate school milestone could not have succeeded without a tremendous amount of support. I cannot accurately list each and every individual whose name deserves recognition, so I first offer my sincere thanks to everyone over the years who has offered me support, advice, encouragement, and growth opportunities that have shaped me into the whimsical researcher that I am today.

I am forever grateful for my incredible advisor, Dr. Bilge Mutlu, for all that he has done to support me over the years. I spent the three years of my master's program adamantly denying that I would continue to my PhD, and spent the next two years rejecting the notion that I would ever apply for a tenure-track faculty job. Bilge patiently and graciously gave me the space and support to find my own path. I am also extremely fortunate to have an amazingly supportive and wise committee. Thank you to Dr. Aws Albarghouthi for his especially head-scratching questions during my qualifying presentation and preliminary exam forced me to rethink and ultimately strengthen aspects of my research vision. Another thanks goes to Dr. Tonya Roberts whose deep knowledge of care practices added a whole new dimension to my work. Thank you also to Dr. Laura Hiatt who introduced me to task planning and challenged me to think critically about the unique HRI problems posed by the care domain. Lastly, thank you to Dr. Emmanuel Senft for providing invaluable mentorship and support as well as pushing me to think practically and holistically about real-world robotics deployments.

I also want to thank many mentors from my undergrad alma mater the University of Cincinnati for ultimately setting me on the path to my PhD. Dr. Tom Mantei and Dr. Jason Heikenfeld saw my potential and conspired to get me in a research settings—it must have worked out. Jason

Autry from the University Honors Program further nurtured my curiosity and reflective nature, which in hindsight has enabled me to become an effective qualitative researcher. Dr. Rupak Majumdar, Dr. Aman Mathur, Dr. Marcus Pirron, and Dr. Damien Zufferey at the Max Planck Institute for Software Systems introduced me to computer science research and in many ways set me on my path toward end-user interfaces.

My graduate studies were accented by two summer internships at the US Naval Research Laboratory. Huge thank you to everyone who mentored me during those summers: Dr. Laura Hiatt, Dr. Mark "Mak" Roberts, and Dr. David Porfirio. Special shout out to the best office mate anyone could ask for, Nhi Tran.

I am also thankful for my many supportive lab mates over the years: Hajin Lim, Arissa Sato, Emmanuel Senft, Bengisu Cagiltay, Mike Hagenow, Curt Hendrichs, Irene Ho, Yaxin Hu, Yuna Hwang, Jailey Johnson, Callie Kim, Yujin Kim, Amy Koike, Christine Lee, Nitzan Orr, David Porfirio, Pragathi Praveena, Daniel Rakita, Andrew Schoen, Mya Schroder, Dakota Sullivan, Kevin Welsh, Nathan White, Michael Xu, Mo Xu, and Olivia Zhang. It is my privilege to defend with Nathan and Bengisu as my talented cohort. Extra special thanks to David Porfirio, the best senior grad student mentor I could have asked for.

I have also been extremely fortunate to have the opportunity to mentor very talented group of undergraduates and masters students. Pedro Henrique Koeler Goulart, Yi Cheng Lee, Soft Liampisan, Yuqing Wang, Allen Chien, it was amazing to work with you all on the final iteration of my caregiving robots system! Additional thanks to Sai Akarsh Ache, Kartikeye Khanna, Mary Kristjanson, Wen Jie Lee, Shanshan Li, Emma Liu, and Zach Potter for supporting my earlier iterations of the work and for allowing me to develop my mentorship skills.

This work and my journey would not have been possible without my community partner. I will leave them anonymous for IRB purposes,

but nonetheless I am incredibly grateful to have had the opportunity to work with so many residents, caregivers, and facility staff over the years. Each study breathed new life into my work and continues to shape my understanding of how robots and technology can help people.

Finally, I would not be here today without the tremendous support of my friends and family. Kirsten Linnabary, on top of being grateful for our forever friendship that has been blossoming since third grade, I am SO looking forward to our tropical vacation once this is submitted! Puck Wen, Leah Kopke, Taylor Foster, and Mili Bhatnagar, despite never having met each other, have each propped me up on a rainy day more times than I can count. Robert, Sheri, and Connor, thank you for being my second family, and many thanks to the EWMA family for providing a steady home base to sustain my Taekwondo and fitness journeys. Rico, thank you for being my boxing coach and for fostering a truly unique and supportive community through Lion's Den Boxing Academy. Last but not least, I owe a huge thank you to my parents, Brent and Margaret, and my siblings, Alyssa and Wayne, for supporting my pursuit of higher education and for their unwavering love and support.

AUTHOR STATEMENT

The research within this dissertation was supported by National Science Foundation (NSF) award IIS-1925043, the NSF Graduate Research Fellowship Program under Grant No. DGE-1747503, the University of Wisconsin–Madison Vilas Associates Award, and a Cisco Distinguished Graduate Fellowship awarded by the University of Wisconsin–Madison. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the NSF.

The work presented within this dissertation is the author's primary work. While she served as the lead researcher, this research is ultimately the result of collaboration with the following individuals: YiCheng Lee, Soft Liampisan, Yuqing Wang, Allen Chien, Pedro Henrique Koeler Goulart, Emmanuel Senft, Tonya Roberts, and Bilge Mutlu. Individual contributions are noted where appropriate throughout the dissertation. In particular, the author acknowledges Emmanuel Senft's contribution to the work presented in Chapter 4, including the design of the methodology, collection and analysis of field data, and writing of the manuscript. The author further acknowledges the contributions of the undergraduate and masters students whom helped develop the system described in Chapter 5: YiCheng Lee (BS), set up initial database and REST API, created VRP optimization code; Pedro Henrique Koeler Goulart (MS), took over development of database and REST API, created node to trigger execution of robot tasks at assigned times; Soft Liampisan (BS), created the React frontend; Yuqing Wang (BS), programmed the Temi robot; and Allen Chien (BS), programmed the Stretch robot.

Portions of this dissertation have previously been published by the author in the following works: Stegner and Mutlu (2022) and Stegner et al. (2023). Other components will be submitted for future publication.

CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABSTRACT

Nations around the world are struggling with challenges related to an increasingly aging population coupled with a growing shortage of caregivers. Intelligent, interactive systems such as robots show great promise in helping to address this care crisis. While a wealth of research exists targeting various healthcare needs, the majority of this work focuses on short-term interactions between the care recipient and the technology and do not fully consider how care robots fit into the broader scope of day-to-day life in the facility. For the long-term, sustained use of technology to support care, we need to consider how the technology fits into the broader ecosystem, considering questions such as: who is managing it? how does it alter existing workflows and routines? what extra resources (especially time) are required? Broadening technology design to encompass these ecological aspects is necessary, but it presents a rich set of challenges for robots and other intelligent systems, such as many stakeholders with different priorities and needs, safety constraints, and highly dynamic environments. Especially considering the critical role of human relationships in care, it is imperative to develop effective ways for intelligent systems to support healthcare practices rather than replace invaluable human contact.

The goal of this dissertation is to help integrate robots into senior living facilities by considering how stakeholders such as caregivers and older adults can make use of autonomous robot capabilities to support their needs. To achieve this end, I present a design journey toward understanding how *end-user development* can support the care ecosystem and facilitate care robot integration. In this dissertation, I first present two design studies to build a case for end-user development and identify key design requirements. Building on this design work, I then present the design and evaluation of the *CareAssist* system an an exemplar end-user development tool that shows promise in helping to facilitate care robot in-

tegration. Overall, I do not suggest that end-user development is the only solution, and instead show that it is a critical component of the broader vision of safe, effective care robots.

1 INTRODUCTION

The population is aging across nations, and the number of caregivers required to provide high-quality care to this population is not keeping up with demand. For example, in the United States, the proportion of adults aged 65 and older is projected to grow from 13.1% in 2010 to 21.4% in 2050 (Pew Research Center, 2014). By 2040, however, experts also predict the United States will have an estimated shortage of 355 000 caregivers (Famakinwa, 2021), leaving some individuals without access to resources or support required for healthy aging. To address this need, researchers have focused on developing technology that can supplement care, *e.g.,* ambient assisted living (AAL) (Cicirelli et al., 2021), smart home technology (Morris et al., 2013), and robots (Abou Allaban et al., 2020).

Robots especially hold significant promise in assisting with care challenges through social capabilities (*e.g.,* Su et al., 2021; Šabanović et al., 2015), mobility (*e.g.,* Pollack et al., 2002; Schroeter et al., 2013), and ability to physically manipulate their environment (*e.g.,* Bajones et al., 2018; Odabasi et al., 2022). Prior work has investigated how robots can help with physical care tasks such as refilling water (Odabasi et al., 2022), helping with ambulation (Médéric et al., 2004), bathing (King et al., 2010), monitoring and promoting safety (Gross et al., 2015), and escorting residents to activities (Pollack et al., 2002). Overall, this impressive body of work has focused primarily on technological capabilities and specific tasks in isolation. However, despite many technical advances, adoption of robots is still limited because of a disconnect between robot platforms and meaningful interventions (Bardaro et al., 2021).

While human-robot interaction (HRI) with older adults has been widely studied, a majority of this body of work has had an isolated focus on specific facets, such as the robot's appearance (Broadbent et al., 2009), acceptance of the robot (Alaiad and Zhou, 2014), which tasks the robot should perform (Smarr et al., 2012), and technical ability to achieve the task (Odabasi et al., 2022). Other research in HRI has uncovered varying preferences in how robots should approach people (Dautenhahn et al., 2006), hand off objects (Choi et al., 2009), or engage in physical touch (Chen and Kemp, 2010). These components together contribute a wealth of knowledge toward the design and development of effective assistive robots, yet bigger-picture considerations for how these robots can fit into the existing caregiving ecosystem remain underdeveloped.

Imagine the following scenario: a care facility purchases a robot to help caregivers with their work. The robot has autonomous capabilities such as the ability to navigate, socially interact, and perform physical tasks such as making deliveries or moving items. Caregivers at the facility can assign the robot tasks to help with their work. While the robot completes its assigned tasks, the caregiver has more time for more meaningful interactions with older adults in the facility.

The above scenario presents many questions, such as how the caregivers should give tasks to the robot, how the robot should interact with older adults as it completes these tasks, how the robot can personalize interactions for each individual, what role older adults should have in making requests to the robot, and what kind of supervision the robot should have while it is operating. To answer these questions, we need to think not only of the specific task the robot is doing, but more so how the robot fits into existing workflows and lifestyles within the care facility. This zoomed-out view of robot integration as an *ecological* approach, where we consider not only individual actors and tasks but also the relationships between them and the actual environment. Little work to date has explored how autonomous robot capabilities can integrate into daily life at an ecological level in the context of caregiving.

Early work by Forlizzi and DiSalvo (2006) demonstrates the importance of ecological considerations in service robot design by examining in-home use of a simple floor-vacuuming robot. This work highlights key design challenges, such as considering the robot as a "social entity" rather than a primarily technological tool. The work further highlights that users changed their cleaning habits to adapt to the robot's limited capabilities, *e.g.,* ensuring the area the robot would vacuum is free of clutter, but that they found the overall benefit of the robot vacuum worth the behavioral modification. Highlighting key aspects of service robot design that we must consider with care robot design, this work serves as motivation for the need to consider care robot integration at an ecological lens. However, the care ecosystem is more specific and involves different stakeholders, routines, and activities than the findings discussed by Forlizzi and DiSalvo (2006). While we suggest similar ecological considerations, including how care robots are introduced and how they alter workflows, my work further expands to care-specific aspects such as medical needs of older adults and integration of multi-stakeholder perspectives.

We can glean much insight into the care ecology by considering established care theory and approaches to care. The World Health Organization (WHO) advocates for "integrated, people-centred health services," also known as *Person-Centered Care* (PCC), as the global standard for care (Sixty-Ninth World Health Assembly, 2016). PCC is an approach to care that emphasizes incorporating individual choice and autonomy into care decisions (Kogan et al., 2016). The goal of PCC is to improve the quality of care and enhance the interactions and relationships that individuals have with healthcare providers (Eklund et al., 2019). PCC has more recently seen increasing prevalence in public policy surrounding dementia care (WHO, 2017), nursing home care (Omnibus Budget Reconciliation Act, 1987), healthy and active aging (SHAPES Guidelines, 2023), end-of-life care (Fang and Tanaka, 2022), and general healthcare (Government of Canada, 2024; Australian Government Aged Care Quality and Safety Commission, 2024; EPSCO, 2023; National Health Mission, Ministry of Health

& family Welfare, Government of India, 2024). This dissertation focuses especially on senior living facilities (Kane and Wilson, 1993; Zimmerman, 2001), where the deployment of care robots is of particular relevance (Carros et al., 2022; Broadbent et al., 2009; Odabasi et al., 2022). Despite the wealth of knowledge surrounding care robot design and PCC as a care standard, there remains a gap in fitting care robots into a PCC ecosystem.

To help close this gap, I propose *end-user development* (EUD) as a critical component for care robot systems, particularly in senior living facilities. EUD is defined by Lieberman et al. (2006) as allowing end users of a system "to adapt systems at a level of complexity that is appropriate to their individual skills and situations." In the context of care robots in assisted living facilities, the end users could span a variety of individuals, including the older adult *residents* and professional *caregivers*. While each of these groups of end users is highly knowledgeable about some aspect of care needs, they are not necessarily trained developers or roboticists, and therefore require appropriately designed tools in order to make good use of care robots.

Rather than building a series of EUD tools and evaluating their fit in the care context, my dissertation presents a design journey toward understanding how EUD can support the care ecosystem and facilitate care robot integration. I first seek to understand the specific challenges and needs of caregiving in the senior living facility context, then envision what tools and systems can address these challenges. The culmination of the design journey is one instance of a tool that we designed, built, and evaluated based on one use case scenario that emerged from preliminary design sessions. This tool focuses especially on enabling professional caregivers to create and manage tasks for care robots, which requires a higher level of abstraction than what is traditionally used in EUD interfaces. As it was not feasible to explore all possible EUD applications that emerged in the early design work, I discuss other possible directions in the Chapter 6.

Overall, my work broadly seeks to help integrate robots into senior living facilities by considering how stakeholders such as caregivers and older adults can make use of autonomous robot capabilities to support their needs. By taking an ecological approach and conducting my research at a local senior living facility, I aim to help bridge the gap between robots in research settings and robots that can be used in a real world setting.

1.1 Thesis Statement

My thesis statement is as follows: **Personalization through end-user development can facilitate the integration of robots into senior living facilities.** The basis of this thesis lies in understanding the factors that make robots acceptable, usable, and useful to both caregivers and care recipients. *Personalization* refers to the depth and breadth with which these systems address individual needs, capabilities, and preferences of both caregivers and care recipients. **End-user development systems** serve as the interface between the care robot and stakeholders, *e.g.,* professional caregivers and care recipients. In this dissertation, I refer to care recipients as *residents* of the senior living facility.

This dissertation provides partial support for this thesis statement through a series of iterative, systematic studies resulting in empirically-derived design guidelines and a research-motivated end-user robotic system. I first build a case for end-user development systems in senior living facilities, then develop a potential end-user system that can help facilitate care robot integration. While there are many other factors that contribute to the adoption of care robots, including cost and technological feasibility, this dissertation focuses only on end-user development systems as a way to facilitate ecological fit of robots into existing care ecosystems. My thesis statement is further supported by a rich body of prior research on caregiving, care robots, and end-user development systems.

1.2 Methodology

To support my thesis, I employed an iterative, multi-phase approach inspired by well-established research practices such as Community-Based Participatory Research (CBPR) (Viswanathan et al., 2004) and Research through Design (RtD) (Zimmerman et al., 2007). CBPR advocates for close interaction with the communities envisioned to benefit from the research efforts, providing more robust and applicable research outputs (Viswanathan et al., 2004). While CBPR can take many forms, I followed this methodology by establishing a local community partner and engaging directly with caregivers and older adults throughout my work to inform research directions and gather feedback on concepts and prototype systems. RtD encourages iterative, hands-on engagement—interaction with research prototypes serves as the lens for understanding new research insights (Zimmerman et al., 2007). RtD became a more relevant methodology as my research advanced, as I benefited greatly from iterative and early feedback from caregivers and older adults.

The research presented in this dissertation builds iteratively off of previous chapters' findings, and consequently, the work as a whole can be viewed as one large system development effort. I first built an understanding of the caregiving ecosystem without robotic assistance, working primarily with caregivers and using ethnographically-inspired and co-design activities. This first step represented a critical entry point into understanding care practices at a level of detail suitable for robotic integration. Building off of this understanding, I worked to develop detailed use-case scenarios, specifically envisioning how the care robots would operate in day-to-day interactions. This step provided design requirements surrounding how robots should behave and what behavioral details users should be able to modify. Finally, I designed and implemented an end-user robotic system based on the use-case scenarios. This system involves a web-based application that allows users to create and manage robot tasks, two robots (each capable of performing at least one care task), and a communication node that manages the robot behaviors according to user inputs from the web app. While a full pilot deployment remains future work, I include formative feedback from demonstrations of the system.

Research Context

My work is heavily embedded in field studies where I am able to work directly with potential end users in a genuine care environment. I have partnered with a local senior living facility where older adults reside in either *independent* or *assisted* living. With *independent living* (IL), they live in private apartments and may receive minimal assistance with daily tasks such as medication management, bathing, or dressing and are otherwise independent (Perkins et al., 2004). *Assisted living* (AL), on the other hand, provides significantly more aid for everything from using the toilet to picking something up off of the floor (Kane and Wilson, 1993). In assisted living, residents have private rooms but gather in communal spaces for meals and activities.

The facility is suburban, private, not-for-profit, and it includes 85 Independent Living (IL) apartments and 60 Assisted Living (AL) apartments. The IL section is staffed with two caregivers during the day, one during the evening, and one on-call during the night. The AL section is staffed with six caregivers at all hours of the day, and one caregiver is assigned to assist ten residents. These caregivers are certified as Certified Nursing Assistants (CNA), and there are other nursing and support staff throughout the day that assist with needs outside of the scope of the caregivers.

Key Stakeholders

My research primarily engages two key stakeholder groups: professional caregivers working at the facility, whom I refer to as *caregivers*, and older adults residing at the facility, whom I refer to as *residents*. Most of my research focuses on the assisted living context, but I also work with residents and caregivers in independent living who express interest. Although many other stakeholders exist within the caregiving domain, such as family or friends of residents and other facility staff including administrators and activity coordinators (Calvaresi et al., 2017), I work primarily with caregivers and residents as they are the main stakeholders who will be in the most contact with the robot. Focusing on caregivers and residents provides a starting point for future research that should consider additional stakeholders.

Robot Platforms

I have primarily used the Stretch RE1 robot from Hello Robot (Kemp et al., 2022), shown in Figure 1.1. Stretch is a mobile manipulator robot that is 55.5 inches, or 141 cm, tall and equipped with lidar, RGB-D camera, microphone, speaker, and actuated arm with a soft gripper. Stretch can lift up to 3.3 lbs, or 1.5 kg, making it suitable to carry household items such as a small book, glass of water, cloth, market, toy, *etc.* I work with Stretch because it has manipulation capabilities, but it is also relatively small and lightweight. Therefore, it can perform simple care tasks while being able to navigate potentially tight spaces commonly found in home environments. Additionally, it is a fairly safe robot due to its low center of mass and contact sensitivity, which makes it suitable to interact with older adults.

In addition to the Stretch robot, I also used Temi (temi USA Inc., 2025) as a social robot capable of delivering simple messages and reminders to residents. Temi is a mobile social robot that is 39.4 inches, or 100 cm, tall and equipped with liar, RGB-D camera, microphone, speaker, programmable tablet, and small carrying shelf suitable to hold small household items such as a book or glass of water. Due to its simple design, low

Figure 1.1: left: Stretch RE1 mobile manipulator robot from Hello Robot. right: Temi mobile robot from temi robot inc.

center of mass, and small footprint, Temi is also relatively safe and suitable to interact with older adults. As a more social robot, Temi can be more suitable for social tasks that do not require manipulation and can provide a more friendly appearance.

1.3 Contributions

In my dissertation, I aim to show that Personalization through end-user development can facilitate the integration of robots into senior living facilities. This body of work advances our understanding of the design requirements, considerations, and potential impact of care robot integration. While there are substantial bodies of work on robots in senior living facilities and end-user development, my dissertation focuses on the unique point of intersection of these fields by highlighting how personalization through EUD tools can facilitate care robot integration. The findings and systems developed have the potential to inform future research, influence design standards, and support the deployment of care robots that are more adaptable, acceptable, and effective in enhancing quality of life for older adults and supporting caregivers. The main contributions are organized into empirical, design, methodological, and systems categories:

Empirical

These contributions include insights into human behavior and needs based on field studies, specifically understanding how the various interfaces developed can facilitate intuitive generation of acceptable robot programs within the care setting. The complete study protocols, materials, and datasets collected have been made available publicly online to the extent possible to support open science initiatives. However, some data and materials may be restricted and unable to be shared, such as videos containing identifiable information of participants. Other user study materials will be made available as subsequent publication of dissertation components.

- A breakdown of caregiver workflows, showing their typical day-to-day tasks and challenges as well as the lack of time to instruct robots using standard computer interfaces (Chapter 3);
- A better understanding of how robotic assistance can benefit caregivers in the form of a highly capable robotic "coworker" (Chapter 3);
- A better understanding of older adults' expectations and needs for robotic assistance in their day-to-day lives (Chapter 4);
- Insight into the usability, acceptance, and ecological validity of *Care-Assist* as an end-user system for personalized care robot interactions (Chapter 5).

Design

These contributions include design implications and concrete scenarios for integrating robots into senior living facilities, specifically focusing on the needs of caregivers and residents.

- A set of design implications for robotic technologies in senior living communities, including supporting caregiver work-flows, adapting to resident abilities, and providing feedback to all stakeholders of the interaction (Chapter 3);
- A set of factors outlining how residents wish to personalize their interactions with care robots, including the robot's speaking style, social interactivity, and how it completes the task (Chapter 4);
- A description of the level of abstraction for an end-user development system appropriate for caregivers in a senior living facility, developed using a *research through design* approach to refine a prototype system (Chapter 5);
- A proposed paradigm of how robots can be integrated as extensions of senior living facilities, specifically focusing on interaction dynamics such as how the robot passes from public to private areas of the facility (Chapter 5).

Methodological

This contribution includes a novel method for effectively working with older adults to design robotic interactions.

- A description of *Situated Participatory Design*, a novel participatory design (PD) method that incorporates realistic, *in situ* interactions throughout the PD process to addresses challenges of designing technologies for older adults, and we discuss *Situated Participatory*

Design, including its benefits and how it applies to other domains and technologies (Chapter 4).

Systems

This contribution includes a system and accompanying implementation of an end-user interface and robot behaviors. The system addresses the unique needs of these stakeholders within the care setting. The proposed system design and prototype code will all be made publicly available online as a resource to other researchers at the time that Chapter 5 is published as a journal or conference paper. However, the main system contribution lies in the design process and detailed description of the interaction modalities.

- The design and implementation of the *CareAssist* system, which incorporates a tablet interface, scheduling node in the form of an adapted vehicle routing problem solver, execution node to manage the robot fleet to complete the tasks, and two autonomous robots (Chapter 5).

Overall, this dissertation makes a multifaceted contribution to the field of human-robot interaction. By combining empirical studies, innovative design methods, and prototypes of robotic systems, it offers a framework for integrating robots into senior living facilities in a user-centered manner. The insights gained and tools developed not only advance our academic understanding but also lay the groundwork for practical applications that can improve the delivery of care, promote independence, and enhance the well being of older adults. Ultimately, this work underscores the importance of empowering end-users, including both caregivers and residents alike, in shaping the future of care robots. Products of this dissertation, including public datasets and open-source code, are listed in the Appendix A.

1.4 Dissertation Overview

The rest of this dissertation supports the thesis through the following five chapters: Chapter 2 provides a synthesis of relevant literature relating to caregiving, care robots, and end-user development; Chapter 3 presents a field study using ethnographic and co-design methods to understand professional caregiver needs and envision opportunities for robotic assistance; Chapter 4 presents a novel participatory design method for designing robotic interactions and case study application with residents in a senior living facility; Chapter 5 presents the iterative design and evaluation of an end-user robotic system that allows caregivers to create and manage tasks for a fleet of care robots; and Chapter 6 provides an overall discussion and conclusion for this dissertation.

2 BACKGROUND

This section includes background information about caregiving, care robots, and end-user development that motivates, inspires, and informs my dissertation.

2.1 Caregiving

This subsection provides background and context on key concepts from caregiving which contribute to my work, including a description of the care tasks which caregivers can assist; an overview of different levels of care within senior living facilities; and an introduction to person-centered care, a nursing theory which influences care practices within senior living facilities.

Care Tasks

Many people eventually require care assistance as they age (Thomas, 1996). The medical community distinguishes activities that are key to being able to live comfortable and independently, classifying them into two levels: *Activities of Daily Living* (*ADLs*) or *Instrumental Activities of Daily Living* (*IADLs*). ADLs refer to basic personal tasks such as bathing, getting dressed, using the toilet, walking, eating food, or transferring between a bed or chair (Spector and Fleishman, 1998). IADLs include activities which involve more complex thinking and planning, such as doing housework, managing medication, preparing or cleaning up from meals, shopping, and using communication devices (Spector and Fleishman, 1998).

Senior Living Facilities

When individuals are no longer able to sufficiently perform IADLs and ADLs, they may be moved to a senior living facility that supports *Independent Living* (*IL*) or *Assisted Living* (*AL*). In IL, residents are almost completely independent, living in their own private apartments. A caregiver may provide "light" assistance with IADLs and possibly ADLs such as bathing or dressing which are predicable and easy to schedule, but caregivers in IL do not assist with ADLs such as using the toilet or ambulating (Perkins et al., 2004). In AL, by contrast, residents receive significantly more care. Each resident has a private (or potentially shared) room, but residents gather in communal areas for meal service and activities. Caregivers are also available at all hours (Zimmerman, 2001) to assist with anything from getting out of bed in the morning to using the toilet (Kane and Wilson, 1993). AL differs from a nursing home as they are not licensed to provide care for individuals with severe medical and disability care requirements (Krauss, 1998).

Person-Centered Care

Person-centered care (PCC) is an approach to care that emphasizes caring for the individual beyond purely medical needs (Kogan et al., 2016). It has been used to enhance care to individuals in *long-term care* (LTC) and also to re-imagine care for persons living with dementia. LTC encompasses a variety of settings with varying levels of regulation and care services. Two major LTC settings include nursing homes, which provide skilled nursing services and assistance with daily living (Krauss, 1998), and assisted living facilities, which mainly support assistance with daily living (Kane and Wilson, 1993; Zimmerman, 2001). PCC lacks a unifying definition (Kogan et al., 2016; Morgan and Yoder, 2011). We therefore rely on review articles on PCC literature (Eklund et al., 2019; Kogan et al., 2016; Sharma et al., 2015;

Li and Porock, 2014; Morgan and Yoder, 2011) to characterize PCC based on common principles. For example, Eklund et al. (2019) identified themes from PCC articles including empathy, respect, engagement, relationship, communication, shared decision making, holistic focus, individualized focus, and coordinated care. Kogan et al. (2016) identified many similar themes, but also placed an emphasis on autonomy, self-determination, facilitating enriched relationships, as well as understanding the person, their experiences, their perspectives.

PCC Models and Frameworks

Many established models of PCC exist in LTC, such as *culture change* (Caspar et al., 2009), the *Eden Alternative* (Thomas, 1996), *Person-Centered Nursing Framework* (PCNF) (McCormack and McCance, 2010), the *Senses* framework (Watson, 2019), *VIPS* (Brooker and Latham, 2015), and the *Green House* model (Cohen et al., 2016). Different models are more prevalent in different regions—culture change is highly prevalent in the United States (U.S.), while PCNF is more widespread in areas of Europe. As care is deeply influenced by societal and cultural values, and PCC has origins in the U.S. (Rogers, 1995), PCC must be adapted to fit different cultural contexts. For example, in Latin America, the focus is more on *Family*-Centered Care due to the strong family systems (Klimesch et al., 2023).

One well-recognized model for PCC in LTC settings is *culture change* (Caspar et al., 2009). A culture change model advocates for specific steps that LTC facilities can take to shift from a more traditional medical approach toward PCC-focused practices (Caspar et al., 2009). There are some established models of culture change, *e.g.,* the Eden Alternative (Thomas, 1996) and GreenHouse (Robinson and Gallagher, 2008; Rabig et al., 2006), which present slightly different guidelines to achieve the same high-level goals. While culture change focuses on the care environment and practices, the Person-Centered Nursing Framework (PCNF) uses the lens of what characteristics a caregiver needs to deliver PCC (McCormack and McCance, 2010). PCNF considers four constructs: prerequisites or attributes of the nurse, the care environment, the care processes, and the person-centered outcomes. While this framework also includes consideration for care processes, it places a unique emphasis on the role of the caregiver and how the skills and attributes of the caregiver can impact quality of care.

Implementing PCC can take significant resources, skills, and time and as a result, LTC facilities vary in the extent to which they adopt even well-defined PCC models (Shield et al., 2014; Sterns et al., 2010). PCC outcomes, *e.g.*, resident quality of life (QOL) or family satisfaction, vary based on the degree of adoption, length of adoption, and type of practices adopted (Duan et al., 2022; Lima et al., 2020; Miller et al., 2018). Other research has shown that even across organizations that have adopted the same PCC model (*e.g.*, GreenHouse (Rabig et al., 2006)), variation can occur in the degree to which PCC practices are implemented and there is a range over which PCC practices can be minimized or maximized (Bowers et al., 2016). For example, the GreenHouse model (Rabig et al., 2006) aims to transform physical environments to focus on small-scale communities to enhance natural companionship through practices such as caregivers preparing meals directly for residents instead of catering from a centralized kitchen (Robinson and Gallagher, 2008; Rabig et al., 2006; Cohen et al., 2016). LTC facilities may have floor plans which limit their ability to fully realize GreenHouse recommendations—instead, they may opt to adopt more feasible practices such as adding home-like personal decor to create a more warm, welcoming environment around the facility (Duan et al., 2022). However, the implementation of these models, despite consistency in values, principles, and practices, can vary across organizations.

Person-Centered Care and Robotics

Although PCC does not explicitly include technology in its models and frameworks, recent literature has begun to consider the intersection of PCC and robots. For example, Carroll (2021) considers the ethics of robotics in care, suggesting that nursing theory should be used to ensure technology is used in a person-centered way. Carroll (2021) further calls nurses to action, stating that they must "partner and lead robotic innovation within healthcare in order to ensure an emphasis and ethos of nursing theoretical contributions to persons, families, and communities." Similarly, Schoenhofer et al. (2019) introduce the Dance of Living Caring, an ethical theory that seeks to maintain the central focus on caring as robotic technology advances. The Dance of Living Caring was developed to guide standards for integrating robots into care environments. Their work suggests the importance of developing actionable guidance for using PCC to inform care robot design.

Tanioka et al. (2019) offer a different approach, providing specific examples of how robots should respond to conversation to reflect PCC principles. For example, the robot should understand and respond to fluctuations in patterns, and it might say something such as, "You seem to be a little tired now, Mr. Jones. I'm going to be quiet while you rest a bit" (Tanioka et al., 2019). This work is a promising step for roboticists, but it only considers a narrow aspect of humanoid robot design.

More recently, HRI researchers have demonstrated how PCC concepts can guide robot design methods (Hsu et al., 2023; Lee et al., 2023). Hsu et al. (2023) used PCC to inform workshop activities in a study for older adults to co-design social robots. As a result, the older adult participants could more confidently "see themselves as having knowledge relevant to social robot design" (Hsu et al., 2023), leading to better engagement and insights. Similarly, Lee et al. (2023) used concepts from PCC to guide the design of interactions with a socially assistive robot for family caregivers and persons living with dementia. They found that using PCC as a guide generated design insights that could otherwise be missed, such as concerns of being considered abnormal. Our work builds upon these ideas by providing a deeper discussion of PCC and its potential to inform care robot design and use.

2.2 Care Robots

Care robots are developed to support many needs and applications, ranging from assisting with bathing (Madan et al., 2024) or lifting residents (Wright, 2018), escorting residents to activities (Pollack et al., 2002), providing medication reminders (Su et al., 2021), monitoring for accidents and falls (Eftring and Frennert, 2016), and refilling water bottles (Odabasi et al., 2022) (see review articles such as work by Sather III et al. (2021), Sawik et al. (2023), Robinson and Nejat (2022), and Khaksar et al. (2023) for a more comprehensive discussion of different care robot designs and uses). We can typically divide them into three categories, although some robots, *e.g.,* Pepper, can fit multiple categories depending on their use.

Service robots are designed with the ability to aid in care tasks such as cooking, cleaning, making deliveries, *etc*. These robots are often mobile manipulators with a variety of appearances including humanoid (*e.g.,* Care-o-Bot (Odabasi et al., 2022), PR2 (Chen et al., 2013a)), zoomorphic (*e.g.,* Lio (Mišeikis et al., 2020), Robear (Davies, 2016)), or mechanistic (*e.g.,* Stretch (Kemp et al., 2022)). In many cases, these robots are "general purpose" meaning that they aim to perform multiple tasks.

Socially assistive robots (*SARs*) (Feil-Seifer and Matarić, 2011) are designed to provide social encouragement to improve adherence to healthy habits and goals, such as exercise routines (Fasola and Matarić, 2013; Carros et al., 2020), medication reminders (Su et al., 2021), cognitive stimulation (Gasteiger et al., 2022; Luperto et al., 2019), or health precautions (Blavette et al., 2022). These robots are often designed based on the needs surrounding supporting that habit, for example, an exercise SAR (*e.g.,* work by Fasola and Matarić (2013)) may need arms to complete the exercise alongside the user.

Companion robots are designed either to engage verbally with users or support tactile interaction (*e.g.,* petting). They serve functions such as cognitive assistance, safety monitoring, or entertainment. Given their social natures, these robots are often cute or friendly in appearance. They may be designed to either move independently (*e.g.,* Pepper (Carros et al., 2020)), sit on a surface such as a table (*e.g.,* Jibo (Ostrowski et al., 2022)), or be held by the user (*e.g.,* Paro (Chen et al., 2022), AIBO (Kramer et al., 2009)).

This subsection briefly overviews the wealth of existing research on care robots, specifically considering design guidelines, implemented systems, and overall adoption and acceptance. While my dissertation primarily focuses on service robots, we can still learn quite a bit from studying design and deployment of all care robots. Even service robots have an intrinsic social presence (Forlizzi and DiSalvo, 2006), and in reality, the line between social, service, and companion robots is often blurred.

Design

Prior work has developed design guidelines and requirements for care robots using a variety of methods, including interviews (Beer et al., 2012; Law et al., 2019), ethnographies (Forlizzi et al., 2004; Pirhonen et al., 2020), focus groups (Badii et al., 2009; Michaud et al., 2010), and participatory design workshops (Lee et al., 2017; Eftring and Frennert, 2016; Šabanović et al., 2015; Winkle et al., 2018). Only a small number of design studies include use of a physical robot (*e.g.,* Lee et al., 2017; Bradwell et al., 2021; Ostrowski et al., 2021), whereas the majority use images (Broadbent et al., 2009), videos (Gasteiger et al., 2022; Beer et al., 2012), or storyboards

(Bedaf et al., 2017) to stimulate discussion. This design work typically focuses on developing robots suitable for a specific task, *e.g.*, managing depression (Lee et al., 2017), mood stabalization (Gasteiger et al., 2022), fall prevention (Eftring and Frennert, 2016), or drink delivery (Bedaf et al., 2017). More general design work by Broadbent et al. (2009) and Bradwell et al. (2021) explores the robot's appearance as well as what tasks it should perform. While the older adults are generally the primary participants, several studies have also included perspectives from other stakeholders such as caregivers (Broadbent et al., 2009, 2012) and family (Moharana et al., 2019; Berry et al., 2017). However, using current design approaches, it is difficult to capture bigger-picture considerations for care robot design, such as understanding how robots can directly support existing caregiver workflows and integrate into day-to-day life at a senior living facility.

Implementation

Perhaps an equally impressive body of prior work has built and tested care robots to perform a variety of care tasks such as bathing (King et al., 2010), escorting residents to activities (Pollack et al., 2002), providing medication reminders (Su et al., 2021), monitoring for accidents and falls (Eftring and Frennert, 2016), and refilling water bottles (Odabasi et al., 2022). These systems address a variety of physical and social needs, highlighting the potential for robots to effectively assist with a variety of ADLs and IADLs.

However, Odabasi et al. (2022) illustrate the difficulty in robot deployment. Their robot roamed a facility to identify, collect, refill, and replace empty water bottles. Despite constraints on the task such as use of a specific bottle, the robot only fully succeeded at completing four out of twenty-nine trials. As AI is rapidly advancing, the capabilities and performance of autonomous robots will also improve. Therefore, more attention will need to be placed on adoption and acceptance of care robots rather than primarily testing technological feasibility.

Adoption

Lastly with regard to care robots, several pieces of literature have discussed factors that are limiting adoption and acceptance. For example, Schroeter et al. (2013) deployed the Hector robot in private homes as a mobile smart home assistant and found that older adults wanted more control to configure robot behaviors, and informal caregivers wanted more input into what the robot was doing. Hornecker et al. (2020) conducted an ethnographic study on the current use of robotic lifts in an assisted living facility found that more emphasis should be placed on the triadic interaction between the caregiver, older adult, and robot rather than only the dyadic interaction between the older adult and robot as most prior work has emphasized. Additionally, the work of Alaiad and Zhou (2014) has identified unaddressed challenges in discrepancies between opinions of caregivers and older adults with regard to what tasks the robot should perform. Finally, Bardaro et al. (2021) discuss the lack of adoption of robots despite advances in technology, identifying that future work needs to work more closely with stakeholders to identify specific needs that care robots can address. Overall, this literature indicates that the current inclusion and consideration of various stakeholders and ecological considerations is not yet sufficient to encourage adoption and acceptance.

2.3 End-User Development

This subsection briefly introduces end-user development (EUD) and end-user programming (EUP) and overviews EUP tools for robots.

Defining EUD and EUP

As autonomous robots become more advanced, it is important to consider how non-expert *end users* can take advantage of autonomous capabilities.

Researchers have turned to EUD principles to address this need. EUD principles outline the importance of providing appropriate methods and interfaces for end users to directly create and customize software programs based on their needs and level of expertise (Lieberman et al., 2006). Lieberman et al. (2006) distinguishes between creating software programs in advance versus modifying existing software programs. *End-user programming* (*EUP*) is a subset of EUD that focuses primarily on creating software programs in advance. While EUD and EUP are both important within robotics, programming tools for human-robot interaction (HRI) tend to focus on EUP because most tools focus on the initial creation of programs (Ajaykumar et al., 2021).

EUP Tools for Robots

Many EUP tools have recently been developed to allow non-roboticists and non-programmers to create robot programs and task specifications for robots. These tools rely on methods to capture the end user's intent such as traditional keyboard-and-mouse visual programming environments (*e.g.,* Schoen et al., 2022; Alexandrova et al., 2015; Leonardi et al., 2019), demonstration (*e.g.,* Huang and Cakmak, 2017; Gao and Huang, 2019), voice-based interfaces (*e.g.,* Walker et al., 2019; Forbes et al., 2015), and, more recently, *in situ* interfaces via mixed and augmented reality (*e.g.,* Cao et al., 2019a,b). Many EUP systems are multi-modal, often pairing speech input with another modality such as demonstrations (Porfirio et al., 2021), touch (Li et al., 2019), and sketches (Correa et al., 2010; Teller et al., 2010). In an evaluation, Li et al. (2019) found that touch inputs can clarify ambiguity from speech inputs. While multi-modal input can be more intuitive and less ambiguous for end users, the majority of EUP tools for robots still require meticulous specification of sequential program steps and logic, which may not be appropriate for use in care settings.

Care-specific EUP Tools

More recently, EUP tools have been developed specifically for the care applications. Mišeikis et al. (2020) provides multiple interfaces depending on the application: an interface for users in a private home settings and an interface for caregivers in a care facility to schedule and monitor robot tasks. Datta et al. (2011) uses an EUP interface to allow users to customize medication reminders, including dosage and instructions as well as timing. An evaluation with six residents at an assisted living facility resulted in 45 interactions with the medication reminder system. Findings showed that the interface allowed caregivers to easily and successfully update the medication information, and that the older adults accepted the system. Quantitatively, the system also allowed for increased record of adverse effects and compliance measures, demonstrating that such systems can also have a positive impact outside of acceptance and usability. Providing the EUP interface was critical in allowing the caregivers to easily manage the medication robot, leading to higher utilization. This study provides a foundation supporting EUP robot tools for caregivers, although the it leaves future work for extension to other care tasks.

3 UNDERSTANDING THE CARE ECOSYSTEM AND CAREGIVER NEEDS

3.1 Chapter Introduction

This chapter serves as a foundation in understanding the care ecosystem in a senior living facility. Specifically, this work builds an understanding of caregivers' work to inform the design of care robots to support caregivers. We envisioned broadly the scenario presented in Figure 3.1, where the caregiver can assign tasks to the robot; while the robot completes the care task, the caregiver has more time for meaningful human-human interaction. However, I lacked the depth of knowledge to make informed decisions regarding how exactly this system should work: what task should the robot do? how do caregivers want to supervise the robot? would caregivers be willing to accept robotic assistance?

Prior care literature provides a thorough overview of the range of ac-

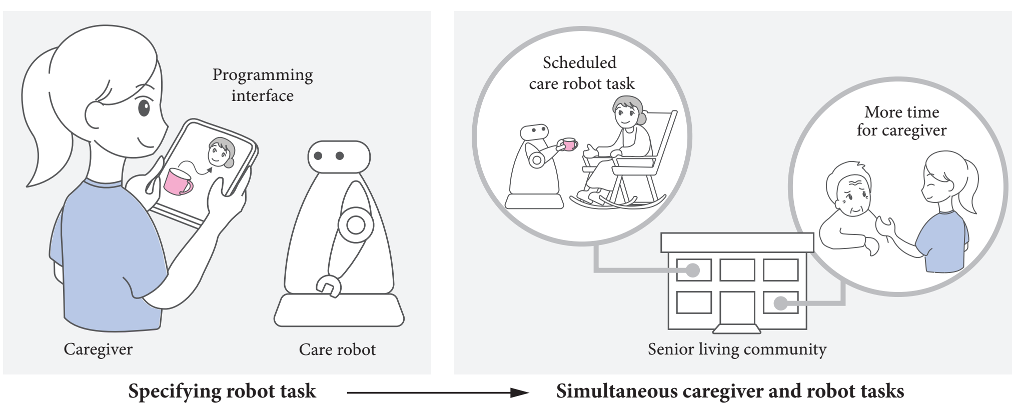


Figure 3.1: A potential scenario where a caregiver can specify routine tasks for the robot to perform. The caregiver can then engage in more meaningful interactions with residents while the robot completes more mundane tasks.

tivities that caregivers engage to support individuals in sustaining and enjoying life. In order to live independently, individuals must be self-sufficient with both *Activities of Daily Living* (*ADLs*), which include basic personal tasks such as bathing, dressing, using the toilet, eating, ambulating, or transferring to or from a bed or chair, as well as *Instrumental Activities of Daily Living* (*IADLs*), which include more complex planning and thinking such as housework, taking medication, preparing meals, shopping, and using communication devices (Spector and Fleishman, 1998). As people age, most will eventually require some form of assistance (Thomas and Applebaum, 2015). Depending on the level of care required, aging individuals may be moved into a *senior living community*, which includes facilities that support *Independent Living* (*IL*) or *Assisted Living* (*AL*). IL facilities provide "light" assistance with IADLs and possibly one or two ADLs such as dressing or bathing, but the residents are almost completely independent and do not need assistance with ADLs such as transferring, ambulating, or using the toilet (Perkins et al., 2004). For example, a resident may require assistance with managing medication and getting dressed in the morning but can otherwise perform tasks necessary to be independent. In contrast, AL offers support at all hours to assist with a range of ADLs and IADLs (Zimmerman and Sloane, 2007). Residents in AL can expect assistance with a range of activities from getting out of bed in the morning to meal preparation and cleanup as well as access to help with unscheduled needs such as using the toilet (Kane and Wilson, 1993).

A wealth of research in the last two decades has explored how autonomous (Law et al., 2021; Schaeffer and May, 1999) and teleoperated (Chen et al., 2013a; Michaud et al., 2007) robots can directly deliver care to individuals in need. This body of literature has explored the specific needs of people with disabilities or age-related challenges, such as difficulty bathing due to limited mobility (King et al., 2010), and has developed robotic solutions that can address these needs, including assisting individuals with ADLs and IADLs (Chen et al., 2013a; Luperto et al., 2019). The development of such capabilities is critical to realize the vision of care robots, but how these capabilities will be utilized by caregivers and how such robots can be integrated into day-to-day care routines and workflows remains relatively under-explored.

To determine how a robot could assist caregivers with their work and to uncover opportunities for robot design, we conducted a field study using ethnographic and co-design methods with caregivers in a senior living community. First, we observed caregivers during their shift with fly-on-the-wall observations to gain contextual insight into their tasks and workflows. Second, we conducted interviews with those caregivers to supplement the observations. The interviews also included co-design activities toward developing an understanding of the caregivers' perspectives on how a care robot could support their work. We report on our findings from an analysis of the resulting data and discuss their implications for the integration of care robots into care routines and workflows.

Our work makes the following contributions:

- A better understanding of how caregivers in AL and IL settings work, including characterizations of day-to-day routines and workflows, through the lens of robotic assistance;
- A set of design implications for robotic technologies in senior living communities, including supporting caregiver work-flows, adapting to resident abilities, and providing feedback to all stakeholders of the interaction.

3.2 Background

Tasks and needs of caregivers

Prior work in gerontology has developed a strong understanding of how caregivers should provide care to residents in senior living facilities. Training manuals (Somers and Thompson, 2008; Garrod, 2020) provide detailed guidelines on assisting individuals with ADLs and IADLs, as well as general interaction considerations such as communicating with someone with cognitive decline and preventing falls. More specialized studies have analyzed specific facets of caregiving, such as the need for personalization of care (Miller et al., 2021), importance of caregiver training (Falk-Huzar, 2017), balancing physical setting with social and organizational context (Zimmerman, 2001), creating a welcoming environment (Johnston, 2019), planning effective events (Fu et al., 2015), and creating positive family-staff relationships (Bauer and Nay, 2011). Additional work been done to develop ethics frameworks for resident-focused issues in everyday settings (Kemp et al., 2021; Powers, 2005).

While caregiving practices have been widely studied, the industry suffers from burnout (Chan et al., 2021). In an effort to better assist caregivers in their day-to-day jobs, *Ambient Assisted Living* (AAL) systems are increasingly used to help monitor residents in care facilities or at home (Rashidi and Mihailidis, 2013) using a combination of smart home sensors (Ghayvat et al., 2018) and wearable technologies (Marques, 2019). However, Offermann-van Heek et al. (2018) found that professional caregivers, particularly of disabled people, were critical of AAL systems and their designs, particularly regarding the potential for continuous monitoring equipment such as cameras and microphones to violate privacy and human dignity. Several works (Aced López et al., 2015; Zulas et al., 2012) have shown success with including caregivers in the design of these AAL systems, pointing to the need to closely consider caregiver needs and perspectives when designing these kinds of technologies.

The experience and burden of informal caregivers who care for family or friends has also been widely studied (Chen et al., 2013b; Montgomery et al., 1985; Grunfeld et al., 2004). Their burden is often considered in two classes: *objective*, meaning the tasks the caregiver must perform for the care recipient, and *subjective*, meaning the emotional toll that comes with providing the care (Jones, 1996). Montgomery et al. (1985) found that while objective burden can be eased through interventions that free the caregiver's time, subjective burden is often linked to factors such as age and income that are not easy to change. Systems such as Ambient aNnotation System (ANS) (Quintana and Favela, 2013) and CareNet Display (Consolvo et al., 2004) have been developed to ease the objective burden of informal caregivers at home. While formal and informal caregivers face different challenges with their work, they share a similar objective burden, such as through the care tasks performed and the need to monitor care recipients.

Existing care robots

Researchers have developed a number of care robots to address the needs and expectations of older and clinical populations. Systems such as Care-o-Bot (Schaeffer and May, 1999), PR2 (Chen et al., 2013a), and Hobbit (Fischinger et al., 2016) were designed to provide general assistance to care recipients, including manipulators that allow for interaction with the environment. Other work has focused on mobile robots for monitoring and promoting safety and well-being by integrating robots with smart environments and sensors (Noury, 2005; Badii et al., 2009; Gross et al., 2015; Nani et al., 2010). While these robots are mainly autonomous (Pollack et al., 2002; Graf et al., 2004; Nani et al., 2010; Dario et al., 1999; Schaeffer and May, 1999), some systems are focused on teleoperation and telepresence for a caregiver to communicate with a resident remotely (Chen et al., 2013a;

Michaud et al., 2007; Luperto et al., 2019). Commercial application of care robots has also gained support recently, with companies such as Pal Robotics,[1] F&P Robotics,[2] Diligent,[3] and Labrador[4] marketing robots gear toward general home assistance applications.

In addition to developing technical capabilities, studies of these systems have assessed their effectiveness in care task performance and care recipient perceptions. For example, Schroeter et al. (2013) deployed the Hector robot in a smart home environment to assist older adults with cognitive impairments for a period of time. While care recipients found the robot useful and enjoyable, family members expressed the desire to set up and control the robot (Schroeter et al., 2013). This study highlighted the importance of considering caregivers in addition to care recipients in care robot design.

This impressive array of systems shows the feasibility of robotic assistance in care settings and helps outline the design space for care robots. They represent significant technological advancements that address long-term care needs, with particular focus on providing effective assistance and creating positive experiences for the resident. However, results from field study deployments show that current caregiver needs are not sufficiently considered in terms of personalized care practices and integration in existing workflows.

Designing care robots with stakeholders

A sizable number of studies have aimed to develop design requirements for autonomous and teleoperated robots for care settings. These studies use methods such as participatory design sessions (Eftring and Frennert, 2016; Šabanović et al., 2015; Winkle et al., 2018), ethnographies (Forlizzi

[1] Pal Robotics: `https://pal-robotics.com/`
[2] F&P Robotics: `https://www.fp-robotics.com/`
[3] Diligent: `https://www.diligentrobots.com/`
[4] Labrador: `https://labradorsystems.com/`

et al., 2004; Pirhonen et al., 2020), interviews (Beer et al., 2012; Law et al., 2019), and focus groups (Badii et al., 2009; Michaud et al., 2010) to understand the needs of older adults living independently and to support autonomy among older adults. Other studies explored how robots can provide assistance in retirement communities and attitudes toward robots through questionnaires and interviews with residents, family, and staff (Broadbent et al., 2009, 2012). Additional studies have looked at how care robots can be used to support informal caregivers, such as family, as they manage care needs in addition to their own lives (Moharana et al., 2019; Berry et al., 2017). All of these studies show how different design approaches with various stakeholders in care robots can create a more complete understanding of care robots.

While much is known about caregiver workflows, less is known about how we can integrate care robots into their workflow successfully. Several studies have begun to examine how care robots can be integrated into care environments. For example, Bardaro et al. (2021) discussed limited adoption of care robots despite technical developments, recommending a co-design approach to identify specific needs that robots can address. Similarly, Alaiad and Zhou (2014) identified factors that affected "usage intent" and found that the caregivers and care recipients had different preferences regarding what tasks the robot should perform. Finally, Hornecker et al. (2020) conducted an ethnographic study of practices regarding a robotic lifting device in gerontological care to identify ways of better integrating robots into these care environments, recommending the consideration of *triadic* interactions involving resident, caregiver, and robot systems instead of *dyadic* interactions involving care recipients and robots. We seek to build on this work by considering more versatile robots and consider the triadic nature of these interactions in our design implications. Prior work illustrates the present need to consider how care robots fit into current caregiver workflows, rather than considering them as independent agents.

3.3 Method

To identify how caregivers might benefit from care robots, we conducted a field study using ethnographic and co-design methods at a senior living facility that offered both independent and assisted living services. We intermittently conducted onsite observations and interviews with caregivers from both care settings during August–September 2021. All study methods were reviewed and approved by an institutional review board (IRB). This study took place during the COVID-19 pandemic, which caused high rates of turnover and frequent pauses to the study due to outbreaks in the facility, thereby negatively impacting the number of participants we were able to work with. Researchers adhered to all regulations of the facility.

Research Context

We collaborated with a senior living facility, which we refer to as "facility" to protect participant confidentiality. The facility is suburban, private, not-for-profit and located in the Midwestern United States. It includes 85 Independent Living (IL) apartments and 60 Assisted Living (AL) apartments. The IL section is staffed by two caregivers during the day, one during the evening, and one on-call during the night. The AL section, has caregivers available at all hours with at least one caregiver per ten residents, which is slightly higher than typical caregiver-to-resident ratios.

Data Collection

Participants

In total, seven caregivers, aged 29–64 ($M = 50.0$, $SD = 12.9$; all female), participated in the study. This skew in participant gender is expected since the majority of healthcare workers (79–89%) are women (Argentum, 2018). Participants' caregiving experience varied between 1 month to 26 years ($M = 11.8$ years, $SD = 9.96$ years). Two participants opted out of sharing demographic and experience data. Of the seven participants, three worked in AL only, three worked in IL only, and one worked in both. Table 3.1 shows caregiver participation, which included a total of 13 sessions. Participants received a flat fee of $20 USD to be observed and $40 USD/hour to participate in interviews as compensation.

Observations

The goal of the observations was to understand caregivers' main tasks and workflows. Observations provide valuable information about the natural context and workflow structures, and they reveal "tacit knowledge" (Polanyi and Sen, 2009 [1966]) that is relevant to human-robot interaction design. To the extent that it was possible due to privacy concerns of residents, we conducted fly-on-the-wall observations in order to minimally affect the observed workflows. Because the nature of the caregiver's work involved entering the private rooms of residents, we obtained permission to observe the care interaction from each resident. If a resident declined, the researcher waited outside of the room while the caregiver assisted that

Table 3.1: Caregiver participation in study activities.

Study Session	**Participant**
AL Observation (day)	B1
AL Observation (partial pm)	AL1
AL Observation (partial pm)	AL2
IL Observation (pm)	B1
IL Observation (pm)	IL1
IL Observation (day)	IL2
IL Observation (day)	IL2
IL Observation (partial day)	IL1
Interviews	AL2, AL3, IL1, IL2, IL3

resident. During some observations, the researcher inadvertently participated in care activities, for example, by holding materials. Observations lasted for either half or all of the caregivers' normal shifts. To protect the privacy of residents, we only took field notes.

Interviews

After the observations were completed, we interviewed caregivers during separate study sessions with the goal of understanding the caregivers' view of their work and its challenges. Additionally, we gathered caregivers' ideas about how a robot might assist with their work. Interviews were semi-structured, including:

1. demographic questions about their work experience;
2. an overview of their typical day;
3. challenges they associate with their work;
4. how an untrained human assistant can help with their work;
5. their general attitude of and expectations for robots;
6. how they imagine a robot can help with their work; and
7. challenges they foresee with a robot in the care facility.

With question six, we provided participants a paper and multicolored pens and asked them to sketch what they would want a robot that helps them to look like. The sketch served as a prompt for us to ask questions regarding the robot's features, abilities, and duties. After the sketches were discussed, we then presented a set of images of robots to the caregiver, including the Stretch (Kemp et al., 2022), PR2 (Chen et al., 2013a), Talos (Stasse et al., 2017), and Lio (Mišeikis et al., 2020). We chose these particular robot images to inspire more creativity among the caregivers and selected robots with different form factors but roughly similar abilities: manipulation, mobility, vision, and hearing. Each robot image was presented individually, and the caregiver was asked to describe what the robot should do to help them. Our focus in the interviews was to understand what care robots need to do to be useful to the caregivers, so we did not discourage unrealistic beliefs about robot abilities. Instead, the researcher used their human-robot interaction knowledge to probe the caregiver about their design choices. The caregivers also asked clarification questions to the researcher to better understand the robot abilities. Each interview lasted 30–60 minutes and was conducted in a private, quiet room at the facility. We recorded audio and video data that we transcribed for analysis.

Data Analysis

Field notes and interview transcriptions were standardized and unitized in text form. We analyzed the data using applied thematic analysis following the guidelines by Boyatzis (1998) and Guest et al. (2011). From the data collection process, we were already familiar with the data prior to beginning analysis. We first identified preliminary themes by reading the data and identifying points of potential significance relating to the research objective. Then, we assigned codes to significant references and events during an iterative coding process. The codebook was modified "as new information and new insights are gained" (Guest et al., 2011).

After the codebook was finalized, we trained a secondary coder to assess inter-rater reliability (IRR). After training, the secondary coder used the code book to assign codes to 10% of the data. Reliability analysis indicated "almost perfect" reliability according to interpretation guidelines provided by Landis and Koch (1977) (Cohen's Kappa, $\kappa = 0.89$). We resolved disagreements through discussion. Once the coding and IRR analysis was complete, we revised the preliminary themes based on support from the codes and data.

To gain a better understanding of the caregiver workflows, we additionally analyzed our field notes using principles from social science framing (Lofland and Lofland, 1971). Social science framing is not a strict procedure, but instead provides considerations for how to organize qualitative data into social and temporal relationships. We used these considerations to identify significant events that shape the flow of the caregiver's shift, such as identifying regular *practices*; brief, unexpected *encounters*; and longer, unplanned *episodes*. These results are presented in the form of a reconstituted timeline of events.

3.4 Results

In our analysis, six major themes emerged about how caregivers work and what they desire from a care robot, which we group into two high-level categories for clarity. The themes are summarized in Table 3.2. For each theme, we first provide a high-level description, and then present supporting quotes from the interviews and observations. Both quotes and observations are attributed using participant ID. We made minimal edits and added annotations to the quotes to improve clarity while retaining the meaning. Study data is available via OSF.[5]

Factors that Shape Caregiving

Our study revealed a number of factors that impacted how caregivers work and what considerations they have while assisting residents. These factors come from a combination of caregiver comments in the interviews and our observations during shifts. While AL and IL care practices share many similarities, we highlight the key differences we observed between them for each factor.

[5]Study data and materials are available through the following *OSF* repository: `https://osf.io/mfkr5/?view_only=4ce32ce172e34c5eab618f654e79c4ed`

Table 3.2: A summary of the themes from our analysis.

Summary of Findings
Factors that Shape Caregiving
Theme 1: Caregiver workflows
AL and IL caregivers have scheduled tasks, but AL has an unpredictable workflow with interruptions. Time management is a common challenge.
Theme 2: Resident needs and preferences
Day-to-day interactions with residents differ based on each resident's abilities, routines, and preferences, which caregivers learn over time.
Theme 3: Communication
Caregivers actively maintain transparency with residents and communicate with each other by documenting care thoroughly.
Desired Role of the Robot
Theme 4: Providing physical support
Caregivers envision a mobile humanoid robot that performs care tasks for residents and detects hazards, such as damp materials or smoke.
Theme 5: Providing mental and emotional support
Companionship and comfort are critical to resident care. Robots should monitor residents' mental states but not provide this social support.
Theme 6: Expectations of interaction modality
Caregivers want robots to handle a mix of scheduled tasks and interruptions. Robots should be overseen by caregivers for resident safety.

Theme 1: Caregiver workflows

Our analysis shows that in terms of task predictability, AL and IL workflows differ greatly. Caregivers in both settings have assigned tasks and encounter unexpected situations that need attention. However, specific day-to-day routines vary greatly from one setting to another. The AL setting has a more unpredictable workflow than IL, as visualized in Figure 3.2 by an exemplar workflow in AL versus IL. While we expected to see such differences in workflow based on previous work that aims to classify these settings (Kane and Wilson, 1993; Zimmerman and Sloane, 2007; Perkins

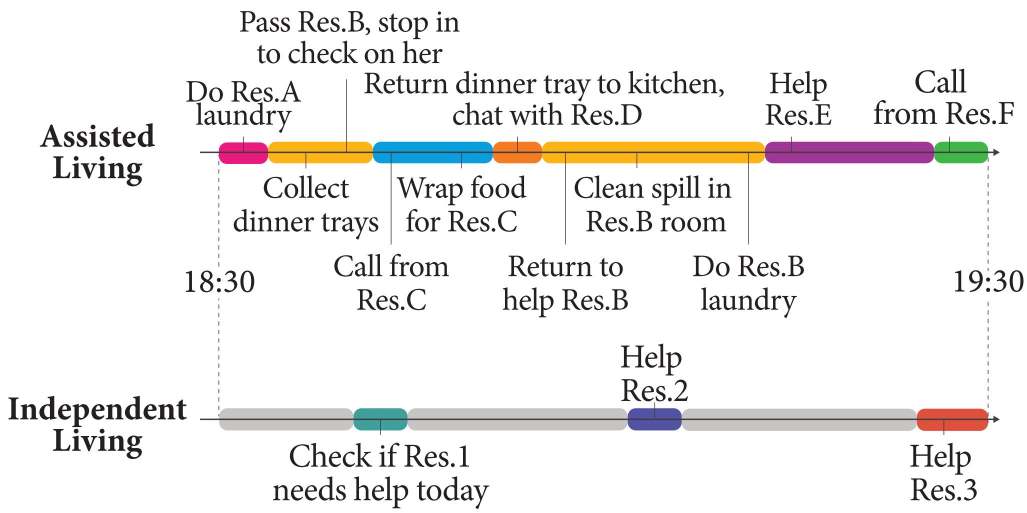


Figure 3.2: Assisted living and independent living caregivers have drastically different workflows. In AL, caregivers are constantly switching between residents in an on-demand style. IL caregivers tend to have a more fixed schedule. The colors above indicate when a caregiver is with a specific resident, and grey denotes caregiver downtime in between tasks.

et al., 2004), our work presents the opportunity for a more detailed account because of how these workflows can impact robot design.

Assisted Living. In the AL setting, caregivers encounter numerous interruptions, which require them to tend to multiple competing requests. These interruptions arise when the caregiver either observes something unexpected that they need to investigate, such as a potential hazard, or when they are paged by a resident in need of assistance. We observed that residents were often left waiting on assistance from caregivers, and that the caregivers often had to leave them mid-task due to interruptions, as shown by the timeline of field note observations in Figure 3.3.

Independent Living. The IL setting, in contrast, follows a much more structured, predictable workflow. The caregivers have scheduled times to

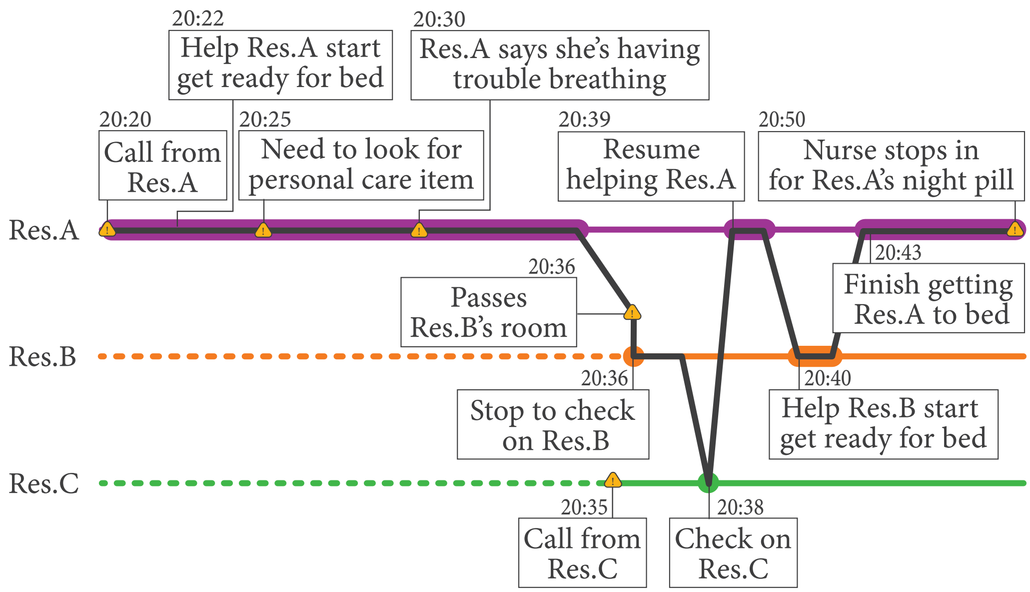


Figure 3.3: Caregivers in AL face significant interruptions in their work. One example is shown here, where the caregiver is helping Resident A get ready for bed. The black line shows the path the caregiver takes trying to help Resident A, but also assist Residents B and C. Residents can be left waiting for a caregiver to return because of their large workload.

assist residents. They "*go at different times through the day*" (IL3) to assist the resident with "*scheduled*" (IL1,IL2) daily tasks such as taking medication and getting dressed. While emergencies can demand their attention away from their scheduled work, such interruptions are "*rare*" (AL3).

Commonalities. Despite the workflow differences, all of the caregivers mentioned time management as a challenge, particularly when multiple residents need help at once. One common thread was the idea of prioritizing tasks based on urgency. The caregivers "*always prioritize the bigger things*" (AL2) such as toileting, rather than smaller tasks such as delivering ice water. They also need to respond quickly to emergency calls because they "*don't know what's going on*" (IL3); the resident could be "*bleeding* *on the floor*" (IL3) or "*really upset*" (IL1). This prioritization can cause some residents with non-urgent requests to be left waiting and potentially unhappy because "*small things are super important to them*" (AL2).

Theme 2: Resident Needs and Preferences

While at a high level, the caregivers of AL and IL have the same qualifications and training, their day-to-day interactions with the residents vary greatly between these two facilities. Prior work has emphasized the need for personalized eldercare (Miller et al., 2021), which we saw reflected in the way that caregivers addressed individual resident needs and preferences. Here, we report how this aspect needs to be approached when designing care interactions between residents and robots.

Abilities. Residents in AL required more assistance, such as toileting, transferring, and ambulating, whereas residents in IL are "*more independent, and they want to stay that way*" (IL3). They only required light physical assistance with tasks such as taking medication, bathing, or changing clothes. The range of physical and mental abilities observed among residents in AL and IL matched prior work in this space (Perkins et al., 2004; Zimmerman and Sloane, 2007).

In both AL and IL, residents can have physical deficits, such as hearing loss or low vision. The field researcher observed instances where the caregiver had to adjust her behavior to accommodate a hard-of-hearing resident. For example, it was noted from observing AL1 that "*Resident is very hard of hearing, so AL1 is talking loudly, directly in her ear.*" This kind of behavior was observed from both AL and IL caregivers. Further, residents might experience mental deficits, such as memory problems or confusion. AL3 describes how she customizes her care for residents who forget to use the call button to request assistance, saying "*There's a couple that just never ever use a call light, but you know you need to check on because they're* *compromised cognitively, and bizarre things happen, you just need to be very mindful of their well-being with their whereabouts and things like that."*

Routines. In addition to individual resident needs, both AL and IL caregivers expressed the importance of a resident's individual routine. In AL, this knowledge of routine proved useful for the caregivers when planning their shifts and understanding normal resident behaviors. For example, AL2 describes how she uses knowledge of her residents' routines to plan for bedtime, saying *''they all go to bed around the same time, and if we've been with them for long enough, we know ... the order to put them in bed."* In IL, the caregivers consider routine from the perspective of timeliness being important to the residents. If the caregiver is late, the resident will worry or potentially be upset about having to wait. IL1 highlights that *"their days can be really really long, so they're on a schedule."* The residents are *"expecting"* (IL3) the caregivers, and can be upset even if the caregiver is only *"five minutes late"* (IL1).

Preferences. Residents also have specific individual preferences, which caregivers learn over time and use to anticipate a resident's desires and to prevent them from repeating requests. However, these resident preferences are not written down anywhere, meaning that each caregiver has to learn them over time. AL2 explains this by saying, *"The kind of blankets they like to put on, and the order of it and ... how they get situated in bed ... they don't put that in ... their medical record."* IL2 echoed a similar sentiment, saying *"[The residents] have a routine, and sometimes they don't even know what the routine is until you start working together, then they figure out, 'Well I like it this way,' ... so you want to make them happy. You want to make them comfortable."*

Theme 3: Communication

Caregivers use a diverse set of communication strategies when interacting with residents and with each other. Considering these communication methods is key to allowing care robots to fit into this social environment.

Communication With Residents. The caregivers communicate directly with residents by being transparent with residents about the caregivers' actions and intentions and by listening to residents dictate to the caregivers what they want or need. When providing care, the caregiver takes additional steps to include the resident in the process. The caregiver asks permission to do tasks and informs the resident of what is being done. This transparency was observed frequently in field notes in both AL and IL. For example, when observing B1 in AL, we noted "*B1 says 'I'm gonna straighten you out, okay?' and the resident replies 'Atta girl, use your muscles.'*" and noted that "*IL2 takes the resident's temperature,* [*then*] *says it to the resident.*" Residents also took initiative to communicate with the caregivers. Particularly in AL, the residents were not shy about instructing the caregiver about how to perform certain tasks. The field notes record an instance of these instructions, noting that "*Resident gives AL2 a to-do list before bed: leave night light on, clean catheter bag, close closet door.*" While residents had call buttons that would summon a caregiver, they typically only used them for urgent or emergent situations and saved small requests to be communicated once the caregiver was present for another reason.

Communication Between Caregivers. Caregivers communicate with each other formally through an electronic charting system that allows them to track what assistance they provide to residents, as well as notes about their general health and well-being. The caregivers "*write down the ... services* [*they*] *provide,* [*and*] *anything that was out of the ordinary*" (AL3). IL3 explains the importance of these notes, saying "*because the* [*previous* *caregiver] leave[s] before I get here, so it's how we communicate. They leave me a note.*" All caregivers were observed charting during their shifts. AL caregivers typically did all of their charting at the end of the shift, whereas IL caregivers typically charted after each resident.

AL and IL caregivers had different styles of interpersonal communication. AL caregivers had much more interaction with other caregivers they would see in passing. They were observed to stop to chat briefly about a resident or general information about the facility. Since IL caregivers are not working on such a large team, they do not have these brief interactions. However, both AL and IL caregivers emphasized "*how good it is to work as a team*" (AL2). IL2 describes that she can "*call for help*" from other staff members to help her out if she is behind.

Desired Role of the Robot

Caregivers provided various insights into how a robot could assist with their work. While we noted differences between the roles of AL and IL caregivers, we did not find noteworthy differences in how they envisioned a robot assistant. They gave feedback on the physical and emotional capabilities of the robot, as well as their expectations of interaction modality. All interviewees expressed that they were open to the idea of robots assisting them, but none had experience with robots outside of seeing them in entertainment or other media. They each voiced a desire to "one-on-one meet" (IL2) a robot and "see where their limits lie" (AL3).

Theme 4: Providing Physical Support

The caregivers expressed desire for highly capable robots to perform complex physical tasks. We did not constrain their discussion to existing robot capabilities, exploring caregiver expectations for future robots.

Physical tasks. As part of the interview, caregivers were asked to sketch their vision of a care robot that could assist with their work, as shown in Figure 3.4. While the caregivers created simple drawings, these drawings prompted in-depth discussions about the envisioned robot's appearance and capabilities.

All of the caregivers drew a humanoid robot with two arms, a smiling face, and a mobile base. While they indicated two arms would be more useful, when shown images of single-arm collaborative robots, the caregivers could still see some value and use for them. IL1 explains her preference, saying "*When I say that it could do what I could do, I have two hands and arms, you know. I think it could do more, and that's why I love the ones with the two hands better.*" IL1 goes on to explain why she drew a smiling face, saying "*I would expect it to have a face, too, and a happy one, because I think we all need some happiness in our life. I don't think it should be too industrial at all.*" The caregivers in AL also described a robot that had "*the capacity to lift*" (AL3) residents, such as "*move a limb*" (AL3) or "*lifting them up ... off*

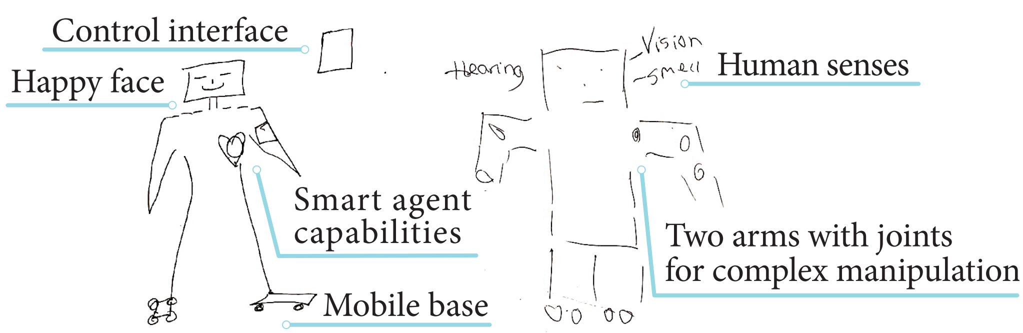


Figure 3.4: During the interviews, caregivers created sketches of how they envision a robot that could help with their work. All sketches portray highly capable robots with two arms and a mobile base. Caregivers highlighted the need for standard sensing capabilities such as vision and hearing, as well as suggesting more novel capabilities such as taste, smell, and touch. Other features included emotional intelligence, incorporation of a smart agent, and a control interface.

the toilet" (AL2). While the IL caregivers did not mention lifting residents, IL3 stated the robot could "*move a table.*" Finally, the caregivers described the desire for a "*waterproof*" (AL2) robot, enabling the robot to help with tasks such as washing dishes or bathing a resident.

Other considerations that emerged relate to the environment in which the care robot would operate. For example, the field notes report that some residents require oxygen, so they have delicate machinery set up and long oxygen tubes running through their living space. Damaging any of the tubes can cause a health hazard for the resident. Additionally, the caregivers expressed wanting a robot to "*clean up spills*" (AL2) and that "*infection control would be huge ... especially in these days with COVID*" (AL3). Finally, due to the home-like environment of the residents' rooms, caregivers state that the robot needs to be able to get "*in smaller spaces*" (AL2). Furthermore, residents often move slowly, whether it is walking or moving in a wheelchair. IL3 expressed that the robot should not "*run into the resident*" and that it "*will try to avoid things.*"

Sensing abilities. Caregivers desired robots with multiple sensory abilities, soft sound detection, and situational awareness. In addition to standard capabilities such as vision, speech, hearing, and mobility, they also mentioned less common sensing abilities, including smell to monitor the environment, taste to help with cooking, and touch to discern if a material is wet. The envisioned uses for each ability are illustrated below:

> **AL3**: [The robot has] some sort of smell in case there's a fire or smoke, or a toaster, [or] a phone charger shorting out or something.
>
> **IL1**: Let's say the robot was cooking and ... she's told the robot the recipe ... and asking the robot, "Well how does that taste? Too much salt, too much that?" [the robot will] know.

> **AL3**: With laundry, touch might be [important]. If they can sense the dampness of the clothes ... Sometimes you can't see the soiling but you can feel the dampness.

Additionally, from the field notes, we saw that when the caregiver knocks on a resident's door, the caregiver had to listen carefully to discern quiet responses from residents.

Lastly, both the field notes and interviews indicate a need for the robot to have social awareness. The field notes report that, at times, residents would stare at the caregivers to get their attention, described as "prior-to-request behaviors" in prior work (Yamazaki et al., 2007). They may not actively seek attention but more passively waiting for the caregiver to come to them.

Theme 5: Providing Mental and Emotional Support

The caregivers viewed their job as more than just the physical assistance they provide to residents in daily activities, emphasizing their role in providing mental and emotional support that residents "*need*" (IL3). In light of the importance of this social support, the caregivers questioned whether a robot should provide such social support.

Companionship. Companionship is a significant part of the caregivers' interactions with residents, and it is evident that they formed close bonds as a result of their regular interactions. IL2 notes that the residents "*look forward to seeing someone*" and that working with the residents over time is "*like being part of the family.*" Because of this bond, residents will "*open up*" (IL1) about their personal life. IL1 describes her relationship with the residents, saying "*I know a lot about them, and even sometimes when they're having problems or issues, they'll talk to me about it. And I'm just there to listen to them ... and if I can help in any way, I will.*" This bond was observed throughout all observation sessions. The caregivers were constantly engaging in small talk and personal discussions with the residents, such as a resident commenting on IL1's change of hairstyle, or a resident revealing their personal goals to B1.

Comfort. In addition to companionship, comforting the resident appeared central to the caregivers' interactions with residents. IL2 describes an instance where a resident was distraught over some maintenance issues in her apartment and needed comfort:

> **IL2**: The resident that I gave the shower to today was talking about being nervous. And I was like, "Just relax, it's okay. Take a deep breath. That's what we're here for. And if you ever need help early in the morning, I get here at 7. Call [with] your help button and I'll come in right away." So trying to make [the residents] as comfortable as possible, because this is their home. This is where they live, and so we want them to be happy.

Another way the caregivers connect with and comfort their residents is by incorporating physical touch in the day-to-day interactions with them. This observation comes from the field notes — for example, IL1 was seen using physical touch to comfort a resident.

Awareness. Specifically regarding a care robot, IL3 mentioned that the robot should be able to infer the resident's mental state, such as a resident's "*level of excitement*." This inference is important because it affects what the caregiver or robot will do next. IL3 envisions a scenario where the robot might need to adjust its plan upon seeing a distressed resident, saying "[*The robot*] *can read that* [*the resident*] *not calm so* [*the robot*] *cannot help her right now,* [*it*] *need*[*s*] *to help her to calm down first*."

Concerns. While the caregivers were “*intrigued*” (AL3) with the notion of having a robot to interact with residents, they expressed concerns about whether the robot would have that “*human factor*” (IL1) in interactions. IL1 could not imagine “*a robot to sit down and give a resident comfort*” because it “*doesn't have a beating heart.*” AL3 worried care robots could create a “*colder society,*” and stated that a care robot would have a challenging time with “*the empathy, the compassion, or friendship.*” Instead, the caregivers were more interested in a robot “*assistant*” to help them have more time to address these social needs of the residents. AL3 explains this idea saying “*If* [*robots*] *can lighten my load a little bit, and I can do more things that matter ... that's a good thing.*”

Theme 6: Expectations of Interaction Modality

Caregivers had a range of ideas about how the robot would know what to do. An idea shared among many was for the robot to be “*voice activated*” (IL1) such that caregivers could simply “*tell it what to do*” (AL2) and it would “*be able to understand and reply to questions or any demands*” (IL2). AL3 describes how she would prefer the interaction to flow, saying “*I like the idea of the robot even being able to say ‘Go check on Mrs. Jones in 307.’ Tell them 20 minutes, that I'm busy.’*” In addition to voice commands from caregivers, “*the resident would tell* [*the robot*] *what to do*” (IL1).

Programming. Another other form of interaction caregivers discussed was the ability to program the robot. Caregivers expressed interest in asking the robot to perform certain tasks or fill-in for a human caregiver as needed. AL3 caregiver expresses her vision to program the robot to check on residents throughout the day:

> **AL3**: I think would be easy to program it to do certain rounds. ... At 1:30[PM], go check for laundry. At 2:00[PM], go check [if

> personal care] products [are running low] and if they're needing anything. At 3:00[PM], just do a simple eyeball checker, you know or auditory or visual check on the resident to make sure they're okay. At 4:00[PM], set the table.

However, AL3 later added to that vision, describing a hybrid approach where the pre-programmed robot would have to handle interruptions in emergent situations:

> **AL3**: I think a lot could be programmed, but obviously I think ... the [caregiver] would be able to interject at some point. Because let's say there's six calls going and someone just fell. Then you're gonna be able to ... say "Roll back, go check in room 307 ... They were supposed to go to bed 20 minutes ago. Are they safe?" Or just notify [the resident that the caregiver is late.]

Hierarchy. When discussing commanding the robot, however, all but one of the caregivers indicated that the robot should follow a hierarchy of authority. AL3 felt that a nurse manager "*would ... need to program it,* [*as far as*] *what do we need to prioritize*" but that it should "*also be sensitive to the* [*caregivers'*] *needs as things come up.*" IL3 mentioned that perhaps the robot should not do everything it might be asked to. She provides an extreme example, saying "*I know it's gonna be hard because ... we had a resident and she said 'I want somebody to kill me' ... Imagine if you had this ... then* [*the robot is*] *not gonna do it*." AL3 and IL2 voiced that perhaps the robot would need some oversight from the caregivers when performing critical tasks that might fail or harm the residents. During mealtime, AL3 thought that "*a staff person would have to ... do a double check to make sure that there's no deviance*" from the diet that each resident should follow, such as "*low salt*" or "*thickened*" liquids. IL2 felt that in the event that the robot has “*malfunctions or something went wrong,*” the caregiver would “*stop*” the robot and “*show* [*it*] *the correct way of doing certain things.*”

3.5 Discussion

Our study seeks to understand caregiving workflows and practices and caregiver expectations of assistive care robots. Many of our results highlight a need for highly capable robots to act as a “coworker,” which aligns with results presented by Sauppé and Mutlu (2015). While we noted numerous differences in caregiving practices between AL and IL settings, AL and IL caregivers did not envision an assistive care robot differently. This lack of difference may be due to the caregivers’ lack of familiarity with the capabilities of an assistive robot or because the tasks where they need assistance from a robot across the two settings are similar. Nonetheless, the results provide valuable insights into care practices and reveal promising opportunities for future design of care robots.

While care robots hold great promise, we must consider how the introduction of these technologies will affect caregivers’ burdens. Care robots will introduce new responsibilities such as assigning tasks to the robot, troubleshooting errors, maintaining the robot, and coordinating robot use among multiple caregivers and residents. These additional demands on caregivers must be offset by care robots that can effectively ease their *objective* burden (i.e., care tasks the caregiver must perform). Care robots might also alleviate caregivers’ *subjective* burden (i.e., the emotional toll that comes with providing the care). Previous work by Wada et al. (2005) found that interacting with a socially assistive robot long-term improved residents’ moods, although similar long-term effects on caregivers are unclear. Considering both the objective and subjective burdens of caregivers will be critical to future design of care robots.

We also consider how our findings from professional caregivers relate to the needs identified by previous work in informal caregiving. Although they have different reasons, both formal and informal caregivers have limited time. Formal caregivers balance multiple residents' needs, and informal caregivers balance caregiving with their personal lives (Chen et al., 2013b). The care robots envisioned in our work could also benefit informal caregivers by relieving some of their objective burdens. Robots such as Hobbit (Bajones et al., 2018) are already being developed for in-home fall monitoring, but adding manipulation capabilities would allow a care robot to complete simple tasks (e.g., fetching food or medicine and picking items up that were dropped) without needing the informal caregiver to be present.

Current robots are not sufficiently capable for care settings, but their abailities are advancing. For example, Moxi[6] makes autonomous deliveries in hospitals. Recent work by Odabasi et al. (2022) shows that robots can perform simple tasks in care settings, while highlighting current limitations in perception, manipulation, and navigation. Although robots such as Tiago (Pages et al., 2016) can overcome some of these limitations, the ability of these bulky and expensive robots to find widespread adoption is unknown. Further, few robots are strong enough to lift humans. For example, the RIBA robot (Mukai et al., 2010) is able to lift a person, but it has not yet been widely used in care settings. Although robots have a long way to go, advancing capabilities make the vision of care robots much more within reach. It is therefore critical to inform the development of these capabilities with an understanding of how care robots fit into the workflows of caregivers to more effectively focus development efforts and to facilitate future adoption.

[6]Moxi from Diligent: `https://www.diligentrobots.com/`

Design Implications

We present a set of design implications that identify opportunities for care robots to support caregiver workflows and practices. Each implication is summarized as a guideline in Table 3.3.

Support

Caregivers envisioned care robots as *assistants* that they could assign tasks to, enabling caregivers to engage residents in more meaningful ways. Care robots must therefore support the caregivers' existing workflows and needs that we describe in Theme 1 and in Theme 2, respectively. We combine these results with the physical capabilities of robots discussed in Theme 4 and the idea of a hierarchy from Theme 6 to identify two ways that robots can support caregivers: physical capabilities of the robot and its ability to fit into a hierarchical structure.

Capabilities. Caregivers indicated that care robots should serve as their *assistants*, providing robust physical assistance and monitoring support to residents. Incorporating multiple functions and abilities into a single robot raises important considerations for physical human-robot interaction. Care machines today are only suitable for a specific task, such as lifting a person, cleaning a spill, giving a bath, or manipulating light items. Despite recent advancements in areas such as *soft robotics* (Whitesides, 2018), creating strong, multipurpose robots that are also safe for elderly residents remains a challenge.

Caregivers also expressed the importance of monitoring the resident's environment to proactively solve issues, such as detecting the dampness of a resident's chair in case they had incontinence. While not dire, these events can significantly affect the resident's quality of life. We need robots that can embody advanced sensing capabilities to create more holistic monitoring systems. One way to expand sensing capabilities is to incorpo-

Table 3.3: A summary of the design implications as guidelines for future care robot design.

Guideline	Example
Support: Capabilities	
Robots should have multiple capabilities such as physically supporting residents, manipulating items, and proactive monitoring.	A robot could lift residents in and out of bed, but also monitor for falls or other assistance that the resident needs.
Support: Control hierarchy	
Robots should report to caregiver directly and clear resident requests with caregivers prior to performing them.	If a resident asks the robot for candy, the robot should confirm with the caregiver whether it can give candy to the resident.
Customization: Caregiver-specified	
Caregivers need to be able to express their domain knowledge of resident needs and preferences to the robot.	The caregiver should be able to set wake-up times, meal times, and drink preferences for each resident.
Customization: Learned	
Robots should adapt over time from input from caregivers and interacting with residents.	If each time the robot tries to deliver water to a resident in the morning, the resident is still asleep, the robot adjusts the time it will deliver the water to after the resident wakes up.
Acceptability: Social Awareness	
Robots must be socially aware of the environment to respond appropriately to the resident's current state.	If a robot tries to deliver a snack to a resident, but that resident is expressing confusion about the robot and feeling unsafe, the robot should not simply leave the snack, but instead alert the caregiver that the resident is in need of human assistance.
Acceptability: Transparency	
Robot actions should be understandable to the resident to maintain their autonomy and be made clear to the caregiver for easy coordination and supervision.	The robot could inform residents about the actions it is performing and maintain a log of the tasks completed, so that the caregiver can verify the status of the robot's scheduled tasks.

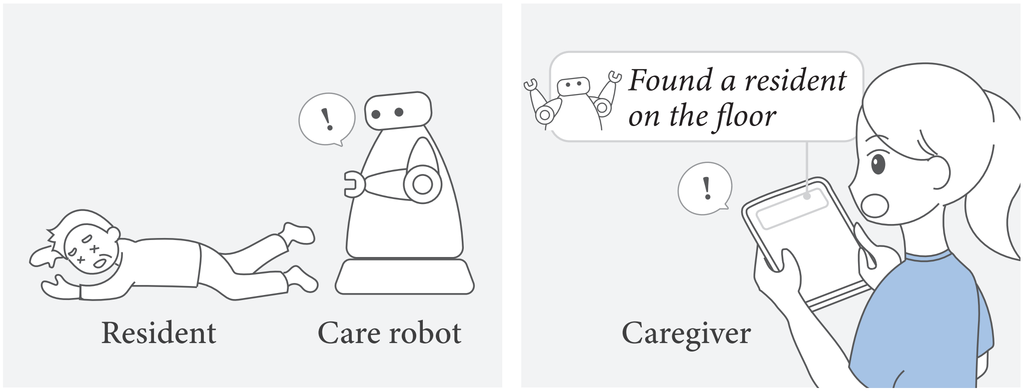


Figure 3.5: *Left:* care robot identifies a fallen resident. *Right:* care robot alerts the caregiver.

rate robots into Ambient Assisted Living (AAL) practices (Aced López et al., 2015; Zulas et al., 2012). While previous work has explored how companion robots can be connected with smart sensors in private homes (Noury, 2005; Badii et al., 2009), we must consider how robots can proactively monitor and respond to events in group living settings. For example, care robots can be used to alleviate privacy concerns that arise with constant monitoring, since a robot can check on residents periodically while otherwise not having access to the space. Figure 3.5 shows a situation where the robot is checking on a resident and finds that they have fallen, so the robot signals the caregiver to address the emergency.

Control hierarchy. Caregivers want to directly command the robot, and a few specifically mentioned concerns about to whom the robot will report and to what extend the robot should take input from residents. In the case where multiple caregivers are working at the same time, the robot needs to manage multiple directives. Does the robot "belong" to a caregiver, such that it only listens to that caregiver unless temporarily handed off to another? We imagine a case where the robot is given a scheduled routine by a "super user" (Ernst et al., 2021) but can accept on-the-fly input from other caregivers during a shift. Depending on what the robot is currently doing (idle, checking on residents, etc.) and what the caregiver has asked, the robot may adjust its schedule. An example scenario is shown in Figure 3.6, where a caregiver asks the robot to interrupt its schedule to handle an urgent task. Care robots must handle task prioritization so that they can handle input from multiple sources.

The robot should also listen to input from the residents, but the goals and priorities of the caregiver and of the resident might conflict (Hasselkus, 1991). Therefore, care robots need to manage potentially conflicting goals. Depending on the resident, overriding the caregiver's task may not be safe, such as the case of a resident who is hesitant to take medication or a diabetic resident who wants the robot to bring candy. These situations represent realistic ethical dilemmas that must be addressed. Recent research in this area includes models and proposals for integrating ethical principles into robot design (Sorell and Draper, 2014; Malle, 2016; Stowers et al., 2016; Vanderelst and Willems, 2020). One alternative defers to the caregiver — the robot will query the caregiver if the resident asks the robot

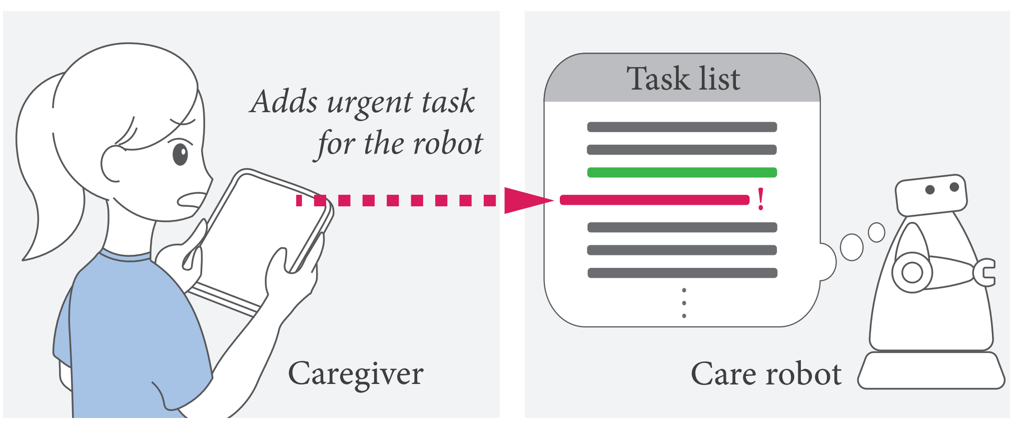


Figure 3.6: *Left:* caregiver assigns an urgent task for the care robot to complete immediately. *Right:* care robot interrupts its scheduled tasks to prioritize the caregiver's new task.

to perform actions that do not fit within the prescribed care. The robot should be designed to follow the care practices developed for the resident while respecting the resident's desire for autonomy by balancing control hierarchy and transparency. For example, if a diabetic patient asks for a piece of candy for morning snack, the robot could communicate to the resident that it has to run this request by the caregiver. The robot could also engage the caregiver in resolving the conflict between the request and the prescribed care and/or ask the caregiver for guidance on how to handle future requests by the resident. This approach maintains the robot's supporting role rather than allowing it to make decisions that could compromise resident care. Since the robot is also learning what it can do for each resident over time, the robot will slowly refine its decision-making and reduce the workload of the caregiver. However, not everything that the robot will learn will be the same. Safety-related tasks might be inflexible, whereas preference-based tasks should adapt over time. As care robots become more capable, designers need to address the complicated dynamic that can emerge between conflicting caregiver and resident goals.

Customization

A common thread summarized in Theme 2 was that each resident has individual abilities, routines, and preferences, which supports previous findings on personalizing care robots (Beer et al., 2012; Winkle et al., 2018; Law et al., 2019). For example, a resident who has trouble hearing may require the robot to be closer and louder compared to a resident who is timid and prefers the robot to be at a distance.

Caregiver-specified customization. We need care robots that can be easily customized by caregivers, such as through end-user programming. Caregivers have extensive knowledge of the individual needs of residents, making them appropriate domain experts for customizing these care robots. The caregiver should be able to customize different robot behaviors for each resident and set a schedule of tasks for the robot to do, such as the scenario presented in Figure 3.7. This recommendation is supported by results from a study by Schroeter et al. (2013), where caregivers in home settings expressed the desire to set up and control the robot. Recent applications of trigger-action programming for robots (Leonardi et al., 2019; Senft et al., 2021) can be a fruitful avenue of exploration for end-user programming of care robots. Existing autonomous care robots, such as Hobbit (Fischinger et al., 2016), use simple command interfaces that are suitable for basic interactions. Further interfaces and programming paradigms must be explored to enable care robots to follow more complex sequences of actions.

Learned customization. Care robots should also adapt to the needs and preferences of individual residents based on past interactions, such as through a combining learning techniques and formal verification. Reinforcement learning has shown promise for adapting robot social behaviors over time, particularly within the education (Gordon et al., 2016; Park et al., 2019) and service (Tseng et al., 2018; Chen et al., 2018) domains.

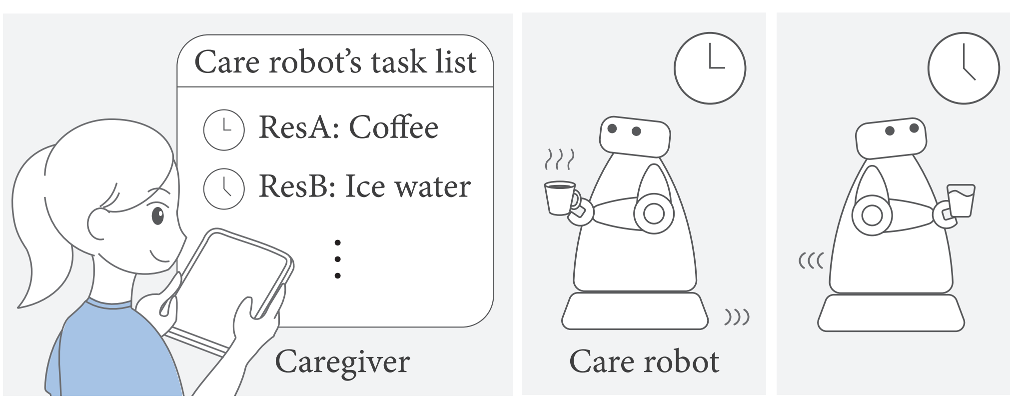


Figure 3.7: *Left:* caregiver customizes drink delivery details for two residents. *Center/Right:* care robot makes the deliveries.

Porfirio et al. (2020) additionally used formal verification to ensure that adapted programs adhere to social guidelines. Verification techniques such as model checking have also been employed in the care setting to increase the trustworthiness of autonomous service robots (Webster et al., 2016; Dixon et al., 2014; Webster et al., 2014). Care robots should learn on their own while ensuring correct and safe behaviors to ease the burden on caregivers who would otherwise have to customize them.

Acceptability

For care robots to be accepted in senior living communities, they must meet the expectations of residents and caregivers. We combine the ideas of social support from Theme 5 and the communication from Theme 3 to consider how robots can be acceptable through social awareness and promoting transparency.

Social Awareness. Caregivers emphasized the importance of social awareness because it allows them to respond appropriately to a resident's state. Upset or confused residents should be addressed differently than jovial or excited residents. Robots need to likewise respond appropriately to various resident states they encounter. As care robots are viewed as social agents to residents in senior living communities (Gross et al., 2015), introducing them to senior living communities creates a triadic interaction between the robot, caregiver, and resident. Whereas the dyadic model between resident and caregiver is clear (i.e., the resident has a need that the caregiver attends), the triadic model involving a robot is not well-developed. We recommend that the robot provides physical assistance as prescribed by the caregiver, but that it is also socially aware of the resident's state so that it can prompt the caregiver to assist when necessary. One example is shown in Figure 3.8, where the robot arrives to help the resident with a task, but the resident is upset. As a result, the robot is

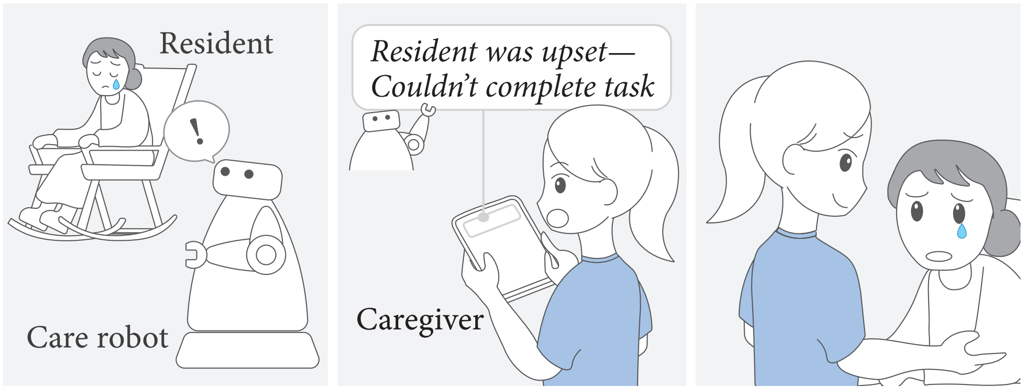


Figure 3.8: *Left:* care robot arrives to help resident, but observes that the resident is upset. *Center:* caregiver receives notification indicating that the upset resident needs assistance that the robot cannot provide. *Right:* caregiver comforts the resident while the robot completes other tasks.

unable to complete the task, so it alerts the caregiver to assist the upset resident. Although developing emotionally intelligent robots (Yan et al., 2021) and socially assistive robots (Law et al., 2019) make up a significant body of research, we must find an acceptable balance of social assistance capabilities in physically assistive care robots.

Transparency. Caregivers also maintain transparency with their actions and intentions when caring for residents, such as asking for consent before performing tasks or informing them of what is going on. Caregivers do so even if the task is straightforward or required by the caregiver (i.e., the resident cannot opt out). This interaction helps maintain resident autonomy by keeping them involved in their care. Care robots must continue to promote this transparency by embodying caregivers' transparency principles. An example scenario is shown in Figure 3.9, where the robot is sent by the caregiver to open the window and clearly communicates its intentions to the resident.

Care robots must also be transparent to the caregivers about their

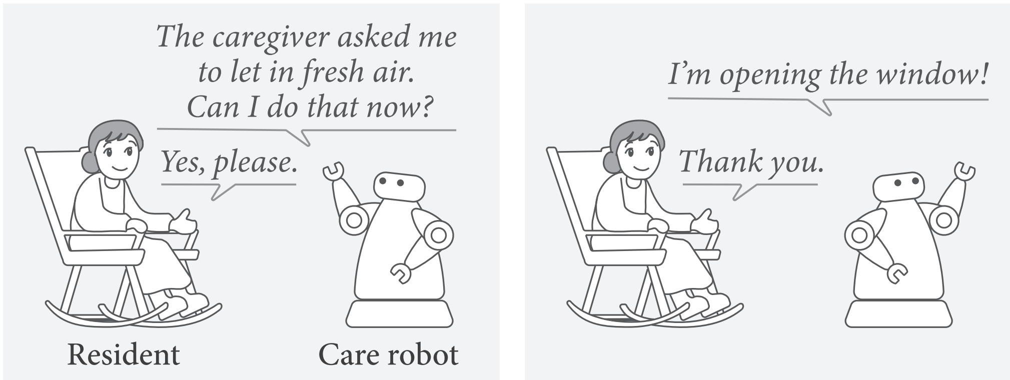


Figure 3.9: *Left:* robot arrives to help resident, and asks permission to complete the task assigned by the caregiver. *Right:* robot narrates its actions to keep the resident informed.

actions. While the robot will not deviate heavily from its instructions, it is possible for the robot to take input from multiple caregivers or residents, or to use learning techniques to automatically refine its task performance. Therefore, the robot should maintain a human-readable care log, where it tracks each task and learned adaptations. To enable caregivers to stay up-to-date with a robot's autonomy and check that a robot is not learning undesirable behaviors, we can draw from *explainable artificial intelligence* (XAI) (Gunning et al., 2019) to promote transparency and trustworthiness in the robot's automated learning approaches.

Limitations and Future Work

While our findings offer insights into how caregivers might use care robots in AL and IL settings, our study has two key limitations that must be addressed in future work. First, we only consider a small number of caregivers from one care facility and do not include perspectives from residents, their families, or non-caregiving facility staff or from stakeholders at other care facilities. Future work should expand on this preliminary study and seek to include more stakeholders and to understand how caregiver practices, workflows, and expectations vary across care facilities. While the skew in participant population (all female) was expected since the majority of professional caregivers are women (Argentum, 2018), it does not account for the minority perspective of men. Future work should consider how the needs and perspectives of other types of caregivers and minorities differ. Second, caregivers reflected on usage opportunities for robots based on images shown by the researcher but indicated that they must see and use the robots in person to provide more concrete ideas. Future work will be required to involve co-design sessions where caregivers experience controlling, programming, and interacting with one or more care robots to better understand their capabilities and limitations.

3.6 Chapter Summary

In this chapter, we sought to understand current caregiving practices at a senior living facility and envision how care robots could be designed to better assist caregivers with their work Stegner and Mutlu (2022). In a two-part field study at a local senior living facility, we first observed caregivers during their shifts and then interviewed them about how they envisioned their ideal robot assistant. During fly-on-the-wall observations, we shadowed caregivers during their shifts to gain insight into the context of their work and understand the typical flow during a shift. Then, during follow-up interviews, we asked caregivers about the challenges of their work. They were also given paper and markers and asked to draw what they would want a robotic assistant to look like. We used this drawing as a starting point to discuss how a robot might be able to assist with their work. During this design activity, we did not limit participants to existing robots because we wanted to envision future opportunities.

The observations provided significant insight into caregiver workflows and practices, particularly highlighting the differences between assisted living (AL) and independent living (IL). Caregivers in both settings had a schedule of pre-determined care tasks, such as bathing or helping a resident prepare for bed. In IL, caregivers often had periods of downtime in between these schedule tasks, whereas caregivers in AL seldom had breaks. Instead, caregivers in AL also had to address a significant number of spontaneous calls from older adults. These unscheduled needs varied from using the toilet to answering a quick question about the activity schedule for the day. However, the caregivers do not receive any indication of the severity of the unscheduled need, so they must react quickly in case of an emergency.

While the workflows in IL and AL differed drastically, all caregivers described essentially the same robot assistant: a highly capable mobile humanoid robot with manipulation capabilities. All caregivers also expressed the desire to give the robot instructions about what task to do, either through verbal specification or some sort of tablet interface. They also indicated that the robot should be able to accommodate both pre-programmed and impromptu tasks.

From this study, I gained a rich understanding of the needs of caregivers. Based on the findings, we envision a robot *coworker* Sauppé and Mutlu (2015) that caregivers can assign tasks such as refilling a cup of water, checking on an older adult, or picking up items that an older adult had dropped on the floor. Caregivers expressed that these tasks take significant amounts of time and prohibit them from more meaningful interactions with older adults.

4 DESIGNING INTERACTIONS WITH RESIDENTS

4.1 Chapter Introduction

This chapter complements the understanding of care robot design and integration developed in Chapter 3 by considering the day-to-day interaction with residents of the senior living facility. How should the robot behave, and what interaction parameters do residents want to change? How will residents feel that a robot is independently interrupting and entering their living space to complete care tasks? What unexpected situations or unanticipated challenges could arise during the course of a robot deployment? In this chapter, we consider such design questions through participatory design activities with residents and supplementary interviews with caregivers.

Participatory Design (PD) is a method that engages key stakeholders of a product or a service in the design process (Lee et al., 2017). PD methods enable designers to create personalized systems that help to address the unique needs of specific user groups. Recent research on technology for older adults has successfully used PD to increase the engagement of this population in the design process (Duque et al., 2019). This increased engagement can lead to higher acceptance of newer technology by better aligning the design of emerging technologies with the needs and expectations of their users (Duque et al., 2019).

As a general methodology, PD encompasses a wide range of activities, which allows for significant flexibility to craft a specific approach that suits both research questions and participants' needs. Typical PD activities, *e.g.*, interviews, off-site workshops, and interactions with low-fidelity prototypes, have a low barrier to use and can provide useful insight into the general design of a robot and the specific tasks it can perform. Although current PD methods demonstrated promise to address the unique needs of older adults, prior literature has identified four key challenges:

1. **Cognitive ability**: Older adults with moderate or severe cognitive impairment may experience challenges in articulating their thoughts and feelings or with engaging in creative thinking, which can limit their ability to contribute to discussions about design ideas such as how they envision future technology could fit into their life (Lindsay et al., 2012);

2. **Physical ability**: Older adults can be physically unable to participate in study activities (*e.g.*, due to physical disability (Rogers et al., 2022) or inability to reach study sites (Duque et al., 2019)), which can lead to certain populations being left out or opting out of participation, limiting representation in design work;

3. **Ecosystem**: Older adults can live in complex environments that include customization of the physical space (*e.g.*, ramps, railings, lifts), rigid day-to-day routines and behavioral needs, other individuals who share the space (*e.g.*, family, caregivers), requiring the design process to take into account the entire ecosystems to reach solutions that are acceptable and usable to all stakeholders (Grönvall and Kyng, 2013);

4. **Other stakeholders**: Older adults may no longer be independent in performing activities of daily living (ADL) and rely on people (*e.g.*, family, caregivers) for support, whose needs, constraints, and preferences must also be considered in the design process (Hwang et al., 2012).

Recent research has addressed some of these challenges, particularly to help older adults better grasp the capabilities and limitations of new technology, through the use of higher-fidelity systems (Bradwell et al., 2021; Šabanović et al., 2015). However, introduction of the technology in a

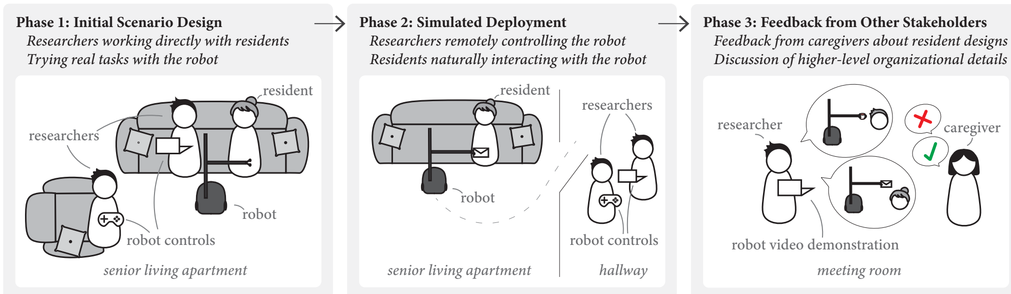


Figure 4.1: We present *Situated Participatory Design* (*sPD*), a participatory design (PD) method specially designed to address the challenges of working with older adults to design assistive technologies. *sPD* includes three key phases: (1) a *co-design* phase to design an initial scenario; (2) a *simulated deployment* phase to test out the interactions in realistic conditions; and (3) a *follow-up* phase where other stakeholders (*e.g.*, care staff) reflect on resulting designs. We demonstrate the use of *sPD* in a case study with the residents and caregivers of a senior living facility and present insights into the benefits of *sPD*.

workshop setting may not be sufficient to capture the necessary ecological considerations and the needs of other stakeholders.

We propose *Situated Participatory Design* (*sPD*), a PD method including elements of user-centered design that addresses some challenges of conducting PD with vulnerable populations as well as design problems where immersion in the use setting is critical to the design process. *sPD* situates the activity in a genuine environment, grounds co-design activities in existing technical capabilities or capabilities that can be simulated for participants, centers design activities around experiencing the interaction (as opposed to imagining interactions), and engages other decision makers in the design process. We use this approach to create an immersive, realistic, and reflective co-design experience. The three-phase method, shown in Figure 4.1, integrates ideas from in-the-wild Wizard of Oz (WoZ) studies (Mitchell and Mamykina, 2021), user enactments (Odom et al., 2012), stakeholder involvement (Vink et al., 2008), and traditional PD workflows.

sPD is not disjoint from PD but represents a carefully selected combination of study activities that can facilitate engagement for older adults by considering their cognitive and physical abilities and can help capture the ecological considerations and other stakeholder needs for assistive technologies necessary for successful acceptance and deployment.

We applied *sPD* at a senior living facility to design interactions between residents and an assistive mobile robot. Our use of *sPD* revealed insights that point to its benefits and limitations. Multiple interactions between participants and the robot uncovered significant differences in what people initially designed compared to what they preferred when the robot was performing the scenario. We report on our findings and discuss the benefits of *sPD*.

Our work makes the following contributions:

1. We describe *sPD*, a PD method that incorporates realistic, *in situ* interactions throughout the PD process to addresses challenges of designing technologies for older adults, and we discuss *sPD*, including its benefits and how it applies to other domains and technologies;

2. We employ *sPD* in a case study with residents and caregivers of a senior living community to design interactions with an assistive mobile robot, and we present findings from the case study;

3. We identify how residents wish to personalize their interactions with care robots, including the robot's speaking style, social interactivity, and how it completes the task.

4.2 Background

Below, we discuss prior work that informs the development of *sPD*.

Participatory Design with Older Adults

Participatory design (PD) has a rich history in human-computer interaction (HCI) to involve stakeholders in the design process. Typical PD activities include watching/discussing videos, creating/considering storyboard scenarios, drawing/sketching ideas, or creating/interacting with low-fidelity prototypes (*e.g.*, paper prototypes) (Duque et al., 2019). The range of technology targeted through PD methods varies widely, including applications that focus on fall prevention (Grönvall and Kyng, 2013), mobile communication devices that connect to TVs (Scandurra and Sjölinder, 2013), new banking technologies (Vines et al., 2012), and systems that promote healthy eating (Lindsay et al., 2012), personal mobility (Lindsay et al., 2012), feelings of personal security at home (Lindsay et al., 2012), and health tracking (Davidson and Jensen, 2013).

The human-robot interaction (HRI) community has begun adopting PD methods with older adults, exploring a wide range of robotic designs such as a social robot to help older adults with depression (Lee et al., 2017), a social robot that hosts GUI-based games for mood stabilization (Gasteiger et al., 2022), a mobile robot to reduce falls (Eftring and Frennert, 2016), and a drink delivery robot (Bedaf et al., 2017). Other work, such as that of Broadbent et al. (2009) and Bradwell et al. (2021), focuses on designing how a robot should appear and selecting what tasks are desirable for a robot to complete. Most of these studies do not include the actual robot, and they instead rely on video demonstrations (Gasteiger et al., 2022; Beer et al., 2012), storyboard images showing what a robot may do (Bedaf et al., 2017), or other images of robots (Broadbent et al., 2009). While these approaches allow for quick, low-barrier design, the simplicity of the prototypes can make it hard for participants to understand the capability and potential of the artifact, the context of its usage, and how it could fit in their living space.

Incorporating robots in all design phases has many clear benefits, although the precise use of the robot in PD varies greatly in previous work. In some cases (e.g., Lee et al., 2017; Bradwell et al., 2021; Ostrowski et al., 2021), prototypes are introduced to participants prior to the design session to enhance their understanding of the robot's capabilities. Ostrowski et al. (2021) also included the robot prototype in the design session itself, but none of these examples conducted any validation with the participants during or after the design process. While this approach seems effective for designing stationary social robots, designing mobile robots, such as some assistive robots, necessitates consideration for the holistic interaction environment. For example, Eftring and Frennert (2016) used PD to design an in-home robot to reduce falls, but never introduced the real robot into the environment until a follow-up field evaluation. Their evaluation found that the robot was too big for some spaces, and participants did not like adding ramps that the robot needed to cross over floor thresholds. Increasing the use of robots through all phases of the PD process could be critical to developing successful assistive robots with older adults.

Other Approaches to Technology Design

In addition to PD, we can also take inspiration from alternative design methods that offer some insights about how to address challenges of designing assistive robots with older adults:

First, *living labs* emphasize the importance of the context where a technology will be used. By using a study environment that mimics real conditions, researchers can understand how a technology will function in that space (Alavi et al., 2020). However, living labs do not emphasize engaging stakeholders as strongly as methods such as PD (Bygholm and Kanstrup, 2017).

Second, *Wizard of Oz* (WoZ) allows participants to interact with a system that is controlled by an operator behind the scenes (Dahlbäck et al., 1993). It has been used in laboratory settings to design interfaces and system behavior through tools such as Ozlab (Pettersson and Siponen, 2002; Larsson and Molin, 2006; Wik and Khumalo, 2020). Mitchell and Mamykina (2021) discusses the need for in-the-wild WoZ studies to capture more natural interactions that reveal usability challenges that would otherwise be missed, but they focus their use of WoZ for system evaluation instead of during the design process.

Third, *role playing* has been used to engage potential end users in the design of future technology (Odom et al., 2012; Strömberg et al., 2004). Odom et al. (2012) specifically discusses how *user enactments* (UE) can allow researchers to quickly explore how technology fits into an environment. While these methods facilitate good participant engagement, the staged setups and lack of usable prototypes limit the ability of participants to experience the technology as they would in their daily life.

The Special Case of HRI in Assisted Living

Assisted living is a type of senior living community for individuals who are no longer able to live independently (Zimmerman and Sloane, 2007). Residents typically live in private rooms with shared dining halls and other common spaces, placing this living arrangement somewhere in between a private residence and a more clinical setting such as a hospital or skilled nursing facility. Throughout the day, residents in assisted living can expect to receive regular help from caregivers for activities necessary for living independently, which can include care tasks such as bathing, dressing, toileting, transferring to or from a bed or chair, laundry, and more (Kane and Wilson, 1993). They may also receive light medical assistance, primarily in the form of physical or occupational therapy and medication management (Kane and Wilson, 1993).

Technology for assisted living settings aims to enhance the livelihood and independence of the residents and ease caregiver burden. For example, ambient assisted living (AAL) incorporates smart home technology into living spaces to improve the safety, health, and well-being of residents (Aced López et al., 2015; Zulas et al., 2012). Socially assistive robots are being developed for applications such as providing health reminders and assisting older adults to manage symptoms of depression (Bradwell et al., 2021). Other robots are being explored to perform tasks such as refilling water (Odabasi et al., 2022), helping with ambulation (Médéric et al., 2004), and escorting residents to activities (Pollack et al., 2002). The technology being used day to day in assisted living settings is also modernizing. For example, we have seen vacuum robots and computerized medication dispensing carts commercially deployed in care facilities.

Despite research advances and industry adoption of new technology, it is not yet clear how assistive robots should fit. To better incorporate robots in care settings, Bardaro et al. (2021) and Hornecker et al. (2020) recommend working with a variety of stakeholders to identify specific needs that robots can address. Stegner and Mutlu (2022) and Alaiad and Zhou (2014) build on this work by identifying complex and potentially conflicting power dynamics in care settings.

As robotic systems are developed, it is critical to consider them in a broader context, such as how the robot will come and go between private and public spaces in the facility, who assigns tasks to the robot, and how to balance caregiver and resident preferences with regard to robot behaviors. However, current design approaches for assistive robots with older adults primarily focus on details such as robot appearance, technical performance, or overall acceptance of the robot. Instead, we need to think about how robots fit more holistically into the assisted living setting. To help address these open questions, we can take lessons from HCI design methods and apply them to HRI with older adults. Specifically, we consider how situated interactions with technology could be used to overcome established challenges of using PD with older adults and understand some aspects of system deployability in real-world environments.

4.3 Research Questions

To successfully relieve caregiver burden and increase resident independence, assistive robots need to address real needs within senior living communities. Robotic systems need to be sufficiently capable, but they also need to meet the expectations residents have regarding how the system can fit into their day-to-day activities and need to be compatible with how caregivers provide care to residents. Motivated by these needs and the challenges identified in §4.1, we pose the following research questions:

RQ1: How can designers effectively engage older adults to better contribute to the design of assistive technologies?

RQ2: How can designers better understand the challenges of integrating assistive technologies in genuine environments, interactions, life activities, and caregiving practices for older adults?

This work explores the research questions proposed above with a focus on robotic systems. Our intuition to answer these questions is that situating design ideas directly in the real environment can provide us with the insights needed.

4.4 Method

The previous work on PD with older adults guided us in crafting *sPD*. In this section, we first discuss our research context, including an overview of *sPD*, case study goal, community partner, participants, and robotic platform. Then, we present the key phases of *sPD* by describing the general concept of each phase and presenting their application in a case study at a senior living facility.

sPD Overview

sPD is an iterative approach to designing technology when the goal is an eventual deployment. We developed *sPD* based on the challenges we identified in §4.1 for PD with older adults relating to cognitive ability, physical ability, ecosystem, and other stakeholders. To address these challenges, we devised an approach that integrates situating the activity in a genuine environment, grounding co-design activities in existing technical capabilities, centering design activities around experiencing the interaction, and engaging other decision makers in the design process. This approach provides the foundation for the following three-phase method:

- *Phase 1: Discovery, co-design, & enactment* — use the real technology *in situ* to explore its capabilities as well as select, design, and enact scenarios;
- *Phase 2: Simulated deployments* — evaluate the designed scenarios multiple times under realistic conditions using in-the-wild Wizard of Oz (WoZ) (*i.e.*, *in situ* use of the real robot with the participant's real belongings, realistic task initiation, and without the researchers present to mediate);
- *Phase 3: Engaging other stakeholders* — conduct separate sessions with other stakeholders (*e.g.*, caregivers) to present participant designs and discuss experiences and concerns.

The evolution from identifying the challenges to formulating characteristics for *sPD* is detailed in Figure 4.2. Each phase builds upon the previously gained knowledge, and this design cycle could be repeated until the design reaches the desired level of maturity.

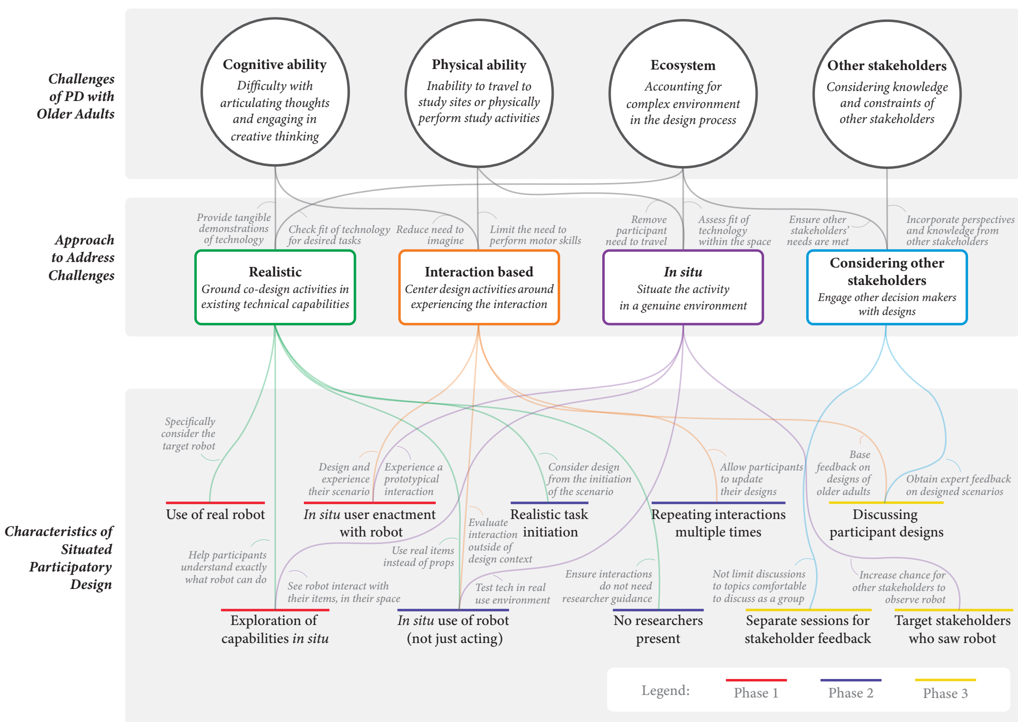


Figure 4.2: Conceptual development of *sPD* from the challenges of PD with older adults to our three-phase method. Motivated by the challenges of PD with older adults identified from previous literature (top row, see §4.1 for more details), we identified a general approach to addressing these challenges through the integration of user-centered design approaches (middle row), formulating key characteristics for *sPD* that instantiate these approaches (bottom row).

Case Study Details

Case Study Goal

Our case study builds on work by Stegner and Mutlu (2022), which offers insights into the day-to-day practices of professional caregivers and the needs of older adults living in assisted and independent living facilities. We use *sPD* to investigate residents' perspectives on how a robot could fit into their daily lives by specifically focusing on light manipulation tasks such as delivering a cup of water or picking an item up from the floor.

Community Partner

We partnered with a suburban, private, not-for-profit senior living facility located in the Midwestern United States. The facility includes a mixture of accommodations, including 60 Assisted Living (AL) apartments and 85 Independent Living (IL) apartments. We primarily worked with AL residents, as this population could benefit significantly from light manipulation assistance, but we also involved IL residents who expressed interest. Most residents in IL are completely independent, but some receive assistance with medication management or other light tasks such as bathing or getting dressed. Similarly to other care facilities, our community partner has faced recent difficulty with staffing and are frequently understaffed or staffed with temporary workers.

Participants

In total, nine residents, aged 77–94 years ($M = 88.3$ years, $SD = 5.8$ years; 6 females; 7 in AL, 2 in IL), participated in the study. We do not report individual characteristics to minimize any risk of re-identification given the small population from which we sampled. However, we can report that many of our participants had mobility, dexterity, visual, or hearing impairments. Participants received $20 USD/hour to participate in Phase 1 and a flat fee of $20 USD to participate in Phase 2. Our community partner helped recruit participants who expressed interest and who were directly able to provide informed consent to participate.

In addition, three caregivers participated in Phase 3, aged 22–54 years ($M = 33.3$ years, $SD = 14.3$ years; all female) with experience varying between 6 months to 5 years ($M = 2.5$ years, $SD = 1.9$ years). Each interview lasted 30 minutes, and caregivers were compensated at a rate of $40 USD/hour for their time.

Robot Platform

We used the Stretch RE1 robot from Hello Robot (Kemp et al., 2022), shown in Figure 4.3, as our robot platform. Stretch is a mobile collaborative robot (cobot) that is 55.5 inches, or 141 cm, tall and equipped with a laser range finder, RGB-D camera, microphone array, speaker, and actuated arm with a soft gripper that can lift up to 3.3 lbs, or 1.5 kg. Throughout the design sessions, we realized that the base capabilities of Stretch were too limited for our use case (*e.g.*, the speakers were not loud enough; the onboard camera was not sufficient for remote operation), and thus we augmented the Stretch robot with three additional cameras and a Bluetooth speaker to conduct the study. The robot's remote operation was conducted through a mixture of a gamepad controller using the default Stretch teleoperation software[1] and a dedicated web app for displaying camera feed and typing sentences for the robot to speak. We initially used the default Google Assistant Red voice, but based on participant feedback during the study we switched to use Amazon Polly with the Joey voice slowed down to 70% as our text-to-speech platform for the robot's prompts and responses.

[1] Stretch teleoperation software: `https://github.com/hello-robot/stretch_body/blob/master/tools/bin/stretch_xbox_controller_teleop.py`

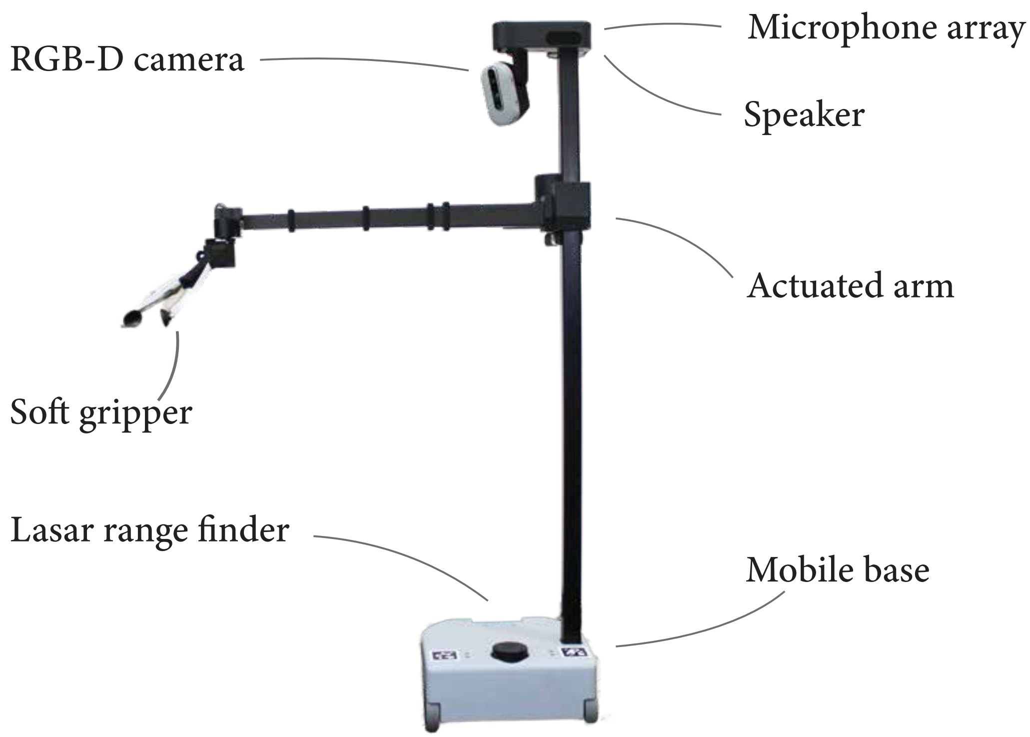


Figure 4.3: Stretch RE1 mobile manipulator robot from Hello Robot. We used Stretch in our case study with older adults.

Procedure

Applying one cycle of *sPD*, we conducted a field study during Summer 2022 at our community partner facility to explore the design space of robot-assisted care activities for older adults. All study methods were reviewed and approved by our institutional review board (IRB). Study materials and results are provided via OSF.[2]

We present the general phase description in parallel with the steps of our case study to illustrate how *sPD* can be applied to a real-world design scenario. We will refer to the facilitators of the design session, *researchers*,

[2]Study data and materials are available on *OSF*: `https://osf.io/ubnw5/`

and users who took part in the session, *participants* (*residents* in Phases 1 and 2, and *caregivers* in Phase 3).

Phase 1: Discovery, Co-design, & Enactment

Description. Phase 1 combines concepts from PD and user enactment. The researchers first introduce participants to the goal of the research and gain an understanding of that participant's individual needs and circumstances. Then, the technology is introduced and participants interact with it based on a scenario that is personally relevant to them. This activity provides an initial scenario design that will be used and modified throughout the rest of the study. Once the initial design is set, the researchers facilitate user enactments, where a researcher remotely operates the technology to allow the participant to walk through their design and provide feedback. Researchers should focus the scenario design based on reasonable capabilities of the technology, although they may have to intervene in instances that the current prototype is not yet able to execute (*e.g.*, opening a door to let the robot in).

Case Study Application. Phase 1 consisted of a single hour-long session per participant. The key elements in Phase 1 include:

1. *Ice breaking & Needfinding*: We started by introducing participants to the goal of the research and the plan for the study. We then asked them to describe their typical day and with which tasks they typically receive assistance. For each task, we noted on a card the type of activity, frequency (how often the resident needs help with it), timing (when do they often need the assistance), scheduling (whether it is planned or unplanned), initiation (who prompts the task to start), and comfort (would they be comfortable with a robot providing this assistance). During this time, the robot was out of the

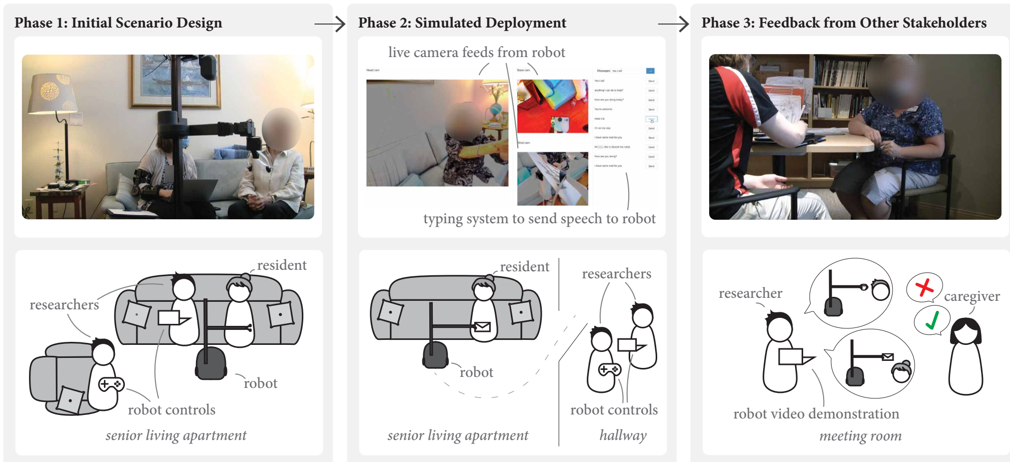


Figure 4.4: Each phase of *sPD* illustrated with pictures from our case study. The first phase involves a *co-design activity* where researchers work with the older adult in their home to design a scenario (left). The second phase involves *simulated deployment*, where the researchers remotely operate a robot using the web app shown and a gamepad controller to complete the scenario with the resident (center). The third phase involves *follow-up interviews* with caregivers at the facility to reflect on resident designs within the context of their care practices and address aspects of the scenarios that are specific to caregivers (right).

room to avoid distraction, and as the participants had yet to see the robot, responses were mostly *a priori*.

2. *Robot Introduction*: We brought the robot into the room and demonstrated and verbally described its abilities. During this step (see Figure 4.4, left), we controlled the robot in full view of the participants, describing to them how we could move parts or make the robot speak. The residents had the opportunity to interact with the robot and ask questions about it or its capabilities.

3. *Interaction Design*: From the tasks that the resident provided earlier, the researchers selected a task for the robot to do based on a combi-

nation of the robot's capabilities and the resident's interest in what a robot should do. Once the task was agreed upon, we used it as a prompt to design the scenario together. As a grounding point, the resident described what steps the caregiver would normally do to complete the task. These steps were recorded on a worksheet. Then, we asked the resident to consider if our robot was doing the task, how should its behavior change.

4. *Enactment*: Based on the resident's initial design, we used the robot to enact the scenario with the resident. During the enactment, researchers were next to the resident and the resident could request changes or provide feedback. In a brief follow-up, the resident answered questions about their experience, *e.g.*, whether the interaction met their expectations and if any changes should be made.

After Phase 1, we arranged for the robot to return for Phase 2 to validate the design through two simulated deployment sessions.

Phase 2: Simulated Deployments.

Description. Phase 2 integrates in-the-wild Wizard of Oz (WoZ) (Mitchell and Mamykina, 2021) through multiple, iterative sessions where researchers simulate the deployment of the technology in a way that reflects the participant's design. The simulated deployment provides the opportunity to uncover ecological considerations that are important to consider for future deployments. Participants are asked to simply use the technology as they had co-designed in Phase 1, and the interaction is completed as realistically as possible. We create the realistic context by using real items instead of props when possible, matching the time to when the participant would typically engage in the scenario, and removing the researchers from mediating the interaction. After the simulated deployment in a short interview with the researchers, the participant is asked to reflect and give feedback on their experience as input into an updated design.

Case Study Application. In Phase 2, we held two sessions lasting approximately 15 minutes each and occurring on different days. The key elements for one single session of Phase 2 were as follows:

1. *Simulated Deployment*: Based on the scenario design that resulted from Phase 1, we controlled the robot through WoZ to have the robot enter the resident's room and complete the scenario. Two researchers who are out of sight of the resident operated the robot: one researcher controlled the robot's movement using a gamepad controller, and the other controlled the robot's speech. Figure 4.4 (center) shows the interface used to stream cameras to assist in remote operation and send speech for the robot to say. The original setup included streaming the microphone data from the robot, but the microphone did not reliably capture participant speech, so the researchers listened through the door.

2. *Reflective Interviews*: After the first simulated deployment, we briefly (3–5 minutes) interviewed the participant about their experience with the robot and gave them the opportunity to propose changes. After the second simulated deployment, we conducted longer (10–15 minutes) interviews to probe into additional wider-ranging questions such as, "After having experienced the interaction with the robot, would you prefer a human or robot to perform the task?" and "Do you see yourself using a service like this in your daily life?"

Phase 3: Engaging Other Stakeholders.

Description. Phase 3 is a follow up to Phase 1 and Phase 2, based on the concept of expert feedback. Since the direct users are not the only stakeholders in the interaction, it is critical to also involve other stakeholders. For example, in the case of assisted living, older adults rely on formal and informal caregivers to provide assistance. This phase seeks to gather feedback on whether the designs of the participants are reasonable and safe and other considerations that may not emerge from working directly with the target users. Whereas the focus of Phase 1 and Phase 2 is a scenario specific to an individual participant, Phase 3 allows other stakeholders to provide input on multiple participants' scenarios at once. This phase also provides an opportunity to resolve sensitive and controversial design decisions, such as features where a participant and an expert might disagree (*e.g.*, a nutritionist recommending minimizing sugar versus the client wanting sweet snacks to be delivered by technology). These insights can fill in missing facets of the design without adding tension between the participants and other stakeholders.

Case Study Application. After completing Phase 2, we interviewed (approximately 30 minutes each) caregivers at the facility. Due to a COVID-19 outbreak, our data collection with the caregivers was shorter than planned. Sessions were conducted in person or through a Zoom video call. Although we aimed to recruit caregivers who had previously seen the robot during Phase 1 or Phase 2 while we worked with the robot with the residents, in practice, staffing challenges at the facility made this approach infeasible. Instead, we recruited caregivers who regularly worked at the facility, as opposed to temporary workers used to cover staffing shortages.

During the interviews, shown in Figure 4.4 (right), the researchers gave an overview of our research aim and asked the caregiver to reflect on their knowledge of the robot, including anything they heard from residents or other staff. Then, the researchers presented the scenarios designed by the residents and asked for their feedback. Finally, the caregivers provided input on key design decisions that they were uniquely positioned to consider, such as who should personalize the robot to each resident's preferences and how much oversight caregivers should have over the robot.

Data Collection & Analysis

We collected three forms of data throughout the study: researcher field notes throughout the various study sessions (*i.e.*, activity cards from Phase 1 and notes from interviews in Phase 2 and Phase 3), participant-generated designs, and video/audio recordings during design sessions and interviews. Since the design sessions are highly contextualized in the real-world environment, we did not transcribe the audio/video data but instead used a bookmarking system where researchers marked points of interest within the field notes to allow quick access to revisit key moments in the video/audio data.

Data was analyzed using a Reflexive Thematic Analysis approach (Braun and Clarke, 2022). The two researchers who conducted the study sessions, who were already familiar with the data, performed the analysis. The first author used open-coding to identify phenomena from the field notes and participant designs, revisiting the recordings as necessary for context. The two researchers then worked together to discuss and refine the codes, following an iterative approach to organize the codes into insights using affinity diagramming.

During the open coding and affinity diagramming, we focused on two high-level ideas in the data. First, we considered the design findings from participants to inform future robot design and deployments. Second, we considered the data as it pertains to *sPD* in order to identify insights we gained from using the method. In this paper, we emphasize the methodological findings and provide only a summary of the findings on robot design, which we still think is informative to understand the benefits and limitations of *sPD*.

4.5 Findings

We present the results from our case study, organized into two sections: (1) design findings from participants to inform future robot design and deployments, (2) insights into *sPD* that emerged from the case study. Findings are supported by researcher observations and quotes from participants. Both quotes and observations are attributed using participant ID, with residents as R1–R9 and caregivers as C1–C3. We made minimal edits and added annotations to the quotes to improve their clarity while retaining their meaning.

Participant Designs and Feedback

Below, we overview the scenarios designed by participants and the design findings based on feedback from participants.

Scenarios.

Participants designed scenarios for a wide range of tasks for the robot, including mail, newspaper, book, or water bottle delivery; refilling ice water; moving a cup of water across the room; and picking items up from the floor. As Phase 1 and Phase 2 progressed, design ideas evolved based on participant experience (see §4.5). Table 4.1 summarizes sample interactions, including the scenario and key behavioral expectations from the robot.

Feedback.

Our analysis resulted in themes on the behavioral expectations for, physical attributes of, interaction quality with, and attitudes toward the robot. The range of preferences supports other work calling for personalized robots and similar systems.

Table 4.1: A selection of scenarios that participants designed for the robot, including significant features of their envisioned interaction with the robot. Each participant selected a task that was relevant to their day-to-day activities and needs. While their designs evolved throughout the study, this snapshot represents their resulting designs at the end of Phase 2.

	R1	**R3**	**R6**	**R8**
Task	Water bottle delivery	Mail delivery	Move cup of water	Cup of ice delivery
How is the task initiated?	Pre-arranged times, or on-demand calls.	Brought when it arrives.	R6 wanted to press a button to call robot.	Pre-arranged time (4 pm sharp).
How should the robot enter?	Knock, wait for a response; Key needed to enter.	Knock/make announcement, enter without waiting.	Knock, wait to enter.	If the door is open, enter; else, knock and enter.
How should the task be completed?	Retrieve the water bottle from refrigerator and set it on the side table.	Bring the mail to R3 wherever they are.	R6 will give the robot specific instructions.	If R8 is in the room, bring it to them; otherwise leave it on the side table.
What other behavior from the robot is desirable?	Light conversation; Prior to leaving, schedule next task.	Voice updates on robot progress; Minimal, polite speech.	Complex conversation; Offer to do anything else before leaving.	Little bit of speech.

Behavioral expectations — Behavioral expectations included preferences on the socialness of the robot; some residents desired a highly conversational agent, while others wanted the task to be completed in silence. Other behavioral expectations included how the robot should gain entry into the resident's space: knock and wait for a response, knock and enter without waiting, or directly enter without warning if the door is open. In some cases, the residents also kept their doors locked, so the robot would additionally need a key to gain access. Several residents also expressed concerns over the how the robot would interact with their personal belongings, which limited the tasks they felt appropriate for the robot to complete. Specific concerns included "security of [the robot having] the mail" (R2) or that the robot would "spill" (R6) something.

Physical attributes — For physical attributes, participants commented on the size of the robot, movement speed, the robot's voice, and the timing of speech. While some participants appreciated the small form factor of the robot, one participant in a wheelchair remarked they "didn't think they could communicate" because the robot was too tall. Participants also perceived the robot's movement as "slow" (R1), which impacted some of their future preferences.

Interaction quality — With interaction quality, the robot's speech was the main factor. We found that the initial style and volume of the robot's voice were too quiet for residents to "understand the words" (R8) and too "high-pitched" (R2) for them to hear, which is what prompted us to change the text-to-speech (TTS) engine and add an external speaker. The timing of the robot's speech during conversations with participants was also challenging. Participants struggled to understand when the robot "paused" (R5) before speaking. Some of them suggested that the robot should provide "a simple [visual] movement" (R5) to signal its processing state, while others felt it would "just take time" (R9) to learn how to "interact" (R9).

Attitude toward the robot — Finally, attitude toward the robot encompassed thoughts on whether the participants preferred a human or robot to complete certain tasks. We observed three main categories of participants. Some preferred a human caregiver even after experiencing the robot. Others felt it was "immaterial" (R2) whether it was a human or robot, as long as the robot was "efficient in supplementing human care" (R3). A few participants felt the robot was more desirable — they sometimes felt they were being a "nuisance" (R8) asking caregiver to help them, while they would be more comfortable asking the robot to do some tasks.

Insights into *sPD* from the Case Study

Below, we present the insights we gained from interacting with the residents in Phases 1 and 2 and caregivers in Phase 3 that emerged as a result of *sPD*. We describe each insight briefly and offer an illustrative example of it from our case study.

Insights from Engaging with Residents in Phase 1

I1: Introducing the robot first helps uncover participant comfort. The robot was maneuvering in participants' private rooms, sometimes getting very close to them to perform handoffs or similar tasks. The physical presence of the robot elicited differing responses.

R4 withdrew from the study because the robot made them uncomfortable. When initially discussing the concept of an assistive robot, R4 was attentive and curious, and even smiled when the robot first entered. However, as the robot was moving around and interacting with R4, their demeanor changed, and they became too distressed from the robot's presence to continue with the study.

Despite this unique example, most participants were comfortable in the presence of the robot, even when it entered into close proximity such as to complete a hand off (*e.g.*, deliver the newspaper). R8 expressed that they were "very comfortable" with the robot approaching them and that they were "confident that he [the robot] was going to stop and [...] not run into me or push me over."

Varying reactions to the robot's presence shows how bringing the robot early in the design process is key to evaluate early on whether the robot could be acceptable.

I2: Exploring robot capabilities directly with residents allows both the residents and the researchers to envision how the robot can address the resident's needs. Since our setup allowed real-time control of the robot, participants had ample time to explore the robot's capabilities. While some residents were content to view a demonstration of the system and verbally ask questions about it, others wanted to see if the robot could do specific tasks that they envisioned. We tried every task participants asked us to try, which gave them a chance to witness the robot's abilities and us a chance to assess the challenges of doing a variety of tasks with real items in a real space.

R6 in particular wanted to explore what the robot could do. During the robot introduction in Phase 1, R6 eagerly wanted to test the robot, asking "Do we try? Shall we try?" Without prompting, R6 had prepared tasks to ask the robot to try during the session: pick up a tissue from floor, move their cup across the room, unscrew the cap from a nutrition drink, and arrange items of clothing in the closet. From having the robot interact with R6's personal belongings, such as their favorite cup, we gained practical insights into the challenges of the robot grasping and lifting real-world items outside of a laboratory setting. While the robot could complete the first two tasks, it was unable to do the others. R6 was disappointed that the robot could not "open cans, like water bottles," although they were pleased overall with the robot's ability to provide assistance.

I3: Experiencing the interaction is an effective way to explore design decisions. During Phase 1, in the initial co-design step, we asked participants how the robot should behave as it completes the agreed-upon scenario. While some residents could articulate an initial version of what the robot should do, not all were able to imagine it. Through the user enactment, they had the opportunity to realize what the robot should do by trying it out.

R5 enjoyed discussing the robot, but expressed difficulty answering questions about what the robot should do at various stages of the interaction. Eventually, they said, "I'll learn what I want it to do by experiencing it and finding out." While we were unable to complete the initial co-design activity, we proceeded with the user enactment. Through the enactment, R5 was able to articulate what the robot should do by experiencing the scenario. For example, R5 could not imagine how the robot should behave once it entered the room. During the user enactment, however, they were naturally talking to the robot and giving it instructions on what to do with the mail it was delivering. This example demonstrates how the enactments helped extract *tacit knowledge* (Polanyi and Sen, 2009 [1966]) from participants that they otherwise struggled to communicate.

Insights from Engaging with Residents in Phase 2

I4: Iterative interactions enable reflection on preferences for robot behavior. These repeated interactions with the robot throughout Phase 1 and Phase 2 allowed participants to reflect on their designs and make changes to how the robot should behave. Some participants, such as R2 and R3, made relatively few changes to their designs after the initial interaction. However, the remaining participants made significant changes as they realized their anticipated interaction with the robot was not what they actually desired.

R9's scenario evolution is visualized in Figure 4.5. Initially, R9 was confident about how the robot should deliver the mail: no speech was necessary, and the robot should not do anything besides the mail delivery. However, after the first simulated deployment, R9 realized that due to "the slowness of it" and their apartment layout, they "couldn't see" what

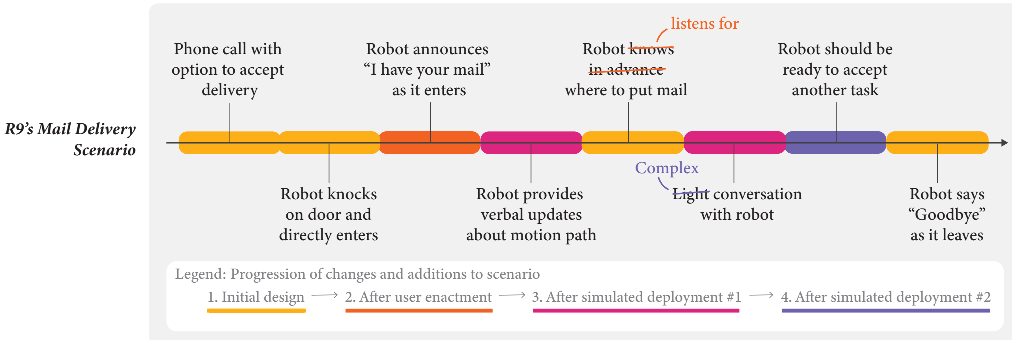


Figure 4.5: The evolution of an example design through Phase 1 and Phase 2 of *sPD*. R9 designed a mail delivery scenario. Their initial design was simple, with limited robot interaction. However, repeated interactions with the robot allowed R9 to reflect on their preferences and iterate through different designs, adding steps or changing steps to make the robot behavior more appropriate. The final design includes verbal updates from the robot about its progress and deeper conversation with the robot.

the robot was doing as it entered. In the first follow-up interview, R9 wanted to "try" getting verbal updates from the robot. R9 expressed, "I don't know if I'll understand it," but they wanted to update the scenario design to try it. Then, at the end of the second simulated deployment, R9 further deviated from the original scenario by instructing the robot to do another task (*i.e.*, deliver a note to the researchers). In the second follow-up interview, R9 commented, "Having more visits made it smoother, easier." With the speech updates, R9 thought that the scenario "worked out much better," but also that the robot should be "made more personal by having conversation." Through repeat interactions with the robot, R9 reflected on and iterated through different designs to see what fit their preferences and needs. Generally, participants' initial impressions of what they wanted from the robot did not always match their true desires, which points to the importance of early, iterative experience with the robot under realistic conditions.

I5: Experiencing the realistic scenario helps participants realize how it fits into their lives. Through repeated interaction, participants had time to reflect on the actual task the robot was doing. Since these interactions were as high-fidelity as possible, it provided context for participants to consider how that scenario fit into their life.

R8 initially asked the robot to deliver the morning newspaper. However, the newspaper arrived late, so the robot was also late with the delivery. After this experience, R8 voiced that the newspaper delivery was "not a good task to set up for the robot." Instead, they wanted the robot to "bring me ice for my afternoon cocktail." While ice delivery is a scenario that was not discussed during the interview, R8 independently imagined it after having the opportunity to reflect. For the second simulated deployment, the robot delivered the cup of ice, and R8 described the experience as "wonderful." In the final reflective interview, R8 remarked that the process helped them "conceptualize how it [the robot] could be a [...] very useful [...] tool for [...] people that are semi-confined." This example shows how experience with the robot and scenario under realistic conditions is a critical component to understand better what people want a robot to do and to conceptualize how it can be useful.

I6: Unexpected situations can appear from experiencing the robot in day-to-day life. Since the simulated deployments in Phase 2 were initiated by the robot without prior notice from the researchers, the interaction start was closer to what might happen in a real life experience. Participants were not specially prepared in the same way they made preparations to host the researchers for the session in Phase 1. Instead, we saw a snapshot of what might really happen when the robot completes the scenario in a deployment.

We experienced three unexpected situations from the simulated deployment. First, R5 had visitor when the robot arrived. The presence of the visitor changed the way the participant interacted with the robot, which subsequently changed how the robot needed to respond. Second, R1 was using a scooter to move around, which we had not seen from previous visits. The scooter was parked in the way of where the robot needed to go, forcing the strategy to complete the handover to change. Third, R8 was not wearing and consequently could not hear the robot speak at all. These unplanned incidents show the need for flexible prototyping tools and for flexible systems in deployment because "every day is different" (R1).

I7: Interacting with the robot without the mediation of the researchers can facilitate problem solving and idea generation. While participants were interacting with the robot, three ideas emerged that we had not considered during Phase 1 because the researchers were no longer present to mediate the interactions.

First, R2 and R6 both felt that they helped the robot with its task. R2 recounts that they felt the robot "didn't know how to get from there [the doorway] to here [the chair]," so R2 "helped" the robot by "putting [their] hand out [...] and he [the robot] came over." Similarly, R6 intervened as the robot attempted to place a tissue in the trash can because they "realized there was a pole in the way" that they thought the robot would "run into." When asked about it, both participants were happy to help, and R6 was especially happy that the robot acknowledged their "teamwork."

Second, R7 expressed that they wanted validation and guidance from the robot. The robot was "marvelous," but R7 felt "inadequate" to interact with it. Therefore, they wanted "instructions" from the robot during the interaction so that they knew what to do.

Third, R7 additionally mentioned that having the robot could help them to find a new role at the facility. They were interested to see if they could learn to use the robot, then help other residents learn as well. This new role could add value to their current life.

The lack of researchers forced residents to directly interact with the robot, causing them to consider the interaction with the robot instead of relying on the researchers' input as some did in Phase 1.

Insights from Interacting with Caregivers in Phase 3

I8: Familiarity with the robot helps shape caregiver expectations for what the robot can do. We tried to interview caregivers who had the opportunity to see the robot in action at the facility, which allowed for more concrete opinions on how this robot is perceived by the caregivers. While not all caregivers had seen the robot, all of them were familiar with it through hearing about it from either other facility staff or the residents. For example, C1 specifically commented that "the size was not overly cumbersome." She further explained that seeing the robot in the facility was "invigorating" and made it "not as leery or scary" compared to when the abstract idea of a robot was first introduced and there were "too many open questions." This excitement is encouraging as it supports the opportunity to use the robot in a future deployment phase.

I9: Common ground creates an environment where we can get meaningful feedback about the robot. Sharing our experiences from working with the residents and reflecting with the caregivers about their daily responsibilities built common ground that led to a mutual understanding of the challenges we were addressing. Common ground created the opportunity for caregivers to provide more relevant feedback. For example, C3 remarked that the tasks the residents designed "would actually be perfect" because she felt they would fit well with her needs as a caregiver. C3 further discussed the need for robots to be cognizant of resident preferences, emphasizing that "every resident has their own preferences about how they like things." This feedback both confirms that the scenarios designed by participants are reasonable and also allows us to better understand how the robot can fit with the caregivers' needs and expectations.

I10: Discussion of the robot's role in assisted living elicits reflection on authority over the robot. At the end of the interview, we discussed more broadly about how the robot could fit into the assisted living environment. This discussion introduced a meaningful reflection about who should supervise and control the robot. All caregivers wanted some level of supervision but also felt that residents should be able to make requests from the robot. This issue of shared control led to C2 explaining the "ethical question" of how to "preserve people's dignity and their ability to make choices" while balancing what would be "safest" to do. Residents may have desires that do not align with their care needs, but it is not clear even among general caregiving practices how to balance care needs with resident wishes.

4.6 Discussion

We proposed *sPD* as a way to engage older adults in the design of assistive technologies and implemented *sPD* in a case study with a robot in a senior living facility. Below, we revisit our research questions from §4.3 and follow with a general discussion of *sPD*.

Discussion of Research Questions

RQ1: How can designers effectively engage older adults in the design of assistive technologies?

Our findings show that facilitating multiple high-fidelity interactions with the robot is an effective way to engage older adults. We observed that the emphasis on *in situ* exploration of robot capabilities and enacting interactions with the real robot fostered engagement in Phase 1. Many participants were curious about the robot or eager to see if it would be able to help them with specific tasks. Prompting them step by step to provide general ideas and personal preferences about what the robot should do throughout the scenario helped them think through the interaction steps. Even if participants were unable to conjure abstractly what the robot should do, the enactment process facilitated idea generation by providing a natural prompt for them to react to—the robot's actions themselves. For example, when the robot extended its arm toward the participant to hand an item over, that participant was prompted to either extend their hands to accept the item, turn it away, or redirect the robot to perform a different action.

In Phase 2, we added further elements of realism by incorporating realistic task initiation, removing the researcher presence from the interaction, and asking the residents to simply use the robot (instead of acting). Whenever possible, the robot performed genuine, relevant tasks for them, such as delivering a real cup of ice that the participant then immediately used with their drink. Solving a real need that the resident had at that moment facilitated engagement, and it also helped to generate more concrete design recommendations from the residents. Facilitating multiple high-fidelity interactions for the older adults allowed them to better envision how the robot should fit into their daily lives and prompted them to reflect more critically on their experience with the robot.

RQ2: How can designers better understand the challenges of integrating assistive technologies in genuine caregiving environments for older adults?

Our findings show that demonstrating interaction designs *in situ*, repeatedly experiencing these interactions, and integrating caregiver perspectives can all help build a better understanding of the challenges associated with integrating assistive technologies into care environments. First, the emphasis on demonstrating *in situ* interactions with the real robot provided a new understanding of technical challenges and environmental considerations. For example, factors such as loud ambient noises (*e.g.*, televisions or music) and the inability of some residents to speak loudly or clearly caused the built-in microphone on the robot to be unable to reliably capture the residents' speech. Such technical challenges would need to be addressed before the robot could be reliably deployed in a senior living facility.

Additionally, engaging residents over the course of multiple sessions on different days provided exposure to some unexpected situations that can arise in day-to-day life. For example, because the study sessions in Phase 2 were initiated without external warning from the researchers and the times were not always set in advance, we experienced situations that could have led to a breakdown based on the basic scenario design. For example, the robot once encountered another resident who was visiting our participant while it tried to deliver the mail, meaning the robot's behaviors and capabilities would need to accommodate an impromptu multi-party interaction. Although anticipating all possible situations is not feasible, our realistic interactions offered a glimpse of the types of emergent challenges the robot might face in a deployment.

Finally, feedback from the caregivers provided different perspectives on the challenges of integrating assistive technologies. While the caregivers agreed that the residents should be able to make requests from the robot, they felt that they needed high-level authority over the robot to ensure residents were not asking the robot for things that could cause them harm (*e.g.*, an individual taking medication asking the robot for foods that might cause a drug interaction). Maintaining residents' autonomy versus supervising their choices is an open question even within conventional caregiving practices. Talking to the caregivers and residents separately provided valuable information, but considering how their perspectives fit together allows a more comprehensive view of integrating technology in daily activities and caregiving practices of older adults.

Discussion of *sPD*

Overall, *sPD* facilitated engagement with older adults and elicitation of considerations for integrating a robot into their daily lives. In the following paragraphs, we discuss the use of this method, focusing on its benefits, other scenarios where it may be applied, and how it fits into the wider context of system design and development.

Benefits of *sPD*

We distilled our findings and contextualized them in the challenges discussed in §4.1, resulting in five benefits that show the potential *sPD* has for research with older adults:

1. *Promotion of inclusive and accessible design* — Since *sPD* is based on having participants interact with the target technology, limitations in participants' abilities to complete the study activities can help emphasize the necessary requirements for technology and interaction design. In addition, conducting the sessions in participants' living spaces allows individuals who are unable to travel to also participate. For example, four participants in our case study might not have been able to come to another study site or take part in some activities since two of them were manual wheelchair users and another two had dexterity impairments).

2. *Better understanding of technology-environment fit by participants and researchers* — The opportunity to explore the robot in the design phase and to experience the interaction during the simulated deployments

provides *participants* with a concrete idea of the robot's capabilities, which helps them ideate and refine what a robot can do for them. At the same time, *researchers* can gain a better understanding of residents' lives, particularly how residents desire to interact with the system. For example, even though we observed some participants struggling to formulate how they desired the robot to interact, through *sPD*, they were able to design acceptable scenarios (see insights I2, I3, I4, I5).

3. *Vetting of designs under realistic conditions* — As members of the target user population who have experienced the robot in genuine relevant use cases, residents' satisfaction with the system in the simulated deployment can serve as a predictor of the acceptance of the technology when it is deployed. For example, all of the residents except R4 were willing to interact with the robot, and most of them asked about the robot after the study concluded.

4. *Early exposure to practical challenges and considerations* — The simulated deployments allow researchers to assess the capabilities that the robot will need and test how well a current system is able to fulfill these requirements (*e.g.*, navigation, grasping, social capabilities). Repeated interactions facilitate observation of uncommon situations, which may increase the robustness of the deployed systems. For example, as shown by insights I6 and I7, we were able to witness uncommon situations and assess what additional sensors and changes to modalities were required to interact efficiently.

5. *Concrete, relevant feedback from other stakeholders* — Engaging caregivers facilitated the assessment of the design ideas generated by older adults and the discovery of new design ideas, and it also raised considerations that residents may not have discussed. Due to the exposure to the robot and common ground developed through mutual

sharing of experiences, caregivers could easily relate to our research, evaluate design ideas, and discuss the need for robot supervision (see insights I8, I9, and I10).

We believe these benefits highlight the promise *sPD* holds for designing with older adults. This method can offer benefits to other domains and populations as well, which we discuss below.

Application to Other Domains and Technologies

We believe that *sPD* is not limited to robotics or older adults but has the potential to benefit the design of technology for other marginalized or vulnerable populations, *e.g.*, children, individuals with cognitive impairment, individuals with blindness or visual impairment, or users with long-term physical disability. For example, certain activities such as cooking, navigation, home exercise, and tutoring are highly dependent on the specific ecosystem of use (*e.g.*, home, community center, school). Designing assistive technologies, such as a smart cane, a cooking assistant, or a robotic walker, to help with such activities can benefit from *sPD*. Introducing the technology early in its context of use and using simulated deployments can provide early and realistic feedback on the feasibility, accessibility, acceptability, and usability of the proposed ideas. We expect each phase of *sPD* to need adaptations to fit the specific population, environment, technology, and use case being considered. For example, the other stakeholders in Phase 3 would change to family members in a home situation and to teachers and other students in a school setting. In settings that do not clearly involve other stakeholders, domain experts familiar with the vulnerable population (*e.g.*, occupational therapists for blind individuals) can ensure that the designs would not interfere with other interventions or cause unintentional harm. Adapting *sPD* to other emerging technologies and domains has the potential to provide similar benefits to what we experienced to design scenarios with an assistive robot, although future work is needed to understand the extent that these benefits translate.

Considering the Bigger Picture

sPD fits within the wider context of assistive technology development as a design step to build toward a more autonomous system. While we used one cycle of *sPD*, more cycles could be added to further improve and explore other aspects of the design. Each cycle can gradually increase the autonomy of the technology, building up to a fully functioning system. For example, we used a full WoZ setup, but next we could use a higher-level Wizard of Oz (WoZ) similar to work by Senft et al. (2019), where the operator provides waypoints for navigation but still handles speech and manipulation. We could alternatively progress to include automation by the end users similar to work by Winkle et al. (2021). The advantage of iteratively increasing autonomy with *sPD* is the increased confidence that the final system will succeed in a more in-depth evaluation or deployment.

Discussion of Design Insights

Through the iterative design process, perhaps most importantly, we gleaned insight into how residents wanted to interact with the robot. As one could expect, no clear interaction patterns emerged to indicate a right or wrong way for the robot to behave. Rather, we gained a better understanding of the different aspects of the robot and interaction that should be personalized. Primarily, we found that residents had different preferences on the robot's voice and speech style. The preference for the robot's voice specifically originated as some residents struggled to hear higher pitches. Secondarily, residents had different preferences on the speech style; some preferred little to no speaking from the robot, whereas others eventually wanted a more conversational robot. We can also note the difference between the conversation being more social versus more grounded in providing updates regarding the robot's task progress or upcoming actions. Finally, residents had different preferences where the robot should place the item it was delivering, whether it was the mail or the water. We also found that this preference on drop off location varied not just between residents but also within residents, meaning that the drop off location should be extremely flexible to specify. Through these three key points for personalization, we have a much better understanding how we need to adapt robot behaviors to suite each resident.

Limitations & Future Work

Our work has a number of limitations that point to future work, regarding *sPD* and our case study, which we discuss below.

Methodology. *sPD* shows potential to help future researchers design scenarios with older adults, but it has three key limitations. First, it involves more setup work compared to other PD approaches. Using the WoZ approach to create realistic interactions means that we need an interface that allows full robot control. Nevertheless, developing this interface provides a starting point for future gradual automation of the system. Through WoZ, we could see what technical issues need to be addressed in future systems before investing the time to automate them. While more time is required up front, we expect that in the long term, it will shorten overall design and development time and lead to a more robust system. Second, while the steps of *sPD* generalize to other scenarios, *sPD* has limited scalability due to the amount of scenario-specific setup involved (*e.g.*, WoZ controls for the target system), and the design findings themselves do not necessarily generalize to other care settings and scenarios. Finally, the use of WoZ also introduces artifacts such as delays while the operator types speech for the robot, which might limit the quality of the participants' feedback.

Case study. Our case study using *sPD* has four key limitations that should be addressed with future work. First, we only engaged with a subset of residents and caregivers. Because participants had to volunteer, it is possible that they represent a more optimistic and accepting view than other individuals who declined participation. Further, we only worked with residents who had the capacity to provide informed consent. Therefore, we did not work with participants with severe cognitive impairments, which excludes many individuals in assisted living. Future work should seek to engage a wider pool of participants to investigate how *sPD* can be applied to address other challenges. Second, our case study included a relatively small number of participants with only one cycle of *sPD*. While this configuration already demonstrated the potential of the method, future work should investigate more long-term effects. The novelty of the robot may wear off over time, and the patterns and preferences of residents may also keep changing over longer exposure to the system. Third, our study involved a single robot platform, which was selected as it provides the required capabilities at a low price point and is designed to work in home settings. Although *sPD* is designed to evaluate a single platform, *sPD* could be used with other platforms or be combined with other PD work (e.g., Bradwell et al., 2021) to explore trade offs and preferences for different platforms and capabilities. Finally, our participants only included residents and caregivers. Future work should incorporate other stakeholders, such as family and other facility staff, into the different design phases to increase the ecological validity of the resulting designs.

4.7 Chapter Summary

In this chapter, we sought to understand how residents would interact with a care robot in realistic conditions Stegner et al. (2023). This project makes two contributions: (1) a novel method called *Situated Participatory Design* (*sPD*) to work with older adults to explore how the robot assistant envisioned in Chapter 3 could fit into their day-to-day lives; and (2) a case study that demonstrates how the repeat, realistic interactions facilitated by our method elicit actionable design insights from older adults Stegner et al. (2023).

sPD is an iterative approach to designing technology with the goal of gaining insights that will lead to eventual deployment. In Phase 1, we worked with the resident to design a scenario for the robot to do that is personally relevant for them. After introducing the robot and selecting a task for the robot to perform, we discussed how the robot should complete the task, such as how it should enter and whether it should talk. Once the initial design was set, we walked through the task in a user enactment, and the resident had the opportunity to request changes. In Phase 2, we conducted simulated deployments, where the researchers used Wizard of Oz (WoZ) to control the robot to perform the scenario as realistically as possible according to the Phase 1 design. After the simulated deployment, we briefly asked the resident to reflect on their experience and updated the design accordingly. Each resident experienced two simulated deployments, allowing their designs to evolve over the course of multiple, repeat interactions. In Phase 3, which we conducted after Phases 1 and 2 were completed, we interviewed caregivers to discuss the suitability of the residents' designs and address bigger-picture issues such as how to balance the resident independence with caregiver supervision of the robot.

We applied *sPD* at a senior living facility with residents to investigate their perspectives on how a robot could fit into their daily lives with a special focus on light manipulation tasks such as delivering a cup of water. We found that the realistic, *in situ* interactions helped residents better understand the robot and better imagine how it can address their needs. Many residents discovered through repeat interactions that their initial perception of how the robot should behave did not match what they wanted in reality.

Using *sPD*, we gained insight into the ways in which residents desired to interact with the robot. We found, for example, that in addition to social interaction, they may give the robot instructions to correct how it should perform the task. We also found that the direct experience with the robot helped residents who otherwise struggled to articulate their desires. These findings contribute to design implications regarding how care robot behaviors need to adapt based on resident preferences, including the robot's voice and amount of social interaction during the task. They also provide insight into how we can successfully glean these preferences from residents and how they may change over time, indicating the need for flexible configuration.

5 *CareAssist*: An End-User Scheduling Interface for Managing Care Robots

5.1 Chapter Introduction

This chapter presents the iterative design and evaluation of an end-user system for integrating robots into a senior living facility. The design of the system is heavily informed by the findings presented in Chapters 3 and 4.

Imagine a scenario, shown in Figure 5.1, where an assisted living facility purchases several capable mobile service robots to alleviate the care burden caused by a shortage of caregivers. The robots are intended to travel from room to room, so that one robot can provide assistance to multiple residents. The robots arrive with out-of-the-box capabilities such as making deliveries and interacting socially. Managing and coordinating such a fleet of highly capable robots requires considering important factors: different robots can have different capabilities–not every robot may be suitable for all tasks; care recipients also have different needs and preferences; and, to complete tasks efficiently, it is important to optimize for distance traveled. Figuring out which robot to go where, when is a non-trivial issue, especially for care staff with limited robotics and programming knowledge. While *end-user development* (EUD) is gaining momentum as a way to enable end users to dictate autonomous robot behaviors, EUD tools appropriate for this use case have not been explored.

To fill this gap, we present the iterative design and development of the *CareAssist* system. Caregivers create and manage *profiles* for each resident that captures their preferences that informs the generation of a robot program for that particular resident. Therefore, even the same general task could be performed differently based on each residents' preferences. Caregivers interact with an interface to specify high-level details of a robot's task. A backend synthesizes the inputs into a full robot program, then uses

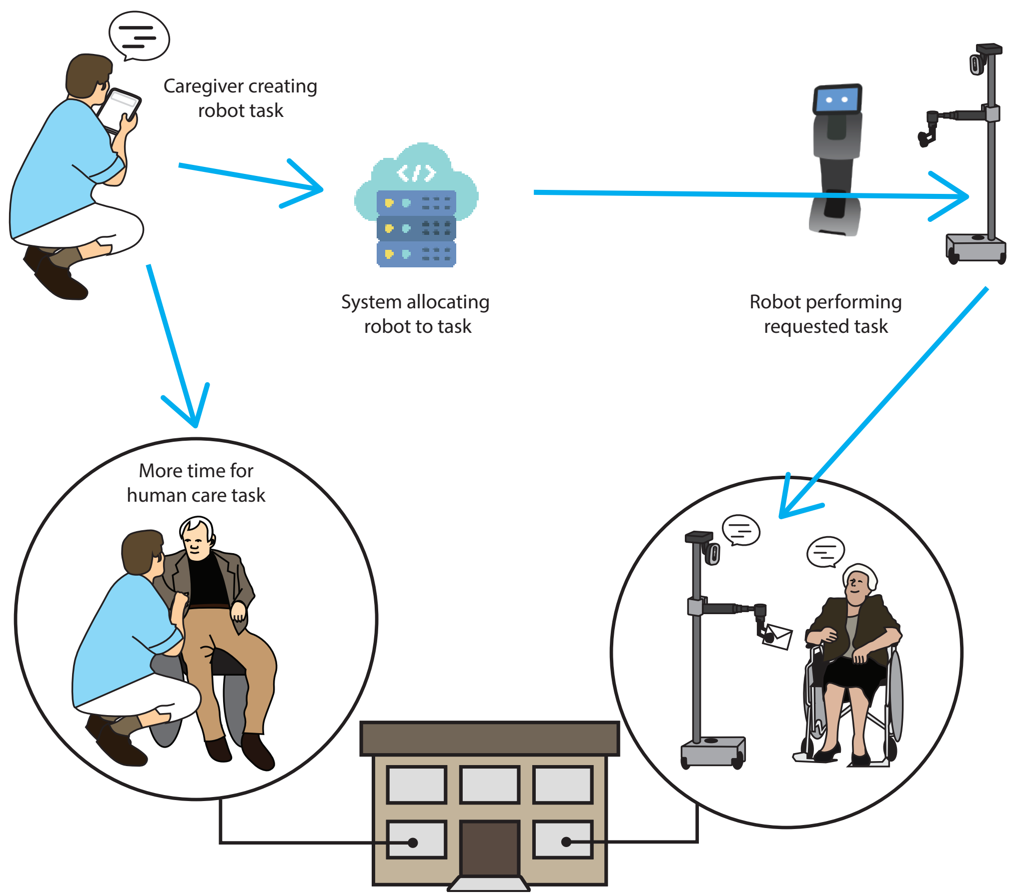


Figure 5.1: Envisioned use case scenario. Caregivers provide high-level instructions via an interface. The system automatically allocates tasks to robots to perform, freeing time for other care tasks.

a scheduling algorithm to assign the task automatically to an appropriate robot on the fleet to complete. When considering the scheduling algorithm, we model the problem as a *vehicle routing problem* due its unique ability to account for the spatial layout of rooms within the senior living facility.

In creating this system, we first built an initial horizontal prototypical interface which we used to gather preliminary feedback in a field study with six caregivers. Incorporating design feedback, we then created the *CareAssist* system, which included the updated interface and two autonomous robots. We evaluated *CareAssist* in a laboratory study with professional caregivers to elicit deeper insight into the interface. Finally, we updated *CareAssist* to address major feedback from the laboratory study, then conducted a field study with both professional caregivers and residents of a senior living facility. The iterative development of the system allowed us to explore multiple facets of the design, including the level of abstraction to present information within the interface as well as usability and acceptance considerations when integrating the robots into a real care facility. Specifically, this work makes the following contributions:

- A series of three user studies that provide insight into the usability and design of the *CareAssist* system;
- A design process of identifying the level of abstraction for an end-user development system appropriate for caregivers in a senior living facility, using a *research through design* approach to refine a prototype system;
- A vision of how robots can be integrated as extensions of senior living facilities, specifically focusing on interaction dynamics such as how the robot passes from public to private areas of the facility.
- The system design and prototype implementation of the *CareAssist* system, which incorporates a tablet interface, scheduling node in the form of an adapted vehicle routing problem solver, execution node to manage the robot fleet to complete the tasks, and two autonomous robots.

5.2 Background

Below, we discuss prior work which informs and supports our system.

Care Robots

Care robots are being developed for use in a variety of applications in the context of assisted living facilities (Trainum et al., 2024; Wong et al., 2024). Such application range from more physical assistance, *e.g.,* escorting residents to activities Pollack et al. (2002), bed bathing Madan et al. (2024), lifting residents (Wright, 2018), and refilling water bottles (Odabasi et al., 2022), to more social assistance, *e.g.,* providing medication reminders (Su et al., 2021), monitoring for accidents and falls (Eftring and Frennert, 2016), and providing social companionship (Broadbent et al., 2024). Deployments of robots in assisted living facilities have revealed the challenges of sustained use and integration into existing workflows. A review article by Wong et al. (2024) especially identified the complexity of using the technology as a factor for lack of adoption. Deployment of a mobile robot refilling water bottles in a care facility by Odabasi et al. (2022) highlights the need for more robust perception to facilitate more reliable interaction with higher success rates. Despite these challenges, robots can be acceptable for caregivers and residents in a care facility, and that technological challenges can be met (Broadbent et al., 2016). Broadbent et al. (2016) suggests that more focus should be paid toward features which can increase utilization of these robotic systems.

To aid in utilization of robotic systems, prior work has also explored providing end-user interfaces for scheduling robot tasks. For example, the Lio robot (Mišeikis et al., 2020), a zoomorphic mobile manipulator designed for use in care settings, has an optional *Nursing Interface* that allows caregivers to schedule tasks and monitor system status of the robot. Another system proposed by Vaquero et al. (2015) uses a scheduling interface to dynamically allocate tasks to a homogeneous fleet of social robots within a care facility. We take these interfaces as inspiration for our *CareAssist* system, which considers scheduling and monitoring tasks for a heterogeneous robot fleet in a care facility.

Multi-Robot Systems

Multi-robot systems have been explored for a variety of applications, including care settings. Darmanin and Bugeja (2017) provides a review of multi-robot systems used in contexts such as surveillance, search and rescue, adversarial environments (*e.g.*, robot soccer team), and cooperative manipulation. These systems can be centralized or de-centralized, and the robot fleet can be homogeneous or heterogeneous. Heterogeneous multi-robot systems have known benefits for allowing robots of different capabilities to work together to achieve more complex effects.

Multi-robot systems have also been explored in the context of caregiving to support residents to remain living independently at home. Li et al. (2013) presents an early heterogeneous system consisting of a electric wheelchair with a mounted robot arm, mobile service robot, and a humanoid Nao robot to assist with independent living and health monitoring. Barber et al. (2022) similarly use a heterogeneous robot fleet consisting of smart home sensors, a small mobile robot, and a table-mounted manipulator robot to provide support in private homes. Previous work in multi-robot systems for assisted living facility utilize a distributed model where robots "bid" on tasks to support dynamic scheduling (Das et al., 2015). Together, these multi-robot systems for care show the tremendous potential of such applications. Our work builds on this literature to address usability and adoption concerns in the assisted living facility context by providing an interface for caregivers to coordinate and supervise robot tasks as part of a cohesive care team.

Vehicle Routing Problem

The vehicle routing problem (VRP) is a generalized version of the well-known Traveling Salesman Problem. (Eksioglu et al., 2009) provides a rich overview of VRP. At its core, VRP is a combinatorial optimization that supports route formulation for commercial or service vehicles, such as delivery trucks. Variants on VRP have been developed based on particular problem constraints, allowing for rich modeling of real-world problems such as delivery time-windows, mandatory break intervals for drivers, refueling, vehicle capacity, *etc.* Constraints can be combined as desired to model the problem. In generating the schedule, the optimization can also consider measures such as maximizing number of deliveries or minimizing distance traveled.

VRP has shown utility in the context of managing robots in care settings (Tatsch, 2020; Sar and Ghadimi, 2024). Tatsch (2020) demonstrates how VRP can capture constraints and considerations within a care facility, such as travel time between locations and time windows for care tasks. While this thesis is a powerful example, it lacks a user interface to facilitate integration into care workflows. Sar and Ghadimi (2024), on the other hand, presents a system similar in structure to *CareAssist*, including a web interface, VRP scheduling node, and execution manager. Their work demonstrates the power of the user-facing interface, although their system focuses only on the task of waste collection and disposal and therefore does not account for user preferences or social interaction. We take inspiration from these past works to envision *CareAssist*.

5.3 Research Context

Although care robots are used in many settings, we focus on the assisted living context. Partnering with a local assisted living facility in the Midwestern United States, we ground our work in the real needs and opportunities uncovered from community-based research. The facility includes 60 assisted living apartments organized into neighborhoods of 10 residents each. Neighborhoods have at least one full-time caregiver on duty at all times to assist residents with tasks such as toileting, ambulation, getting dressed, taking medication, getting water, serving meals, laundry, hygiene, *etc*. The facility also staffs other care personnel such as housekeepers, activities coordinators, nurses, physical therapists, *etc.*, to provide holistic care to residents. However, despite the facility's resources, turnover and short staffing is especially high among caregivers. The facility often relies on staffing agencies to provide temporary caregivers to fully staff shifts.

5.4 Robot Platforms

For this work, we are using the Temi (temi USA Inc., 2025) and Stretch (Kemp et al., 2022) robots. Temi is a commercially available mobile personal robot with a footprint of 100H x 35W x 45D centimeters. Stretch is a mobile manipulator research platform with a footprint of 141H x 34W x 33D centimeters. Both Temi and stretch are equipped with basic features such as a microphone and speaker for voice recognition and speech detection and LiDAR and depth sensors for autonomous navigation. Temi includes a programmable touchscreen interface and a tray for object delivery, while Stretch includes a compliant gripper that can carry up to 2.5 kgs. Temi runs an Android-based operating system and provides access to its core capabilities through a semi-open SDK. Stretch runs a Linux-based operating systems and provides access to its core capabilities through a Python API and ROS2 compatibility. These robots were selected for their capabilities, as well as safety features. Both robots have low centers of mass, which is a critical safety consideration against tipping. Further, Stretch's arm includes contact sensing and its geometry provides simple and predictable kinematics.

5.5 Prototype: End-User Programming Interface

In this section, we describe our initial prototypical interface design and evaluation that ultimately served as a foundation for *CareAssist*. We began with a horizontal prototype demonstrating the overall flow and breadth of the system's features to create the opportunity for early input from caregivers before investing the time for a fully-developed system. Focusing on the programming interface provides a sufficient starting point for envisioning the rest of the system. In what follows, we describe the prototypical interface design, formative evaluation, and key lessons that inform *CareAssist*.

Prototypical Interface Design

We first built a horizontal prototypical interface demonstrating the flow of the system. The use case is that each caregiver would have a tablet interface, and they could spontaneously create robot tasks depending on their spontaneous needs during their shift. This design is informed by findings from Chapter 3 indicating that caregivers in assisted living are juggling many unscheduled resident needs, as well as recent end-user programming work by Porfirio et al. (2023) demonstrating quick, on-the-fly robot programming for novices. Each component of the prototypical interface is described below and shown in Figure 5.2, left.

Robot Tasks While we did not implement autonomous robot capabilities at this stage, we heavily considered which tasks the robots should complete. Based on the robot capabilities, we brainstormed the following list of candidate tasks to discuss with caregivers: delivering water or snacks from outside the room, fetching a snack or drink from inside the room, welfare check, giving a message or reminder, helping prepare for meal service, and patrolling for fall hazards.

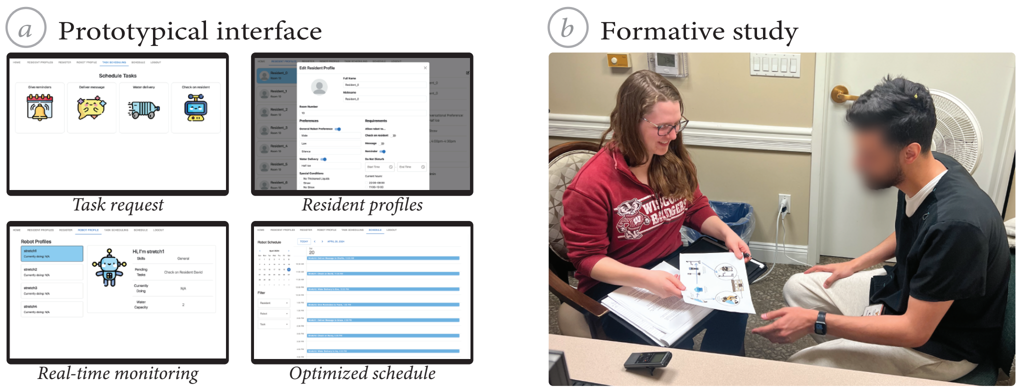


Figure 5.2: *left*: Screenshots of the prototypical *CareAssist* interface design. *right*: An image from the formative study conducted at our partner facility.

Resident Profiles To capture the preferences and needs of each individual resident, each resident has their own profile. The profile contains basic information such as their name, nickname, and room. It also contains preferences regarding how the resident would like to interact with the robots, including settings for the robots' voice tone and level of conversation, and *do not disturb* hours that the resident does not want the robots to enter their room. Finally, the profile captures task-specific information such as the resident's drink preferences.

Task Scheduling Caregivers can configure robot tasks. The task specification focuses on *what* the robot should do, not requiring deep technical knowledge of *how* to achieve it. Caregivers select the resident's name and time window for the task completion, then they specify task details. This feature was intentionally left open for feedback from caregivers to gauge the level of detail that they wanted to specify for the task. For example, they could specify the one or more high-level actions for the robot to complete, *e.g.*, deliver the water and check on the resident, or they could have the ability to edit lower-level task details such as where in the resident's room the water should be delivered. Based on the caregiver's inputs, the system would synthesize a full robot program and schedule the task for a robot. The exact steps would be personalized using resident profiles.

Task Monitoring The task monitoring page allows caregivers to monitor a live feed of what each robot is doing, including where the robot is in the facility, video stream of the robot's camera (assuming it is in a public area), what action the robot is currently completing, and what the robot will do next. The task monitoring page also allows the robot to ask questions or sent the caregiver alerts about the task, such as if the resident wants to change the task or if the robot needs help.

Formative Study

To evaluate our prototype, we conducted a qualitative field study at our partner facility to elicit feedback from caregivers at our partner facility. We interviewed six professional caregivers aged $27 - -61$ ($M = 46.3$, $SD = 13.0$; 5 female, 1 male). Their professional caregiving experience ranged from $1.5 - -34$ years ($M = 13.4$, $SD = 10.8$). The study was approved by an institutional review board (IRB), and caregivers were compensated at a rate of $40 USD for their time.

Conducting field studies with caregivers at our partner facility presents a challenge due to limited time availability of the caregivers to participate. Rather than run several long interviews, we opted to split the protocol into three sequential parts completed by two caregivers each: first, discussing the robot tasks and resident profiles; second, discussing the task specification, and finally, discussing the task monitoring. Utilizing this split allowed us to have more detailed conversations about each topic.

All interviews were voice recorded and conducted in the care facility, either in a quiet common area, caregiver station, or meeting room. For all three sections, we presented an overview of the care robot system's goals and current status. For **Part 1**, we introduced images of the Stretch and

Temi robots and explained what kinds of tasks the robots could perform. For each task, we asked the caregiver to indicate how useful the task would be and explain how they complete the care task as a part of their work. For **Part 2**, we introduced the resident profiles and task scheduling interface. Coupling these features together allowed us to explore what details should be captured in resident profiles versus specified with the task scheduling. We also probed into what level of detail the caregivers wanted to specify the tasks. Finally, in **Part 3**, we discussed the task monitoring, specifically focusing on what kind of information the caregivers wanted to receive from the robot and how the monitoring would fit into their workflows.

Implications of Formative Study

Findings from the formative study were consolidated from the experimenter's notes. Despite the small numbers, we found good consensus among caregivers in their feedback. At a high level, caregivers supported the use of the mobile service robots to assist with care tasks. In Part 1, caregivers indicated that water delivery and reminders were especially good tasks to implement. They also suggested that it would be helpful if the robot could help set the tables with silverware and drinks to prepare for meals. The rationale behind these tasks was they are all low-skill yet time-intensive tasks that pull the caregivers away from more sensitive tasks. In Part 2, we focused feedback on the resident profiles and task scheduling around those three tasks. The caregivers felt the type of information included in the resident profiles was sufficient. However, they suggested an alternative task scheduling paradigm, with the rationale that during the shift, the caregivers would not have time to use the interface. Instead, the tasks should be set in advance, such as at the start of the shift, so that the robots can automatically provide assistance. In particular, the place setting task should recur daily without the need for constantly including it. The caregivers also emphasized that the robots need to know how to do the tasks in advance—requiring the caregivers to specify more detail besides the task, residents, and time frame would create too much burden for realistic use. Finally, in Part 3, the caregivers similarly mentioned that the robots must work independently. One suggested that a designated caregiver such as the shift supervisor could be in charge of monitoring and assigning tasks to the robots, since the shift supervisor is also in charge of oversight of the other caregivers during the shift. These findings point to concrete design changes that lead to the development of the *CareAssist* system.

5.6 *CareAssist*: End-User Scheduling Interface

The premise of the updated *CareAssist* system remains the same as the prototype: caregivers have an interface that they can use to easily schedule care robot tasks without requiring technical knowledge of robots or programming. Based on the findings of the formative study, however, the paradigm is that the majority of robot tasks will be set prior to the shift, *e.g.,* in the morning, and the robots will complete their scheduled tasks throughout the day. In case of a sudden change, caregivers can always edit the schedule. We formulate the task scheduling problem as a vehicle routing problem due to similarities between vehicle routing and our multi-robot heterogeneous fleet scheduling. Below, we describe the full system, including user roles, interface design, scheduling algorithm, and robot task execution.

User Roles and Permissions

The system is designed around role-based access control to support multiple types of users: administrators, caregivers, and residents, each with access to distinct functionalities. This role distinction ensures that sensitive or administrative tasks are only accessible to appropriate users while allowing caregivers and residents to interact with the system at different levels of complexity and responsibility.

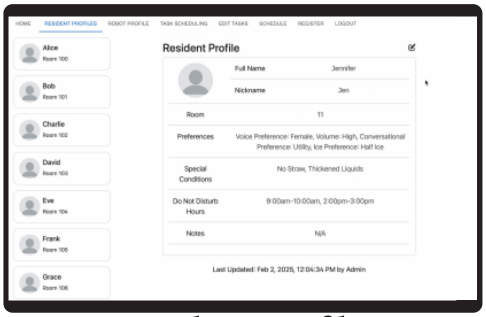
Administrators are responsible for registering and managing both residents and assistive robots. They have access to all user profiles, robot configurations, and scheduled tasks, and they oversee the full infrastructure of the care environment. Caregivers support administrators and interact more directly with residents. They can view and update resident profiles and manage robot task schedules. While residents have access set up for the system, implementing a resident-friendly interface remains future work.

Using the Interface

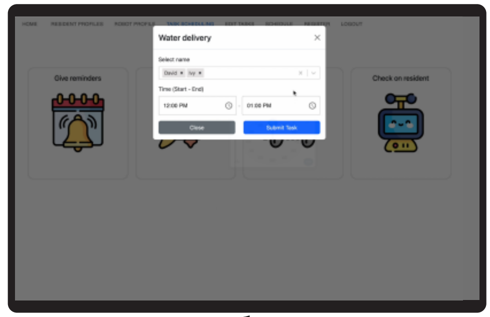
The *CareAssist* interface, shown in Figure 5.3, serves as the user's access point to configuring and controlling the overall system. The interface is divided into two key features, the profiles and the task scheduling, each described below.

Resident and Robot Profiles

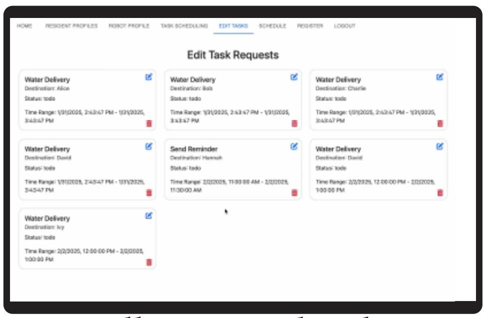
Once a resident is registered, their profile reflects their personal care preferences. These profiles include details such as specific needs for water and ice delivery, preferred interaction styles with robots, any medical or behavioral considerations, and designated *Do Not Disturb hours* when the robots should not enter. Robot profiles are also maintained within the system to track capabilities, assignments, and availability. Caregivers and administrators can both access and update resident and robot profiles to ensure that care plans remain accurate and personalized over time. This collaborative approach supports consistency across shifts and fosters trust in resident care.



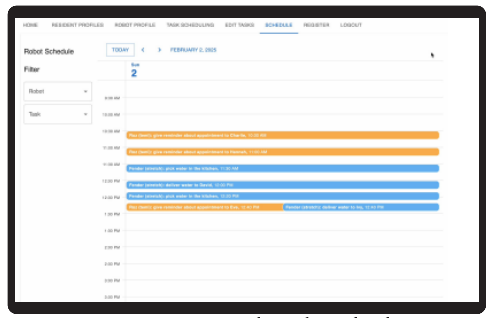
Resident profiles



New task request



All requested tasks



Optimized schedule

Figure 5.3: Screenshots of key features of the *CareAssist* interface.

Robot Task Scheduling

The system supports two assistive robots, Temi and Stretch, that can perform a predefined set of tasks. These tasks include delivering water, providing wellness check-ins, sending reminders, and delivering messages to residents. Caregivers and administrators can schedule these tasks in the Task Scheduling page, and can edit or delete scheduled tasks in the Edit Tasks page. Scheduled tasks are made visible to users through a calendar, which provides a daily view of each robot's agenda. Users can filter this view by robot or task type to facilitate efficient coordination and avoid schedule conflicts.

Robot Task Management and Coordination A core functionality of the system is task scheduling for two types of robots—Temi and Stretch. Users in caregiver or administrator roles can assign a predefined set of tasks to these robots, including delivering reminders, sending messages, and water delivery. Scheduled tasks are made visible to users through a calendar, which provides a daily view of each robot's agenda. Users can filter this schedule by robot or task type to facilitate efficient coordination.

Dynamic Task Editing The system also supports dynamic updates to scheduled tasks. Users may delete any upcoming task as long as it is more than 15 minutes from its scheduled execution time. Additionally, tasks that remain in the to-do state may be edited, allowing for last-minute changes in task parameters or assignments.

Generating Robot Schedules

Generating the robot schedules from task requests involves allocating tasks a fleet of robots to perform tasks efficiently while adhering to operational constraints. Because the schedule must account for both task completion time as well as transit time required to traverse the facility, we model the problem as a *Vehicle Routing Problem*, which is the generalized version of the classic Traveling Salesman problem. The system models this problem as a tuple (M, T, R), where:

Map. $M = (V, E)$ is a graph representing the facility. Here, V denotes a set of locations, *e.g.,*rooms, depots, and $E \subseteq V \times V$ represents edges with weights $d_{u,v}$, the distance between location u and v.

Tasks. T is a set of tasks, each $t \in T$ defined by (TID, d, s_t, e_t, P_t), where TID is a unique identifier, d is the destination of the task, $[s_t, e_t]$ is the time window for completion, and P_t specifies task specific parameters such as message to deliver.

Robots. R is a set of robots, each $r \in R$ characterized by (RID, b, c_t, u, S), where RID is a unique identifier, b is battery life, c_t is time taken to be fully charged, u is capacity, and S_r is the robot's skill set.

Formulation as a Time Constrained Vehicle Routing Problem

The Vehicle Routing Problem has many variants, so we specifically use the Time Window Vehicle Routing Problem (TWVRP) due to the congruence between the objectives and constraints of TWVRP and our scheduling needs. Our instantiation of the TWVRP is set to maximize number of successfully scheduled tasks and uses the following constraints: time windows, capacity restrictions, mandatory break intervals, and skill matching. To achieve this reduction, a pre-processing step transforms the input data into a structure compatible with TWVRP, followed by the definition of the optimization model.

Pre-Processing Prior to using the TWVRP algorithm, the system constructs a task graph from the facility map, M, and tasks, T. The pre-processing step involves two key transformations:

- **Task Graph Generation** A directed cost graph $G_c = (N, A)$ is derived, where N includes a subset of nodes from V such as the depot and key facility locations, and A represents arcs with weights corresponding to the shortest travel distance between these nodes. For each pair of nodes $(n_i, n_j) \in N$, the travel cost is computed based on the underlying map M.
- **Cost Matrix Construction** The directed cost graph G_c is then converted into an $|N| \times |N|$ time matrix, denoted as C, where $C[i, j]$ represents the travel distance from node n_i to node n_j. Diagonal entries $(C[i, i])$ are set to zero, and off-diagonal entries are popu-

lated with the arc weights from G_c, reflecting the cost of navigation between task locations.

Objective Maximize the total number of tasks completed in all robots in the system. Define $x_{rt} \in \{0,1\}$, where $x_{rt} = 1$ if robot $r \in R$ is assigned to task $t \in T$, and 0 otherwise. The objective function is:

$$\text{maximize} \sum_{r \in R} \sum_{t \in T} x_{rt}$$

Constraints

- **Time Window Constraint.** Tasks must be completed within the specified time window. Each task t must be completed within $[s_t, e_t]$. Let a_{rt} be the arrival time of robot r at task t. Then:

$$s_t \leqslant a_{rt} \leqslant e_t \quad \forall r \in R, t \in T \text{ where } x_{rt} = 1$$

- **Task Ordering Constraint.** The water delivery task involves pickup-delivery pairs, meaning that the cup must be picked up before it can be delivered. For pickup-delivery pairs, let t_p and t_d be the pickup and delivery tasks. If assigned to robot r:

$$a_{rt_p} + d_{p,d} \leqslant a_{rt_d} \quad \text{and} \quad x_{rt_p} = x_{rt_d} = 1$$

- **Capacity Constraint.** Robot r has a limited capacity to hold cups of water.

- **Skill Constraint.** Not every robot can complete every task, for example the Temi robot could not make a water delivery where it must place the cup on a table because it does not have an arm. Robot r can perform task t only if its skills S_r include the required skills:

$$S_t \subseteq S_r \quad \forall r \in R, t \in T \text{ where } x_{rt} = 1$$

- **Battery Constraint.** Robots must ensure they do not run out of battery. Robot r must return to depot every b_r minutes. For a subtour from depot t_d back to depot t'_d via tasks $t_1, t_2, \ldots, t_k$:

$$s_{r,t'_d} - s_{r,t_d} \leqslant b_r \quad \forall r \in R$$

Executing Robot Tasks

Once a task schedule is generated, a separate execution node facilitates communication with the robot fleet. When it is time for a specific robot to complete a scheduled, task, the execution node sends task details to the robot. The robot is then responsible for mapping tasks with their respective low-level behaviors (*i.e.,* the task of delivering a reminder requires the robot to go to a location and display the text on the screen), as well as updating their currently assigned task with the appropriate task state. Task states indicate whether the scheduled task has not yet started (**todo**), currently being completed (**in-progress**), or already completed (**done**).

When the schedule is generated, the execution node saves the first **todo** task for each robot to a database table. Each table has a unique endpoint that the robots can query to obtain the initial task details. Subsequent tasks are broadcasted over a socket connection directly to the robots.

Each robot updates the execution node when the task state of their current task changes. When the robot finishes or cancels a task, the subsequent **todo** task on the schedule for that individual robot is assigned, ensuring the robot has its next task. Once it is time to start the task, the robot updates the execution node that that task status is now **in progress**. As the robot progresses through the scheduled task, it sends updates regarding which action it is doing and broadcasts a message to the interface if it needs assistance. Once a task is finished or times out, the robot sends a final task status update and moves on to the next scheduled task.

The current system supports three behaviors, each described in detail below and visualized in Figure 5.4. The navigation behavior is required to complete the subsequently described behaviors.

Navigation

Both robots navigate autonomously through the care facility using their own built-in mapping and navigation stacks. The navigation setup begins with manual mapping of the environment. During this process, various key locations, such as resident rooms, hallways, and common spaces, are assigned waypoints with unique, descriptive names. Each waypoint stores spatial data including the robot's coordinates and orientation. To account for physical barriers such as doors, we define intermediate waypoints: "before-door" and "after-door" positions. These intermediate waypoints allow the robot to recognize when a door may be obstructing its path. If the robot fails to reach the "after-door" waypoint from the one before it, it concludes that the door is closed and prompts nearby individuals for help via an on-screen message and voice requests. The robot also broadcasts a help request to the interface in case there are no bystanders to help. Once

Navigation *Reminder or message* *Water delivery*

Figure 5.4: Three behaviors supported by the *CareAssist* robot fleet.

the path is clear, the robot can proceed with the task. This structured approach ensures that the robots can perform tasks autonomously while safely managing common obstacles in the dynamic senior living facility.

Messages and Reminders

Upon arriving at a destination, the robot uses voice prompts to alert nearby individuals. These alerts may include messages such as "Here is a reminder that the Fun and Fit exercise class is at 10am tomorrow," or "The nurse says that it's time for your medication." Optionally, the robot also uses its onboard sensors to detect the presence of users in the room. If someone is detected, the robot slightly adjusts its orientation and may approach the user to improve the communication experience.

Water Delivery

The water delivery is a two-step task. The robot first must pickup the appropriate water cup, then deliver the cup to the resident. Cups are affiliated with residents using a place mat with an Aruco tag. The robot recognizes the Aruco tag linked to the resident and selects that cup for delivery. A similar place mat system is implemented for delivery to allow flexible delivery. Residents can place the delivery mat on any tabletop surface near the edge, and the robot will place it wherever the place mat is located at that time.

Implementation

The *CareAssist* system's hardware components are shown in Figure 5.5a. The interface was implemented using a component-based architecture built with React. The backend was implemented using Python 3.10, specifically using the Google OR Tools library as an off-the-shelf vehicle routing problem solver. The front end, back end, and robots communicate using a

(a) *CareAssist* system (b) Lab study with professional caregivers

Figure 5.5: *left*: The *CareAssist* system includes a tablet interface and two robots. *right*: An image from the laboratory evaluation with professional caregivers.

combination of RESTful APIs and socket connections. Temi is programmed using Android Studio and the custom Temi SDK. Stretch is programmed with a custom Python 3.10 and ROS2 Humble.

5.7 *CareAssist* Lab Study

Due to the challenges of extensive study sessions with caregivers in our community partner facility, we opted to conduct thorough laboratory-based evaluations as an initial step toward system evaluation. The laboratory sessions, shown in Figure 5.5b allow us to train caregivers to use the interface and gather detailed, focused feedback. The study was approved by an institutional review board (IRB). Below, we describe the participants, procedure, and key insights from our laboratory evaluation as well as subsequent updates made to the *CareAssist* system.

Participants

We recruited seven participants (6 female, 1 male) aged 18−−33 ($M = 23.4$, $SD = 5.5$) with professional caregiving experience in an assisted living facility ($n = 4$) or hospital setting ($n = 3$). The study was approved by an institutional review board (IRB), and caregivers were compensated at a rate of $40 USD for their time. Participants were recruited from across the campus community, screened for eligibility, and paid $25 USD per hour for completing the study session.

Procedure

All study sessions were be conducted in a quiet, private lab space. After obtaining informed consent, participants were given an overview of the goal of the *CareAssist* system. Participants were trained via a live demonstration to use the key features of the interface. After the training, the participant completed the following scenarios:

1. *Scenario A:* Sally, Jim, Betsy, and James all need water in the morning. James has medication, so he needs his water delivered promptly between 9:00–9:10 am. Sally, Jim, and Betsy prefer to have their water between 10:00–11:00 am after the morning activity is completed. Add these events to the schedule.

2. *Scenario B:* During the morning activity, Betsy has a medical emergency and is taken to the hospital—so we don't want the robot to deliver Betsy's water anymore. Cancel the delivery.

3. *Scenario C:* Open exploration. You can play around with the interface and ask any questions.

While completing the scenarios, the participant was asked to "think aloud" to give the experimenter insight into their thought process, and the experimenter asked follow-up questions in between scenarios. Immediately after completing the scenarios, the participant completed the SUS questionnaire, then the experimenter asked additional questions regarding user experience, perceived utility, and potential impact.

Finally, the experimenter demonstrated the robot capabilities: first the Temi robot giving a reminder and then the Stretch robot delivering a cup of water. The experimenter asked for feedback regarding each robot and further discussed the participant's perspectives on the use of the robots in an assisted living facility to supplement care staff.

Sessions were video and audio recorded. The experimenter also took detailed notes and reflections to jump-start the analysis process. While in the future, a thematic analysis (Braun and Clarke, 2022) procedure will be used to extract key insights from interview transcripts, we present now preliminary takeaways based on the experimenter notes.

Key Insights from the Lab Study

Overall, feedback on the *CareAssist* system was quite positive, with the SUS questionnaire yielding an average usability score of 93.6 ($SD = 8.0$). Participants in particular felt that the system was easy to use and aligned with existing software they already use as part of their work. The information contained in the resident profiles was highly relevant to the tasks the robots would perform, although some participants felt that information regarding resident medical needs or restrictions should be directly pulled from a central charting system rather than tracked separately. Participants felt the task scheduling was straight forward to use and quick to learn. While the scheduling interface was simple and quick to use, participants expressed that specifying all robot tasks daily could become cumbersome. Several participants also mentioned that they would like the system to provide a more explicit rationale when it failed to schedule a task request. When using the interface, the participants overall prioritized efficiency and safety. Several participants mentioned opportunities to increase efficiency, such as adding voice-to-text when specifying messages for the robot to deliver. One participant further explained that the system would require more safeguard against accidentally deleting the wrong task by accident.

Demonstrating the robotic capabilities generated further rich discussion. Overall reception of the robots was positive, although many participants felt that the Stretch robot moved too slowly as it delivered the cup of water. Temi was well-received, especially for its cute appearance. One key topic included a rich discussion surrounding the inability of our robots to open doors and how that would impact utility. Our robots currently had no way to open doors on their own, so we discussed alternatives such as waiting for a bystander to ask to help or sending a notification via the *CareAssist* interface to ask a caregiver to come open the door. Participants were concerned that relying on bystander assistance would not be efficient, so we discussed the need for the caregiver to go open the door to help the robot. Participants had split opinions on opening the doors for the robots. With the reminder delivery, most participants did feel that if they had to open the door for the robot, they would prefer to deliver the reminders themselves. However, one participant felt adamantly that they would happily open the door for the robot and let it finish delivering the reminder because then they would not have to worry about remembering all of the reminders that individual needed in that instance. Opinions with the water delivery were more evenly split, with some participants viewing that the robot must complete the entire task, while other participants felt a partial delivery could be useful. In other words, the robot could still carry the water and left it outside of the resident's room such that a caregiver could bring it inside eventually.

Overall, participants saw immense potential in the *CareAssist* system to ease their workload and expressed interest to use it or a similar system at their work as soon as possible. This lab study provides validation for the usability and design of the *CareAssist* system, indicating that the tasks we have selected are appropriate and that the higher-level abstraction of managing resident profiles and scheduling robot tasks is appropriate for caregivers during their workflows.

CareAssist System Updates

While overall feedback and usability of the *CareAssist* system was positive, we made two major updates based on findings from the laboratory study. First, we updated the scheduler to provide a specific reason if requested tasks could not be scheduled. The two possible reasons included a conflict with that resident's *do not disturb* hours or that the robot is not available to add the task to the schedule. Second, we added the ability to set recurring events. The recurring events are specified using the same procedure described in §5.6, with the addition that the user also selects which days of the week the task should be repeated. The recurring task would be rejected if it conflicts with already-specified recurring tasks. Overnight, the system would run a processing script to update the schedule with all repeating task requests. The caregiver could then add, update, or remove task requests in the morning rather than starting from nothing.

5.8 *CareAssist* Field Evaluation

To supplement our laboratory study and provide further field validity, we conducted a field evaluation at our partner facility. In the field evaluation, shown in Figure 5.6, we worked with both care staff and residents to develop a more holistic understanding of the *CareAssist* system and its potential impact in a real care setting. The study was approved by an institutional review board (IRB). Below, we describe the participants, procedure, and key findings from our field evaluation.

(a) Resident interactions (b) Care staff interactions

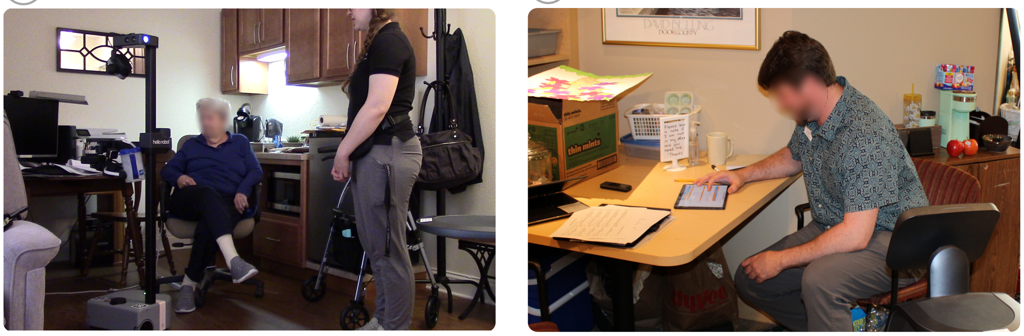


Figure 5.6: We conducted a field evaluation of *CareAssist* at our partner facility. *left*: Residents interacted with both robots and provided feedback based on their experience. *right*: Care staff provided feedback on both the interface and with interacting with the robots.

Participants

We worked with a total of 10 care staff aged 21−−63 ($M = 34.9$, $SD = 16.2$), including 2 males, 7 females. While our primary target was caregivers, we also spoke to other staff who were interested in learning about the system and providing feedback: six caregivers, one life enrichment coordinator, one speech language pathologist, and one volunteer who helped with social activities. Note that one care staff member did not provide demographic information due to time constraints. Care staff were compensated $40 USD per hour for completing the study. We further worked with 11 residents aged $65 - -97$ ($M = 86.9$, $SD = 9.1$), including 1 male and 10 females. Residents were compensated $20 USD per hour for completing the study.

Procedure

Below, we describe the separate procedures used for care staff and residents. All study sessions took place at our partner facility. In addition to these study sessions, the experimenter also walked around the facility several times to observe factors such as how many residents kept their doors open versus closed and how many bystanders the robot might encounter.

Care Staff

The procedure for the care staff followed the same procedure outlined in §5.7 with two key differences. First, due to time constraints, care staff were shown a live demonstration of the interface, but did not complete the scenarios or SUS questionnaire. We prioritized interactive discussion due to the high usability established in the lab evaluation. Second, similarly to the formative study, it was not feasible to conduct the full protocol with all care staff. We conducted four longer interviews (20 min) that focused on demonstrating the interface, with robot capabilities demonstrated as time allowed. The remaining were much more brief and instances where either when the care staff wanted to discuss their thoughts on seeing the robots at the facility in passing about the robot or when the care staff happened upon a resident in a session and briefly joined the conversation. Using this flexible approach allowed us to gather as much feedback from care staff as possible while respecting their time constraints.

Residents

Each resident study lasted approximately one hour. During the study, the experimenter first introduced the overall idea for the *CareAssist* system, then the experimenter introduced each robot individually. For each robot, the experimenter demonstrated the range of personalization the resident could control as a way to interactively set their profile, specifically the voice volume, style, and amount of speech. Once the parameters were set, the experimenter demonstrated the robot doing the task and discussed the resident's impression. The experimenter repeated the demonstration as many times as the resident requested, although most opted for two or three demonstrations for each robot. Finally, the experimenter asked for more general feedback about incorporating the robots into their daily life, such as how the robots should handle the doors being closed.

Key Findings

The field evaluation yielded a rich set of multi-dimensional results. Sessions were video or audio recorded as time permitted. While in the future, a thematic analysis (Braun and Clarke, 2022) procedure will be used to extract key insights from interview transcripts, we present now preliminary takeaways based on the experimenter notes and reflections. Below, we describe key takeaways from both the care staff and residents as well as general observations from within the facility.

Care Staff

From the care staff, the overall reception to the idea was quite positive. The interface received similarly positive feedback from the lab evaluation and the tasks seem overall like they could be quite helpful. The recurring tasks feature was well received as a way to provide desired levels of efficiency in using the system. The robots were also well received overall. There were many positive reactions to Temi being very cute, friendly, and nice. Stretch had less visibility because it was harder to roam the facility with it, but the staff thought it had a lot of potential to help. They felt that it could deliver more than just water in the future.

Especially as it was a divisive but critical topic from the lab evaluation, we discussed in depth as much as possible about the door situation—in the end, it seems fairly critical that the robot could gain entry to the rooms to complete the task. Only one care staff felt the water delivery could be useful if the robot can only bring it outside of the door, and the enrichment coordinator felt it could still be helpful to remind only residents with open doors about upcoming activities.

Residents

From the residents, we also received largely positive feedback. We found that the level of personalization contained in the resident profiles appears to be the appropriate starting point for setting initial preferences, but that additions such as talking speed would be critical in future iterations. Several residents also expressed that they did not want Temi to display a face because it made them uncomfortable.

We also found general positive reception to the robots, although the more capable the individual, the less impressed they were, especially with the water delivery. Some residents felt that the water delivery would be extremely useful, such as residents confined to wheel chairs who frequently get thirsty. Other residents felt that the robot moved too slowly to provide any assistance and that they were more capable to get water on their own. There were also some instances where the robot had trouble with the water delivery. In one instance, the resident wanted the cup delivered to the seat of their walker, which is a soft/uneven surface so the cup fell when it was set down. In the other instance, the resident's carpet was somehow tough for the robot to turn on, so it did not get the cup very close to the correct delivery location. With the reminder task, several residents thought it will be great if they can "RSVP" through the robot whether they will actually attend or not, and also several wanted to be able to query the robot for more information about the activities instead of just receiving a static reminder.

Facility Observations

In several instances, the experimenter went around the floor with one of the robots to observe things such as how many doors were open/closed, how often we encountered other people (residents or staff), and any obstacles that may present a challenge for the robots. There were not many people out and about, with the exception of just before/after meal time or when an activity was happening. About 80% of the doors were always shut. We also saw typical obstacles such as cleaning or medication carts partially blocking the hallway, residents either alone or with a care staff taking up entire hallway, and, in one instance, a door opened suddenly into the hallway blocking the way.

5.9 Discussion

We have presented the iterative design and evaluation of *CareAssist*, an end-user system for care robots in a senior living facility. Based on the premise a senior living facility has robots that can go room to room helping residents with different tasks, we built an initial horizontal prototype that caregivers could use to create and manage tasks for a fleet of care robots. We used a horizontal prototype as a design probe in a formative field study with six caregivers at our partner facility to fine-tune the interaction paradigm. Through the formative study, we found that the interface needs to support high-level task specification and automatically fill in low-level task details to appropriately fit into existing caregiver workflows and needs. We also identified water delivery and giving reminders as critical tasks that robots could help in our partner facility. We then built the *CareAssist* system prototype, including a tablet interface and two autonomous robots. With the interface, caregivers make task requests that are synthesized into an optimal schedule using a *vehicle routing problem* solver. To evaluate the system, we conducted a laboratory study with seven professional caregivers. Caregivers were trained to use the interface, used the interface to schedule sample robot tasks, and watched live demonstrations of robots completing the tasks. Throughout the study, caregivers provided feedback about usability and acceptance. After another round of interface updates, we conducted a follow-up field evaluation to glean insight into ecological fit of our design solution. In the field evaluation, we interviewed a total of ten care staff and eleven residents. Through this work, we have explored several major facets of the system design.

Interface representation — First, we developed an appropriate level of abstraction for caregivers to easily create and manage robot tasks. The system uses a higher level of robot coordination for quick, efficient task specification. Leveraging increasing autonomous robot capabilities, we assume that robots do not require instruction at the action level, but instead can parameterize a task plan based on information captured in resident profiles. For example, robots can adjust the voice tone for each resident to accommodate their preferences and needs. We found through our formative study that coordination at this higher level is more appropriate to fit into existing caregiver workflows and needs.

Multiple User Types — Second, *CareAssist* incorporates support for multiple users and multiple access levels. The different access levels ensure that potentially sensitive or overly technical information is only accessible by the appropriate users. For example, caregivers may need to view and edit resident profiles, but they should not have access to add or modify robots. This separation also simplifies the information that caregivers are required to process—only select administrators will need to consider low-level robot-specific details.Although we did not explore a resident-facing interface as a part of our *CareAssist* implementation, our multi-user setup would support future additions for residents to directly update their preferences or even make task requests. Our field evaluation in particular highlighted the interest and need for residents to directly make updates or requests. For example, residents may want to make their own *do not disturb* times for the robot not to bother them that day, or residents may become thirsty and want to request the robot to bring some water. However, caregivers expressed concern that the *CareAssist* interface was currently too complicated and included unnecessary details for the residents to use. This discussion highlights the need to consider different interfaces for different end users, where each interface is tuned toward each user groups' needs and preferences.

Transitioning from Public to Private Spaces — Finally, the field evaluation especially draws attention to a unique aspect of the *CareAssist* system: the robots are moving between public and private areas of the facility as they travel from resident to resident. Designing a robot that can navigate between both areas is more complicated than building a physical device that allows the robot to open doors. For example, some residents may be comfortable with robots having access to enter their room if the door is shut, but other residents close their doors to signal that they do not want to be disturbed. Some residents further envisioned that they could have an app or another way to signal (*e.g.*, a sign on the door) to the robot that it should not disturb them. In addition to the meaning behind an open or closed door, residents also had different preferences for how the robot should gain entry into their space. For example, some felt that as long as they knew the robot was coming, it should enter on its own, but others wanted the robot to wait for permission prior to entering. This exploration reveals that even something as simple as a door can have considerable implications for personalization needs. This topic is not widely discussed in care robot literature because robots in care facilities tend to either operate in common areas or remain entirely in an individual resident's room.

Limitations & Future Work

The system has several key limitations that point to future work.

First, the system requires a field deployment to better understand the implications and impact of robotic assistance in a senior living facility. A proposed protocol for such a field deployment is detailed in Appendix B.

Second, the implementation includes a small selection of tasks and robots. Although these tasks are grounded in real care activities and motivated by caregiver feedback, ultimately there are many other tasks that mobile service robots could perform. Future work should expand the interface and robot capabilities to include a wider range of tasks.

Third, the system currently assumes a pre-defined task template for each task for each robot. Given our small set of robots and tasks, we could feasibly define each template. To support further task flexibility, future work should incorporate a task planner to dynamically generate robot task plans, such as the goal-oriented robot programming tool developed by (Porfirio et al., 2024).

Finally, the robot interaction are currently very basic in an effort to develop robust, field-worthy implementations. This limitation is especially due to current limitations in reliable in-the-wild voice interaction with older adults. As technology develops further, we see a fantastic opportunity to explore the intersection of social and service robots in the care context.

Overall, the *CareAssist* system presents a solid foundation for inspiring future work.

5.10 Chapter Summary

In this chapter, we present the iterative design of an end-user interface for configuring and scheduling tasks for a heterogeneous fleet of care robots. This work builds on the design findings described in Chapters 3 and 4. An initial formative study using a prototypical interface revealed a critical shift from *action* level to *task* level coordination. For care robots to truly assist caregivers in their existing workflows, the robots must have the autonomous capabilities to operate independently, with minor and infrequent assistance.

We built the *CareAssist* system, consisting of a tablet interface, scheduling node, execution node, and Temi and Stretch robots. The interface allows users to configure resident profiles, which include their preferences regarding both robot interaction and task details. The interface also allows users to create task requests and manage automatically generated schedules of robot tasks. The schedule is automatically generated using a vehicle routing problem algorithm. The algorithm optimizes the number of scheduled tasks while balancing constraints relating to time windows for completing tasks, robot capabilities, and robot battery life. Once a schedule is generated, the execution node coordinates with the robot fleet to ensure scheduled tasks are completed on time. We conducted a lab evaluation which illustrated the usability of the interface and promise of the system. In a follow-up field evaluation, we worked with both residents and care staff for a more comprehensive understanding of the implications of the *CareAssist* system.

This chapter presents one example of an end-user interface that takes large steps toward supporting the integration of robots in senior living facilities. Shifting focus to the task scheduling level and incorporating multiple robots better aligns with how caregivers approach their work. The addition of resident profiles further enables personalized, multi-user support. We further call attention to the unique design needs as the robots must travel between public and private areas of the care facility. The *CareAssist* system demonstrates the culmination of a holistic, community-based design process that resulted in a novel system that addresses real-world need.

6 GENERAL DISCUSSION

6.1 Summary and Significance of Work

The preceding work provides partial support for my thesis that **personalization through end-user development can facilitate the integration of robots into senior living facilities.** This support is demonstrated through an incremental design and development process. While each chapter makes a specific, isolated scientific contribution, the sum of these chapters represents an additional contribution when presented as a holistic, community-based design process.

We first build a case for end-user development (EUD) in senior living facilities through a qualitative exploration of care needs in Chapters 3 and 4. Based on these care needs, we arrive to design implications and requirements which point to EUD as a promising solution. From observing and interviewing caregivers, we learned that they have a high priority on resident safety and quality of life. While caregivers were open to the idea of robotic assistance, they felt it is necessary for the robot to integrate as part of the care team. Caregivers expressed the need for a way to assign specific tasks for the robot and that the robot needs to provide updates on its care tasks so that all members of the care team are informed. We also found that tailoring care tasks toward individual resident needs and preferences requires detailed knowledge of each individual that is not always documented in medical records, such as learning preferences for when residents like to get ready for bed or how much ice they like in their water. Working directly with residents to design interactions reinforced the need for personalization and provided deeper insights into which aspects of the interaction may need personalized. Even when the robot is completing the same basic care task, such as making a simple delivery, it may need to alter its voice type (male vs female tones), amount of social interactivity, and even the exact location that the delivery item should be placed. These findings together make an argument that only relying on pre-specified behaviors are insufficient for the senior living facility context, and that the residents and caregivers as the end end users of these care robot systems require some level of control to personalize behaviors according to their needs. I do not suggest that EUD is the *only* solution toward integrating robots in senior living facilities, but that it is a critical piece of a very complex puzzle. Future advancements in robot autonomy and artificial intelligence will further bolster this integration, but we still require a human-machine interface to allow successful use of this technology. For these reasons, I posit that EUD *is* critical for successful use of care robots.

We then followed a Research through Design (RtD) (Zimmerman et al., 2007) approach to develop the EUD system presented in Chapter 5. This system coalesced into an EUD system for creating and scheduling personalized care robot tasks based on resident preferences (captured in resident profiles) and robot availability. Caregivers can easily generate task requests based on what task the robots should perform for which residents in a given time window. The task requests are then translated into an event schedule where each event is assigned to a specific robot based on robot availability and capability. The schedule is optimized based on completing the maximum number of tasks with the least amount of travel time per robot, while accounting for battery life of each robot. For our implementation, we focused on water delivery (using Stretch and Temi) and giving messages/reminders (using Temi) as our tasks. The system is directly inspired by the findings in Chapters 3 and 4. Chapter 3 supports the paradigm of a robotic assistant that caregivers can assign and supervise tasks for residents, especially that a direct interface will be required and it also provides insight into the tasks that caregivers would find helpful and suitable for robots to perform. Our system focuses on giving reminders and delivering cups of water, which is a subset of desired tasks that intersects our robots' capabilities. Chapter 4 provided insight into which aspects of the interaction should be personalized for the residents. The interface captures desired voice style, volume, amount of conversation, and permissible tasks as a coarse starting point for personalization. These facets represent easily articulated aspects of a personalized interaction that could be achieved with our robots, but future refinement would be required to fine tune behaviors from subsequent interactions. Through the RtD process, we further explored novel aspects of the interaction, including the appropriate level of abstraction for caregivers to easily coordinate the robot schedules and resident preferences, as well as the interaction dynamics of how the robot passes from public to private areas of the facility.

Overall, through the incremental process from initial ethnographic exploration to iterative design and evaluation of an EUD solution, we provide a realistic pipeline for this style of research. This dissertation makes empirical, design, methodological, and systems contributions in support of my thesis statement. I hope that this body of work can serve as inspiration and foundation toward continued exploration of end-user development tools specific for the care context.

6.2 In Pursuit of a Field Deployment

The work presented in this dissertation is a solid foundation in demonstrating that end-user development can facilitate the integration of robots into senior living facilities. A critical next step in continuing this work should include a field deployment of the end-user system presented in Chapter 5 to fully understand the implications and impacts of integrating care robots. In the spirit of encouraging future field deployments and work in this area, I include in Appendix B a protocol for a field deployment.

To achieve a successful field deployment, solutions to key reliability and safety issues must first be integrated. Such topics, while critical in care robot systems, were outside of the scope of this work but remain crucial for future deployments. While technologies that enable autonomous robots, *e.g.*, navigation, manipulation, and perception, are rapidly advancing, fully autonomous systems lack robustness and stability for the applications desired for the senior living facility context. Reliability challenges emerge when combining isolated components of interactions, with failures potentially disrupting caregiver workflows. For example, even if a robot delivering a cup of water succeeds 99% of the time, we found that the 1% that it fails will create a substantial burden for caregivers because they structure their workflows assuming that the robot will offload the water delivery task.

In addition, safety concerns, such as the risk of a robot toppling or failing during crucial tasks, remain a key concern (Subburaman et al., 2023). Older adults are often classified as a vulnerable population due to factors such as physical or cognitive decline and age-related disability. A robot that topples or tips over could cause severe harm, and an older adult may not be able to safely move out of the way in time. Robots may also pose a safety concern by reacting inappropriately to social situations, such as an older adult living with dementia who suddenly becomes agitated or confused. Assessing and reacting appropriately to an older adult's psychological state is highly nuanced.

To achieve a robust field deployment, the above safety and reliability issues must be addressed. Doing so will require close collaboration with caregivers and nursing researchers to define what a safe, robust, and reliable robot should look like. Once these standards are defined, then it will be more clear how to achieve a reliable field deployment of care robot systems in this context.

6.3 A Reflection on Community-Based Participatory Work

The work presented in this dissertation is informed heavily by community-based participatory research (CBPR) (Viswanathan et al., 2004) methodology. The close interaction with my community partner has greatly shaped my dissertation, and as such I find it appropriate to document the journey, including the benefits and challenges of this style of research. These details are often excluded from research manuscripts, yet represent a large body of knowledge and effort that I hope can be a reference for other researchers.

General Approach and Timeline Working with a community partner requires dedicated, intentional communication. It took us nearly two months to establish initial contact with our partner facility. When we finally met with representatives from the senior living facility, it was crucial to establish trust. I found it necessary to re-frame my thinking from "here is the research I will do" into a collaborative "I am interested in exploring solutions to this problem, here is what I would like to try, but I am open to discussing how this fits to your needs and resources." This small re-framing allowed open communication and gave the community partner power in the research process.

Payment system Once we established a mutual interest in working together, we had to figure out logistics, especially how participants would be paid. The facility has policy forbidding care staff from accepting money, so we sought an exception based on the nature of our work. We also agreed that, with the exception of conducting observations, we would not work with caregivers during their shifts—we organized sessions during their breaks or before/after their shifts. Payment for residents was also a separate process, because the facility discouraged residents from having cash in their rooms. As an alternative, we deposited the money into the resident's spending account at the facility and gave them a receipt as proof of payment. These processes worked well once they were established, although it did take several additional weeks to get the approval.

Recruiting process Finally, we had to establish our recruiting processes, and then we could move forward with our research. The recruitment was heavily influenced by the facility's as well as Institutional Review Board (IRB) policies. All of our recruiting happened through in-person recruiting activities. When recruiting caregivers, we were unable to post fliers or send emails, so we approaches caregivers in passing at the facility and invited them to participate. When recruiting residents, we worked with the facility administration to identify suitable residents, which in our case included only residents who could provide informed consent (*e.g.*, we did not work with individuals with dementia). The facility administration was happy to help us recruit; however, due to the power dynamic between residents and administration, we had to do the face-to-face recruiting ourselves to ensure consent was freely given.

Challenges

Conducting CBPR is a difficult process. Below are several key challenges that I faced and some strategies that I used to overcome them:

Maintaining the relationship in between studies After collecting data for one field study, it took a great deal of time to analyze the data and plan and prepare next steps. During this in-between time, which sometimes lasted up to a year, I struggled to maintain the relationship with the community partner. This gap lead to two major challenges. First, staff turnover at the facility was common, just as it is in other care facilities and settings. In one instance, the contact I was coordinating study activities left her job while I was away at a summer internship, and her replacement did not know anything about our work. We essentially had to start over explaining our work to her and are still trying to rebuild the connection. Second, we struggled to maintain a consistent participant pool. Residents often either passed away or had to withdraw due to medical complications, and caregivers frequently changed jobs. This high turnover means that while I was getting very familiar with the facility, I always had to spend a significant effort on recruiting new participants.

One way that I helped ease this challenge over the course of my work was to plan intermediate visits to check in with residents who previously participated in my research. I stopped by once a month to chat with them, providing updates on my research and listening to any stories they wanted to tell. This activity was not data collection, but it helped significantly to maintain the community partnership. However, as I am just one person, I was unable to maintain these check ins while I was away at internships or caught working on other projects. Nonetheless, I found this strategy to be a good option for bridging longer gaps between studies.

Managing expectations about robots I observed two key sources of expectations for robots that presented challenges in my work.

First, science fiction (sci-fi) played a significant role in participant expectations. Quite often, when I would introduce robots or the idea of robots to participants, they would react by referencing or comparing it to a sci-fi robot that they remembered such as from the Jetsons or Star Wars. Especially when working with older adults, I believe that they use their experience with sci-fi robots as a way to relate to the new or unfamiliar notion of interacting with a real robot. The influence of sci-fi on robotics is not a new idea (for example, see work of Saffari et al. (2021)), and it was interesting to experience this influence during our research process. Most often, participants had grand ideas of what robots can do, and then when I showed them my much more basic robots, they were underwhelmed. The way that we overcame this feeling of disappointment was by demonstrating some utility for the participants. Once a participant realized that the robot could do something useful for them, specifically something that they could not do for themself, they became more accepting of the robot.

Second, there was often a skill discrepancy between what participants wanted the robot to do and what it could actually do. This discrepancy was not an issue when abstractly discussing assistive robots, and in fact was quite helpful for envisioning the future of assistive robots. However, we sometimes faced challenges when creating prototypes if the participant really wanted the robot to do a task that it could not perform. For example, one resident was captivated with the idea that the robot could unscrew the cap of her nutrition drink. Caregivers often expressed needing help with physically demanding care work such as lifting residents or repositioning them in bed. While these tasks are the focus of other research, *e.g.,* (Wright, 2018; Jiao et al., 2023), my work focuses on mobile service tasks. To reconcile the differences, I often discussed their need while also explaining that the robots I have available cannot do that specific task. Whenever possible, however, I also discussed a compromise to how the robot could support the task. For example, with the bottle opening, we discussed a solution where the robot could bring the nutrition drink to the caregiver to open, then bring the opened drink back to the resident to consume. In the end, these discussions helped strengthen my understanding of user needs and led to creative solutions. Unfortunately, due to limitations in time and resources, it was not always possible to pursue every creative solution that we co-designed.

Benefits

Despite the challenges discussed above, conducting community-based participatory research (CBPR) also presents several benefits.

Grounding in genuine care setting Conducting studies in the senior living facility provided grounding in a genuine care setting. I observed real care interactions as the basis for all subsequent work. Having the multi-sensory experience of being in the facility shaped my perspective of not only the kind of care work but also the flow and pace of activities. Talking to caregivers during their break or immediately after their shift led to honest reflections and stories about what their daily experience was like. For example, a caregiver shared their experience balancing their care activities with comforting a terminal resident. Another caregiver shared her prompts to encourage a resident with Parkinson's disease to walk more fluidly after getting "locked up." The same benefit was seen working with residents. Because we worked with them in their own homes, they could easily reference their living environment when discussing their activities. We also developed a shared understanding of the facility instead of starting from scratch each session to understand their responsibilities. This experience contributed greatly to my understanding of care practices and shaped how I envisioned care robot systems.

Seeing real impact and potential Bringing my work out of the lab setting into the senior living facility helped both myself and my participants see the real impact and potential of this work. I could see the long-term benefits of pursing this research—eventually, we will have better care robot designs that can have more sustained, positive impact. I also got to witness the impact and potential of conducting CBPR. Over the sessions, I developed a professional friendship with the residents who regularly participated. They looked forward to participating, whether it was as a fun activity to fill the time or as a way to contribute to society. From this experience, I could see the research had an immediate benefit to the community as well as the long-term research contribution.

Enhanced ideation Working with the senior living facility shaped new ideas and research directions that I would have never previously considered. Perhaps one of the hardest lessons to learn was to listen to what participants are saying instead of trying to pitch them fancy research solutions. However, this lesson ended up being one of the biggest strengths of CBPR. In the end, I was able to synthesize the real-world observations and cutting-edge research solutions into promising directions grounded in the real world. Most notably, the work presented in Chapter 5 was originally supposed to be something different: a *programming* interface as opposed to a *scheduling* interface. However, proposing the initial programming interface, receiving blunt feedback from caregivers that this system would not work for their needs, and ideating a realistic solution resulted in a new system direction that was also academically interesting but also addressed the real needs I observed from the facility. In addition to the system we actually built, the preliminary design work presented more ideas and future directions than could be realized in one dissertation.

6.4 Limitations

While limitations of each individual study are discussed within each corresponding chapter, below I reiterate and emphasize overall limitations of the work presented in this dissertation.

Generalizability

The work presented in this dissertation resulted from working with one senior living facility as a community partner. While working with a single facility presented a great opportunity to explore deeply one concrete use context, ultimately the extent that the work generalizes to other facilities is unknown. Factors such as regional differences (Rosengren et al., 2021) and socioeconomic disparities (National Academies of Sciences, Engineering, and Medicine, 2022) mean that the needs and design requirements uncovered through our community partner do not generalize to all facilities. Nonetheless, certain aspects of my work should generalize. First, if introduced carefully, older adults are very open to using technology such as robotics, mostly in the context of lightening the perceived load of caregivers or increasing the quality of their own care. Second, caregivers do not have time to use complex interfaces on desktop computers, showing the need for high-level, quick interfaces. Third, design insights need to be situated in realistic contexts and repeated to fully develop and understand the ideas. Finally, the focus on the specific tasks of water delivery and giving reminders generalize as these tasks are critical for providing high-quality care yet often time consuming for caregivers. However, aspects such as facility policies, the precise steps and requirements for completing care tasks, and the available robots can vary by facility. When discussing generalizability, I also find it relevant to introduce the idea of *transferability* (Hellström, 2008) from social science research. Transferability advocates to understand the 'fit' between the context of the presented work and other applications. To aid in transferability, I have tried to capture the facility, resources, and process as accurately as possible in hopes that future researchers and designers will glean insight into their own use cases based on the work presented here. Eventually, once enough highly contextualized research is conducted, reviews and meta-reviews can eventually lead to stronger claims of generalizability that we often seek in research findings.

Limited participant perspectives

I am often asked when presenting portions of this work about the reactions of caregivers and residents to the robots. Overall, the reactions are overwhelmingly positive and optimistic. While this sounds like fantastic news for rebutting the long-held notion of skepticism toward care robots and assistive technology generally (Astell et al., 2020), it instead points to a key limitation of this work. I can only work with participants who consent, and those willing to consent to interacting with and discussing the robot represent a positively biased population. I have met many skeptical or uninterested individuals during my recruiting efforts, but I cannot force them to participate to give their dissenting perspectives. Similar participant selection bias is formally documented across other robotics research (Igarashi et al., 2019, 2023), even indicating that personalities of volunteers are more extroverted compared to a representative sampling.

While we must respect participants who do not wish to consent to participate in research, we do need to consider this bias when conducting design sessions and evaluating systems. Future work should find new methods to engage less eager participants to capture a range of perspectives. For example, perhaps asking for a brief (5–10 minute) interview to understand their hesitation without asking them to engage in the full study protocol or interact with robots could help capture a wider range of perspectives.

Pace of technology development

While the initial design studies could be conducted on a relatively shorter time frame, developing the system presented in Chapter 5 took considerably longer. Designing the system is one matter, but building the system takes considerably longer. Even though our contribution lies primarily in the interface, it is difficult to evaluate the interface fully without some demonstration of robot behaviors. Developing autonomous robot systems takes a great deal of time and effort, even with a skilled team of developers to assist with implementation. We ultimately aimed for a pilot deployment in the field, which further increased development time. Instead of setting up the system once in a lab to run a study, we had to consider the field deployment: setting up the SLAM/navigation map, handling the networking connection, hosting the server in the cloud, *etc.* We also faced constraints when choosing between implementing the cutting-edge system versus a simpler system that would have a higher chance of success. The most compelling example of this was when designing the Stretch robot's grasping behavior for delivering the water. While we initially tried to use a computer vision model to perceive and grasp the cup, this approach proved unreliable. We eventually designed a much simpler system where the robot aligned to an aruco tag and grasped whichever cup (or other item) was placed at the grasp location. Iterating through these solutions and fine-tuning a reliable approach takes a great deal of time and engineering effort, which lead to a long delay in preparing for the pilot deployment which we wanted to conduct. As autonomous robot capabilities improve, I am optimistic that this development time will continue to decrease, allowing for more rapid development and testing of robust robotic solutions in the future.

6.5 Open Questions and Future Work

The work presented in this dissertation points to several open questions and directions for future work.

Other aspects of personalization

Personalizing is highly detailed – open question is what other interaction aspects can be distilled/noted in interface/system (e.g. tonya mentioned stroke patient missing use of one arm may want approached from working side); ALSO what exactly should be captured in an interface vs learned/refined over time; ALSO how to let different stakeholders access/manage the same information (different "portals" to control the care robot system)

Other interactions

The design work presented in Chapters 3 and 4 revealed many potential interactions and opportunities for end-user interfaces. However, the work presented in 5 focuses on one interaction: the caregiver configuring resident preferences and making requests for the robots to perform care tasks. Future work should explore what interfaces, either extensions of the scheduling interface or separate systems, can facilitate other critical interactions. For example, I believe that it will be critical for residents to be empowered to manage their preferences and make requests of the robots directly. Little work has explored end-user development of robots for older adults, especially considering physical or cognitive decline that is often associated with living in an assisted living context. Creating solutions that work for a wide range of capabilities will be an interesting avenue for future work, as well as considering how to practically reconcile potentially conflicting resident and caregiver requests.

Additionally, the current system assumes that the care robot already knows the basic steps toward completing a task. As each care facility has different layouts and systems, it will be important to consider how these tasks are created in the first place. For example, use of other end-user robot programming tools such as *Tabula* (Porfirio et al., 2023) or *Polaris* (Porfirio et al., 2024). I have conducted some initial exploration into the use of these or similar interfaces, *e.g.,* (Stegner et al., 2024), and I believe that these types of interfaces could be adapted for use in this context. However, further co-design with caregivers and residents would be required to understand the adaptations necessary for use in this context.

Finally, attention should be given to interactions that occur while the robot is completing a task. These interactions could include how caregivers supervise and receive updates on the robot's progress, how the resident can query what the robot is doing, and how the robot may ask for help if it needs help.

Overall, there are many additional interactions to consider when integrating robots into senior living communities. I also believe that more interactions and needs will emerge through further pilot deployments.

Other contexts

My work explores the specific context of senior living facilities. However, many other care contexts could benefit from robotic assistance. Senior living facilities are less regulated than nursing homes, for example, yet share many care activities and needs. Extending this research for nursing homes will involve a deeper understanding of policy and regulation surrounding care, which will lead to new design requirements and opportunities.

Additionally, care is trending toward supporting "aging in place" initiatives where older adults receive care support in their homes (Wiles et al., 2012). In such settings, caregivers face challenges in administering care, such as traveling long distances or balancing other commitments. One possible approach to using robots in this context is a paradigm where a robot is in the older adult's home, and that robot either operates autonomously to aid the older adult or the caregiver directly controls the robot. This paradigm raises questions such as, what computational methods and interfaces will empower caregivers to effectively remotely operate robots? How can advances in natural language understanding enable older adults to successfully use robots in their homes, especially to specify routine tasks with complex branching or looping logic? How can a robot communicate when it is controlled by the caregiver versus operating autonomously? These questions could be addressed using similar research methodologies as the ones used in this dissertation to develop distinct yet related interfaces and interaction paradigms.

Other tasks and robots

My research focuses on service robots with limited manipulation capability to perform relatively simple (yet helpful) care tasks. While these robots can present significant value if used appropriately, it is not clear what the future of commercial care robots will look like. For example, there have been recent advancements in humanoid robots that promise the "general purpose robotic assistant" that caregivers envisioned in my design work. While a substantial amount of development and safety testing needs to happen before these robots are ready for use in the care context, we need to consider how robots of different capabilities can integrate into the care ecosystem. As robots become more and more capable, eventually the problem of robotic integration mirrors to a large extent the problem of coordinating care work among human care teams (Morgan et al., 2024).

Even while we wait for these general purpose robots, future work can still explore other robot form factors and capabilities. For example, recent advances in robot-assisted feeding (Bhattacharjee et al., 2020), lifting (Wright, 2018) and bed bathing (Madan et al., 2024) show the promise of an expanded set of care tasks that existing robots can perform. Adding these care tasks into a robot's repertoire introduces new questions regarding how robots can integrate into care teams, especially regarding oversight, monitoring, and record keeping.

Finally, I see the potential for multi-robot collaboration. For example, perhaps a mobile robot can deliver a food tray, while another robot is able to perform the feeding task. Multi-robot collaboration has already been explored in applications such as search and rescue (Darmanin and Bugeja, 2017), but integrating these collaborations into the social care environment will require further exploration and adaptation.

6.6 Conclusion

This chapter concludes with a final summary of this dissertation. Following a research through design (RtD) (Zimmerman et al., 2007) and community-based participatory research (CBPR) (Viswanathan et al., 2004) approach, I and my collaborators iteratively delved deeply into the needs of a senior living facility and envisioned how robotic assistance could offload caregiver burden and support resident independence. We first conducted observations of caregivers during their shifts and follow-up interviews to gain a deep understanding of existing care workflows and practices. This preliminary study supported the vision for care robots as part of the care team, serving as highly skilled robot "coworkers" (Sauppé and Mutlu, 2015). Building off of our initial vision for integrating robotic assistance, we then worked with residents of the facility to co-design interactions with a care robot using our novel method *situated participatory design*. From this co-design, we gained an understanding of different parameters that residents would like to adjust when interacting with care robots, especially voice tone, amount of social interaction, and task-specific details such as where to place delivered items. Finally, we synthesize these design findings into an end-user interface to allow caregivers to personalize care robot interactions for each resident. As a result of early feedback from caregivers, the interface focuses on *scheduling* care robot tasks rather than *programming* individual behaviors. Iterative laboratory and field studies validated the design of the system and provided insight into the use of care robots in this context. Plans for a future pilot field deployment are presented as a way to validate the system.

This dissertation begins with a wide exploratory question regarding how care robots can support care practices in senior living facilities, then narrows down to propose one possible end-user interface to facilitate care robot integration. The breadth of initial research directions spurred by the design work far exceeds the work that could be completed to finish the dissertation, yet still provides promising avenues for future research and consideration. Ultimately, this dissertation provides partial support that end-user development is a critical component toward facilitating integration of robots in senior living facilities. It also demonstrates a productive pipeline for conducting community-based care research, while documenting my unique journey through this process. My hope is that as robotics and artificial intelligence advances, future research will continue to take advantage of participatory methods as a means for realizing novel, real-world robotics systems research.

A PRODUCTS OF DISSERTATION

Below is a list of products of this dissertation, including links to open-source datasets and code.

- From Chapter 3—Experimental protocol and materials, as well as field notes from eight half-day observation sessions, and interview transcripts and participant sketches from five follow-up interviews:
  - `https://osf.io/mfkr5/`
- From Chapter 4—Experimental protocol and materials, as well as interview transcripts from a case study of *Situated Participatory Design* with nine residents and three caregivers:
  - `https://osf.io/ubnw5`
- From Chapter 5—Experimental protocol and materials, as well as interview transcripts from the iterative design and evaluation of *CareAssist* with a total of 23 caregivers and 11 residents spread across three study phases:
  - `https://osf.io/p8kmx/`
- From Chapter 5—A code repository for the *CareAssist* system, including the interface, backend, and two autonomous robots:
  - `https://github.com/Wisc-HCI/careassist`

B PROTOCOL FOR FUTURE FIELD DEPLOYMENT OF *CAREASSIST*

The final step of the *CareAssist* evaluation would be another round of updates and then a field deployment. While the deployment falls outside of the scope of this work, designing such a study is non-trivial. Drawing from my past experiences both in senior living facilities and in evaluating end-user tools, I have envisioned how a realistic initial deployment could go and included the study design and rationale to benefit future researchers. This section includes an overview of the research questions, study design rationale, detailed study timeline and activities, and suggested data collection and analysis.

Research Questions

Our goal involves running a pilot deployment of our multi-robot system in a real senior living facility, incorporating our task scheduling interface. This pilot deployment provides an excellent opportunity to explore a wide range of research questions:

1. How effective is the interface in...
    1.1. enabling caregivers to assign tasks to robots?
    1.2. capturing resident preferences in their profiles?
2. What are caregivers' and residents' perceptions of robot system...
    2.1. initially?
    2.2. at the end of the deployment?
3. How successful are the robots in completing their tasks?
4. How do caregivers and residents react to robot failures?

5. What impact do caregivers and residents anticipate from the robot system on day-to-day routines?
6. What unexpected interactions emerge over the course of the deployment?
7. What are the anticipated or observed challenges in deploying the robotic systems in a senior living facility?

This list reflects the wide range of considerations for a pilot deployment and showcases the multi-faceted data we anticipate collecting. Ultimately, we intend to conduct an exploratory investigation, so the specific research questions we can answer will depend heavily on the events experienced during the deployment. This preliminary list can serve as a starting point for shaping how we observe and follow up on interactions in the facility.

Study Design Rationale

When designing the pilot field study, we must consider several factors that influence the design. First and foremost, we must develop a plan that is acceptable to the partner facility. In our case, caregiver time, as well as the time of other care staff, represents a precious resource. In contrast, we can more easily accommodate study sessions with residents as a "fun activity" for them. Thus, we base the field study design on the concept that we primarily work with the residents and interview caregivers as they show interest or availability. Sessions with residents will be longer, more frequent, and more holistic, while we will keep sessions with caregivers brief and focused on specific feedback about the system.

Our overall goal entails conducting a qualitative pilot study on experiences and perceptions of the multi-robot system. Due to the early stage of this work, we focus on the initial setup and early impressions rather than collecting long-term deployment data. Success in this pilot field study can lead to longer deployments for more in-depth investigations.

Detailed Study Timeline and Activities

We propose a deployment lasting approximately two to four weeks, although the actual study period may be longer. Phase 1 will consist of one to two weeks for setup, including onboarding residents to the study and demonstrating the interface to caregivers. Depending on the progress of Phase 1, we may pause before Phase 2 for additional fine tuning and development. We might need to repeat some activities from the Phase 1 before proceeding to Phase 2. In Phase 2, our goal focuses on maximizing genuine human-robot interaction. We want the robots to operate as autonomously as possible, with limited human-led interventions (*e.g.*, opening doors or restarting in case of errors). The following subsections break down the proposed study timeline and activities in more detail.

PHASE 0: Recruiting and Network Testing

Before formally beginning the study, we need to recruit participants. We will recruit residents through door-to-door on-foot recruiting in the facility. We also suggest obtaining consent from the residents during the initial recruitment to save time in future study sessions. While we could recruit caregivers at this point, we may have better luck catching them the following week based on their spontaneous availability.

In addition to recruitment, we must double-check network connections and scout potential locations to set up areas for the robots to use as home bases for charging and for mock kitchen areas. For example, the mock kitchen areas should be close to the actual kitchen area, but due to logistics or safety precautions, the robots may not be able to enter the designated kitchen space.

This phase should not last more than one to two weeks. If we cannot recruit all residents during Phase 0, we can continue recruitment during Phase 1.

PHASE 1: Setup

Phase 1 involves the initial setup phase, during which we prepare for the pilot deployment interactions. Although this step is a setup phase, it will still provide valuable insights into introducing robotic systems and the considerations for future deployments/products.

The highest priority in Phase 1 involves setting up the robots in the field and performing basic tech testing to ensure everything functions as expected. This setup includes generating an initial map of the facility and testing demo programs of robot tasks, such as delivering the cups of water. This activity should take one to two days without requiring direct interaction with care staff or residents.

After the initial robot setup, we will dedicate the remainder of Phase 1 primarily to onboarding residents and interviewing caregivers.

Resident Onboarding We anticipate each resident onboarding session will last 1–1.5 hours and draw heavily from Phase 1 (initial scenario design) of *situated participatory design*. However, this field study is constrained by our actual system development–the scope of how residents can customize interactions and robot behaviors will depend on what we can configure in the resident profiles of the system. Our idea is to introduce the robots and tasks, configure resident preferences, and let them see the robots performing tasks to help them become accustomed to the robots. For residents doing the water delivery task, we need to explain the ArUco tag mat system and assist them in deciding where to place it. This session also allows the resident to opt out of a specific robot or task. We want to remain as flexible as possible during this session while clearly communicating any limitations of the robot system.

After configuring the resident's profile, we need to map their room using both robots. This process may take some time, so one researcher should complete the mapping while another continues engaging with the resident. During Phase 1, we want to prompt residents to reflect on the following questions:

1. What are your initial impressions of the robots?
2. What is your initial comfort level and thoughts about the tasks the robots can perform?
3. What initial concerns or apprehensions do you have?

Once we complete the initial setup, we can schedule some tasks for Phase 2. While in a real use case, the caregiver would schedule these tasks, scheduling some tasks directly with the resident provides a starting point and avoids logistical issues coordinating with caregivers in a tight time frame.

Caregiver Interviews Caregiver interviews, in contrast to longer resident onboarding sessions, will be brief and focused. Our primary goal is to gather feedback on the overall system and interface. Depending on the caregiver's availability, the interview may not address all desired topics. Speaking briefly to multiple caregivers about different aspects of the system will yield a composite overview of opinions on the system overall.

We seek feedback on two primary aspects. First, we want insights on the interface. To gather this feedback, the researcher should provide a high-level overview of the system and demonstrate how to use the interface. Due to limited time, we cannot conduct full training on the system or perform a proper usability evaluation. However, the demonstration and feedback approach will help validate the interface design and functionality. Based on the demonstrations, the researcher can ask questions such as:

1. What are your initial impressions of the interface?
2. Do you envision using this kind of interface during your shift?

Second, we seek initial impressions of the robots and tasks. We will use a mixture of live demonstrations and videos of the robots performing the care tasks. Based on the videos, the researcher can ask questions such as:

1. What are your initial impressions of the robots?
2. How do you think residents will react to these robots?
3. What initial concerns or hesitations do you have about introducing these robots?

Caregiver and resident feedback at this early stage can guide future observations and prompts during Phase 2.

DEVELOPMENT BUFFER

This break serves as a buffer to account for any development efforts required to fix or adjust elements of the system before Phase 2 begins. We anticipate the break could last anywhere from a weekend to one or two weeks, but we will keep it as brief as possible to maintain the study's momentum.

PHASE 2: Pilot Deployment

Phase 2 will facilitate as many robot tasks and human-robot interactions as possible. The goal is for the robots to complete tasks for different residents throughout the day, including morning, afternoon, and evening sessions, to yield rich interaction data. The pilot deployment will require supervision from researchers while the robots operate, but we also want to remain open to exploration to see what actually unfolds. The researcher must balance observing and supervising the robot while allowing realistic interactions. For example, if the robot encounters a failure, as long as the failure does create a dangerous or risky situation, we should first observe reactions to the failure before intervening to reset the system.

Resident Experience

During the one to two weeks of deployment, the researcher should check in with residents about their experience regularly, such as at the end of each day. These check-ins should remain brief, approximately 5–10 minutes in length, and the questions should include prompts about their daily experience:

1. Did the robot come? Which robot?
2. What did the robot do?
3. How did it go?
4. How did you feel about it?
5. Should we make any updates to your profile?
6. Did something go wrong? What happened and what was it like for you?

Given the limited modifications available to the resident profiles, the researcher should specifically note interaction aspects not captured in the profile that the resident wants to personalize.

At the end of Phase 2, we will conduct longer 15-30 minute interviews to capture reflections on the overall deployment:

1. How was your overall experience? What went well? What could be improved?
2. Can you envision using a system like this now or in the future?
3. How did interacting with the robot impact your daily routine or experience?
4. Do you have any concerns about this kind of system?
5. Are there any other thoughts you would like to share?

Caregiver Experience

The researchers will continue conducting brief interviews with caregivers. Ideally, we will include the same caregivers who used the interface in Phase 1, but due to staffing challenges and limited availability, we will welcome any interested caregiver. For new participants, the researcher will provide a brief overview of the system, including the scheduling interface. In cases where caregivers did not see the robots operating throughout the facility, we can show brief videos demonstrating the robots' capabilities. Then, for all caregivers, the researcher should ask the following questions as time permits:

1. Did you see the robot around the facility? What was it like? What were your impressions?
2. What aspects would you want to monitor regarding the robots completing these kinds of tasks?
3. How do you think a system like this would impact your daily routine?
4. Would you be interested in using a system like this in the future?
5. What concerns do you have about this kind of system?

Suggested Data Collection and Analysis

We should collect as much multi-modal data as possible to create a rich dataset. The primary data sources will include:

- Transcripts from interviews with caregivers and residents
- Researcher notes from observing deployment
- Logs detailing what each robot does and the results

Adding structure to the data collection will simplify analysis. For example, the researcher notes should include a structure indicating the time, robot, and task, in addition to observations to ensure that we can match notes to interview data and robot logs. During interviews, we recommend taking brief notes to capture key ideas for easier navigation through the transcripts. Lastly, recording reflections after each robot shift during Phase 2 will provide additional data and insights into the experience, helping to prevent the researcher from forgetting key insights over the course of the deployment.

Analyzing this dataset will likely require multiple analysis approaches, each framed within a clear lens. The research questions can serve as a guide, but we must also leave room for unanticipated findings to emerge. Researchers should utilize thematic analysis (Braun and Clarke, 2022) or other qualitative analysis methods as appropriate, based on cursory insights into the data and emerging ideas.

REFERENCES

Abou Allaban, Anas, Maozhen Wang, and Taşkın Padır. 2020. A systematic review of robotics research in support of in-home care for older adults. *Information* 11(2):75.

Aced López, Sebastián, Fulvio Corno, and Luigi De Russis. 2015. Supporting caregivers in assisted living facilities for persons with disabilities: a user study. *Universal Access in the Information Society* 14(1):133–144.

Ajaykumar, Gopika, Maureen Steele, and Chien-Ming Huang. 2021. A survey on end-user robot programming. *ACM Computing Surveys (CSUR)* 54(8):1–36.

Alaiad, Ahmad, and Lina Zhou. 2014. The determinants of home healthcare robots adoption: An empirical investigation. *International journal of medical informatics* 83(11):825–840.

Alavi, Hamed S, Denis Lalanne, and Yvonne Rogers. 2020. The five strands of living lab: a literature study of the evolution of living lab concepts in hci. *ACM Transactions on Computer-Human Interaction (TOCHI)* 27(2): 1–26.

Alexandrova, Sonya, Zachary Tatlock, and Maya Cakmak. 2015. Roboflow: A flow-based visual programming language for mobile manipulation tasks. In *2015 ieee international conference on robotics and automation (icra)*, 5537–5544. IEEE.

Argentum. 2018. The senior living employee. Accessed: 04-11-2022.

Astell, Arlene J, Colleen McGrath, and Erica Dove. 2020. 'that's for old so and so's!': does identity influence older adults' technology adoption decisions? *Ageing & Society* 40(7):1550–1576.

Australian Government Aged Care Quality and Safety Commission. 2024. A report on the outcomes of our public consultation on draft guidance documents on the new strengthened aged care quality standards. Public consultation outcomes summary.

Badii, A, I Etxeberria, C Huijnen, M Maseda, S Dittenberger, A Hochgatterer, D Thiemert, and AS Rigaud. 2009. Companionable: Graceful integration of mobile robot companion with a smart home environment. *Gerontechnology* 8(3):181.

Bajones, Markus, David Fischinger, Astrid Weiss, Daniel Wolf, Markus Vincze, Paloma de la Puente, Tobias Körtner, Markus Weninger, Konstantinos Papoutsakis, Damien Michel, et al. 2018. Hobbit: providing fall detection and prevention for the elderly in the real world. *Journal of Robotics* 2018.

Barber, Ramón, Francisco J Ortiz, Santiago Garrido, Francisco M Calatrava-Nicolás, Alicia Mora, Adrián Prados, José Alfonso Vera-Repullo, Joaquín Roca-González, Inmaculada Méndez, and Óscar Martínez Mozos. 2022. A multirobot system in an assisted home environment to support the elderly in their daily lives. *Sensors* 22(20): 7983.

Bardaro, Gianluca, Alessio Antonini, and Enrico Motta. 2021. Robots for elderly care in the home: A landscape analysis and co-design toolkit. *International Journal of Social Robotics* 1–25.

Bauer, Michael, and Rhonda Nay. 2011. Improving family–staff relationships in assisted living facilities: the views of family. *Journal of advanced nursing* 67(6):1232–1241.

Bedaf, Sandra, Patrizia Marti, and Luc De Witte. 2017. What are the preferred characteristics of a service robot for the elderly? a multi-country focus group study with older adults and caregivers. *Assistive Technology*.

Beer, Jenay M, Cory-Ann Smarr, Tiffany L Chen, Akanksha Prakash, Tracy L Mitzner, Charles C Kemp, and Wendy A Rogers. 2012. The domesticated robot: design guidelines for assisting older adults to age in place. In *Proceedings of the seventh annual acm/ieee international conference on human-robot interaction*, 335–342.

Berry, Andrew BL, Catherine Lim, Andrea L Hartzler, Tad Hirsch, Edward H Wagner, Evette Ludman, and James D Ralston. 2017. How values shape collaboration between patients with multiple chronic conditions and spousal caregivers. In *Proceedings of the 2017 chi conference on human factors in computing systems*, 5257–5270.

Bhattacharjee, Tapomayukh, Ethan K Gordon, Rosario Scalise, Maria E Cabrera, Anat Caspi, Maya Cakmak, and Siddhartha S Srinivasa. 2020. Is more autonomy always better? exploring preferences of users with mobility impairments in robot-assisted feeding. In *Proceedings of the 2020 acm/ieee international conference on human-robot interaction*, 181–190.

Blavette, Lauriane, Anne-Sophie Rigaud, Salvatore Maria Anzalone, Clément Kergueris, Baptiste Isabet, Sébastien Dacunha, and Maribel Pino. 2022. A robot-mediated activity using the nao robot to promote covid-19 precautionary measures among older adults in geriatric facilities. *International Journal of Environmental Research and Public Health* 19(9):5222.

Bowers, Barbara, Tonya Roberts, Kimberly Nolet, Brenda Ryther, THRIVE Research Collaborative, Patrick Brown, Lauren Cohen, David Grabowski, Susan Horn, Sandy Hudak, et al. 2016. Inside the green house "black box": Opportunities for high-quality clinical decision making. *Health Services Research* 51(S1):378–397.

Boyatzis, Richard E. 1998. *Transforming qualitative information: Thematic analysis and code development*. Sage.

Bradwell, Hannah Louise, Katie Edwards, Deborah Shenton, Rhona Winnington, Serge Thill, and Ray B Jones. 2021. User-centered design of companion robot pets involving care home resident-robot interactions and focus groups with residents, staff, and family: Qualitative study. *JMIR rehabilitation and assistive technologies* 8(4):e30337.

Braun, Virginia, and Victoria Clarke. 2022. Conceptual and design thinking for thematic analysis. *Qualitative Psychology* 9(1):3.

Broadbent, E, K Loveys, G Ilan, G Chen, MM Chilukuri, SG Boardman, PM Doraiswamy, and D Skuler. 2024. Elliq, an ai-driven social robot to alleviate loneliness: progress and lessons learned. *JAR life* 13:22.

Broadbent, Elizabeth, Ngaire Kerse, Kathryn Peri, Hayley Robinson, Chandimal Jayawardena, Tony Kuo, Chandan Datta, Rebecca Stafford, Haley Butler, Pratyusha Jawalkar, et al. 2016. Benefits and problems of health-care robots in aged care settings: A comparison trial. *Australasian journal on ageing* 35(1):23–29.

Broadbent, Elizabeth, Rie Tamagawa, Ngaire Kerse, Brett Knock, Anna Patience, and Bruce MacDonald. 2009. Retirement home staff and residents' preferences for healthcare robots. In *Ro-man 2009-the 18th ieee international symposium on robot and human interactive communication*, 645–650. IEEE.

Broadbent, Elizabeth, Rie Tamagawa, Anna Patience, Brett Knock, Ngaire Kerse, Karen Day, and Bruce A MacDonald. 2012. Attitudes towards health-care robots in a retirement village. *Australasian journal on ageing* 31(2):115–120.

Brooker, Dawn, and Isabelle Latham. 2015. *Person-centred dementia care: Making services better with the vips framework*. Jessica Kingsley Publishers.

Bygholm, Ann, and Anne Marie Kanstrup. 2017. This is not participatory design - a critical analysis of eight living laboratories. *Studies in health technology and informatics* 233:78—92.

Calvaresi, Davide, Daniel Cesarini, Paolo Sernani, Mauro Marinoni, Aldo Franco Dragoni, and Arnon Sturm. 2017. Exploring the ambient assisted living domain: a systematic review. *Journal of Ambient Intelligence and Humanized Computing* 8:239–257.

Cao, Yuanzhi, Tianyi Wang, Xun Qian, Pawan S Rao, Manav Wadhawan, Ke Huo, and Karthik Ramani. 2019a. Ghostar: A time-space editor for embodied authoring of human-robot collaborative task with augmented reality. In *Proceedings of the 32nd annual acm symposium on user interface software and technology*, 521–534.

Cao, Yuanzhi, Zhuangying Xu, Fan Li, Wentao Zhong, Ke Huo, and Karthik Ramani. 2019b. V. ra: An in-situ visual authoring system for robot-iot task planning with augmented reality. In *Proceedings of the 2019 on designing interactive systems conference*, 1059–1070.

Carroll, Karen. 2021. Robotics: considerations for practice. *Nursing Science Quarterly* 34(3):253–255.

Carros, Felix, Johanna Meurer, Diana Löffler, David Unbehaun, Sarah Matthies, Inga Koch, Rainer Wieching, Dave Randall, Marc Hassenzahl, and Volker Wulf. 2020. Exploring human-robot interaction with the elderly: results from a ten-week case study in a care home. In *Proceedings of the 2020 chi conference on human factors in computing systems*, 1–12.

Carros, Felix, Isabel Schwaninger, Adrian Preussner, Dave Randall, Rainer Wieching, Geraldine Fitzpatrick, and Volker Wulf. 2022. Care workers making use of robots: Results of a three-month study on human-robot interaction within a care home. In *Proceedings of the 2022 chi conference on* *human factors in computing systems*. CHI '22, New York, NY, USA: Association for Computing Machinery.

Caspar, Sienna, Norm O'Rourke, and Gloria M Gutman. 2009. The differential influence of culture change models on long-term care staff empowerment and provision of individualized care. *Canadian Journal on Aging/La Revue canadienne du vieillissement* 28(2):165–175.

Chan, Crystal Y, Gary Cheung, Adrian Martinez-Ruiz, Patsy YK Chau, Kailu Wang, EK Yeoh, and Eliza LY Wong. 2021. Caregiving burnout of community-dwelling people with dementia in hong kong and new zealand: a cross-sectional study. *BMC geriatrics* 21(1):1–15.

Chen, Luefeng, Min Wu, Mengtian Zhou, Jinhua She, Fangyan Dong, and Kaoru Hirota. 2018. Information-driven multirobot behavior adaptation to emotional intention in human–robot interaction. *IEEE Transactions on Cognitive and Developmental Systems* 10(3):647–658.

Chen, Shu-Chuan, Boyd H Davis, Ching-Yi Kuo, Margaret Maclagan, Chun-O Chien, and Mei-Feng Lin. 2022. Can the paro be my buddy? meaningful experiences from the perspectives of older adults. *Geriatric Nursing* 43:130–137.

Chen, Tiffany L, Matei Ciocarlie, Steve Cousins, Phillip M Grice, Kelsey Hawkins, Kaijen Hsiao, Charles C Kemp, Chih-Hung King, Daniel A Lazewatsky, Adam E Leeper, et al. 2013a. Robots for humanity: using assistive robotics to empower people with disabilities. *IEEE Robotics & Automation Magazine* 20(1):30–39.

Chen, Tiffany L, and Charles C Kemp. 2010. Lead me by the hand: Evaluation of a direct physical interface for nursing assistant robots. In *2010 5th acm/ieee international conference on human-robot interaction (hri)*, 367–374. IEEE.

Chen, Yunan, Victor Ngo, and Sun Young Park. 2013b. Caring for caregivers: designing for integrality. In *Proceedings of the 2013 conference on computer supported cooperative work*, 91–102.

Choi, Young Sang, Tiffany Chen, Advait Jain, Cressel Anderson, Jonathan D Glass, and Charles C Kemp. 2009. Hand it over or set it down: A user study of object delivery with an assistive mobile manipulator. In *Ro-man 2009-the 18th ieee international symposium on robot and human interactive communication*, 736–743. IEEE.

Cicirelli, Grazia, Roberto Marani, Antonio Petitti, Annalisa Milella, and Tiziana D'Orazio. 2021. Ambient assisted living: A review of technologies, methodologies and future perspectives for healthy aging of population. *Sensors* 21(10).

Cohen, Lauren W, Sheryl Zimmerman, David Reed, Patrick Brown, Barbara J Bowers, Kimberly Nolet, Sandra Hudak, Susan Horn, THRIVE Research Collaborative, and David Grabowski. 2016. The green house model of nursing home care in design and implementation. *Health services research* 51:352–377. PMID: 26601799.

Consolvo, Sunny, Peter Roessler, and Brett E Shelton. 2004. The carenet display: lessons learned from an in home evaluation of an ambient display. In *International conference on ubiquitous computing*, 1–17. Springer.

Correa, Andrew, Matthew R Walter, Luke Fletcher, Jim Glass, Seth Teller, and Randall Davis. 2010. Multimodal interaction with an autonomous forklift. In *2010 5th acm/ieee international conference on human-robot interaction (hri)*, 243–250. IEEE.

Dahlbäck, Nils, Arne Jönsson, and Lars Ahrenberg. 1993. Wizard of oz studies: why and how. In *Proceedings of the 1st international conference on intelligent user interfaces*, 258–266.

Dario, Paolo, Eugenio Guglielmelli, Cecilia Laschi, and Giancarlo Teti. 1999. Movaid: a personal robot in everyday life of disabled and elderly people. *Technology and Disability* 10(2):77–93.

Darmanin, Rachael N, and Marvin K Bugeja. 2017. A review on multi-robot systems categorised by application domain. In *2017 25th mediterranean conference on control and automation (med)*, 701–706. IEEE.

Das, Gautham P, Thomas M McGinnity, Sonya A Coleman, and Laxmidhar Behera. 2015. A distributed task allocation algorithm for a multi-robot system in healthcare facilities. *Journal of Intelligent & Robotic Systems* 80: 33–58.

Datta, Chandan, H Yul Yang, Priyesh Tiwari, I Han Kuo, and Bruce A MacDonald. 2011. End user programming to enable closed-loop medication management using a healthcare robot. *Social Science*.

Dautenhahn, K., M. Walters, S. Woods, K. L. Koay, C. L. Nehaniv, A. Sisbot, R. Alami, and T. Siméon. 2006. How may i serve you? a robot companion approaching a seated person in a helping context. In *Proceedings of the 1st acm sigchi/sigart conference on human-robot interaction*, 172–179. HRI '06, New York, NY, USA: Association for Computing Machinery.

Davidson, Jennifer L, and Carlos Jensen. 2013. What health topics older adults want to track: a participatory design study. In *Proceedings of the 15th international acm sigaccess conference on computers and accessibility*, 1–8.

Davies, Nicola. 2016. Can robots handle your healthcare? *Engineering & Technology* 11(9):58–61.

Dixon, Clare, Matt Webster, Joe Saunders, Michael Fisher, and Kerstin Dautenhahn. 2014. "the fridge door is open"–temporal verification of a robotic assistant's behaviours. In *Conference towards autonomous robotic systems*, 97–108. Springer.

Duan, Yinfei, Christine A. Mueller, Fang Yu, Kristine M. Talley, and Tetyana P. Shippee. 2022. The relationships of nursing home culture change practices with resident quality of life and family satisfaction: Toward a more nuanced understanding. *Research on Aging* 44(2):174–185. PMID: 33973498, https://doi.org/10.1177/01640275211012652.

Duque, Ezequiel, Guilherme Fonseca, Heitor Vieira, Gustavo Gontijo, and Lucila Ishitani. 2019. A systematic literature review on user centered design and participatory design with older people. In *Proceedings of the 18th brazilian symposium on human factors in computing systems*. IHC '19, New York, NY, USA: Association for Computing Machinery.

Eftring, H, and Susanne Frennert. 2016. Designing a social and assistive robot for seniors. *Zeitschrift für Gerontologie und Geriatrie* 49(4):274–281.

Eklund, Jakob Håkansson, Inger K Holmström, Tomas Kumlin, Elenor Kaminsky, Karin Skoglund, Jessica Höglander, Annelie J Sundler, Emelie Condén, and Martina Summer Meranius. 2019. "same same or different?" a review of reviews of person-centered and patient-centered care. *Patient Education and Counseling* 102(1):3–11.

Eksioglu, Burak, Arif Volkan Vural, and Arnold Reisman. 2009. The vehicle routing problem: A taxonomic review. *Computers & Industrial Engineering* 57(4):1472–1483.

EPSCO. 2023. Council conclusions on "the transition of care systems throughout life towards holistic, person-centred and community-based support models with a gender perspective". Document no. 16094/23.

Ernst, Jette, Charlotte Jonasson, Simone Minana, Johanna Dubij, and Stinna Adler. 2021. Human–robot exchanges in the organizational space: the social dynamics of new work configurations in a danish hospital department.

Falk-Huzar, Erica. 2017. The need for caregiver education and training in the assisted living industry. *Adult Learning* 28(3):125–127.

Famakinwa, Joyce. 2021. Report sheds new light on looming caregiving crisis. Accessed: 10-29-2021.

Fang, Chao, and Miho Tanaka. 2022. An exploration of person-centred approach in end-of-life care policies in england and japan. *BMC Palliative Care* 21(1):68.

Fasola, Juan, and Maja J Matarić. 2013. A socially assistive robot exercise coach for the elderly. *Journal of Human-Robot Interaction* 2(2):3–32.

Feil-Seifer, David, and Maja J Matarić. 2011. Socially assistive robotics. *IEEE Robotics & Automation Magazine* 18(1):24–31.

Fischinger, David, Peter Einramhof, Konstantinos Papoutsakis, Walter Wohlkinger, Peter Mayer, Paul Panek, Stefan Hofmann, Tobias Koertner, Astrid Weiss, Antonis Argyros, et al. 2016. Hobbit, a care robot supporting independent living at home: First prototype and lessons learned. *Robotics and Autonomous Systems* 75:60–78.

Forbes, Maxwell, Rajesh PN Rao, Luke Zettlemoyer, and Maya Cakmak. 2015. Robot programming by demonstration with situated spatial language understanding. In *2015 ieee international conference on robotics and automation (icra)*, 2014–2020. IEEE.

Forlizzi, Jodi, and Carl DiSalvo. 2006. Service robots in the domestic environment: a study of the roomba vacuum in the home. In *Proceedings of the 1st acm sigchi/sigart conference on human-robot interaction*, 258–265.

Forlizzi, Jodi, Carl DiSalvo, and Francine Gemperle. 2004. Assistive robotics and an ecology of elders living independently in their homes. *Human–Computer Interaction* 19(1-2):25–59.

Fu, Musetta Chang-Chi, Shih-Yin Lin, Basia Belza, and Marianne Unite. 2015. Insights of senior living residents and staff on group-singing. *Activities, Adaptation & Aging* 39(3):243–261.

Gao, Yuxiang, and Chien-Ming Huang. 2019. Pati: a projection-based augmented table-top interface for robot programming. In *Proceedings of the 24th international conference on intelligent user interfaces*, 345–355.

Garrod, Barb J. 2020. *Advanced caregiving training manual: A complete guide covering all levels of elderly care*. Dorrance Publishing Co.

Gasteiger, Norina, Ho Seok Ahn, Christopher Lee, Jongyoon Lim, Bruce A Macdonald, Geon Ha Kim, and Elizabeth Broadbent. 2022. Participatory design, development, and testing of assistive health robots with older adults: An international four-year project. *J. Hum.-Robot Interact.*

Ghayvat, Hemant, S Mukhopadhyay, B Shenjie, Arpita Chouhan, and W Chen. 2018. Smart home based ambient assisted living: Recognition of anomaly in the activity of daily living for an elderly living alone. In *2018 ieee international instrumentation and measurement technology conference (i2mtc)*, 1–5. IEEE.

Gordon, Goren, Samuel Spaulding, Jacqueline Kory Westlund, Jin Joo Lee, Luke Plummer, Marayna Martinez, Madhurima Das, and Cynthia Breazeal. 2016. Affective personalization of a social robot tutor for children's second language skills. In *Proceedings of the aaai conference on artificial intelligence*, vol. 30.

Government of Canada. 2024. Person-partnered care (ppc) framework. Accessed: 19-Sep-2024.

Graf, Birgit, Matthias Hans, and Rolf D Schraft. 2004. Care-o-bot ii—development of a next generation robotic home assistant. *Autonomous robots* 16(2):193–205.

Grönvall, Erik, and Morten Kyng. 2013. On participatory design of home-based healthcare. *Cognition, technology & work* 15(4):389–401.

Gross, Horst-Michael, Steffen Mueller, Christof Schroeter, Michael Volkhardt, Andrea Scheidig, Klaus Debes, Katja Richter, and Nicola Doering. 2015. Robot companion for domestic health assistance: Implementation, test and case study under everyday conditions in private apartments. In *2015 ieee/rsj international conference on intelligent robots and systems (iros)*, 5992–5999. IEEE.

Grunfeld, Eva, Doug Coyle, Timothy Whelan, Jennifer Clinch, Leonard Reyno, Craig C Earle, Andrew Willan, Raymond Viola, Marjorie Coristine, Teresa Janz, et al. 2004. Family caregiver burden: results of a longitudinal study of breast cancer patients and their principal caregivers. *Cmaj* 170(12):1795–1801.

Guest, Greg, Kathleen M MacQueen, and Emily E Namey. 2011. *Applied thematic analysis*. Sage publications.

Gunning, David, Mark Stefik, Jaesik Choi, Timothy Miller, Simone Stumpf, and Guang-Zhong Yang. 2019. Xai—explainable artificial intelligence. *Science Robotics* 4(37):eaay7120.

Hasselkus, Betty Risteen. 1991. Ethical dilemmas in family caregiving for the elderly: Implications for occupational therapy. *American Journal of Occupational Therapy* 45(3):206–212.

Offermann-van Heek, Julia, Martina Ziefle, et al. 2018. They don't care about us! care personnel's perspectives on ambient assisted living technology usage: scenario-based survey study. *JMIR rehabilitation and assistive technologies* 5(2):e10424.

Hellström, Tomas. 2008. Transferability and naturalistic generalization: new generalizability concepts for social science or old wine in new bottles? *Quality & Quantity* 42:321–337.

Hornecker, Eva, Andreas Bischof, Philipp Graf, Lena Franzkowiak, and Norbert Krüger. 2020. The interactive enactment of care technologies and its implications for human-robot-interaction in care. In *Proceedings of the 11th nordic conference on human-computer interaction: Shaping experiences, shaping society*, 1–11.

Hsu, Long-Jing, Janice K Bays, Katherine M Tsui, and Selma Sabanovic. 2023. Co-designing social robots with people living with dementia: Fostering identity, connectedness, security, and autonomy. In *Proceedings of the 2023 acm designing interactive systems conference*, 2672–2688.

Huang, Justin, and Maya Cakmak. 2017. Code3: A system for end-to-end programming of mobile manipulator robots for novices and experts. In *Proceedings of the 2017 acm/ieee international conference on human-robot interaction*, 453–462.

Hwang, Amy S, Khai N Truong, and Alex Mihailidis. 2012. Using participatory design to determine the needs of informal caregivers for smart home user interfaces. In *2012 6th international conference on pervasive computing technologies for healthcare (pervasivehealth) and workshops*, 41–48. IEEE.

Igarashi, Toshiharu, Misato Nihei, Jumpei Mizuno, Takenobu Inoue, and Minoru Kamata. 2019. Subject selection bias in intervention experiments with socially assistive robots and the impact on the representativeness of the population. In *Social robotics: 11th international conference, icsr 2019, madrid, spain, november 26–29, 2019, proceedings 11*, 44–53. Springer.

Igarashi, Toshiharu, Ikuko Sugawara, Takenobu Inoue, and Misato Nihei. 2023. Research participant selection bias in the workshop using socially assistive robots for older adults and its effect on population representativeness. *International Journal of Environmental Research and Public Health* 20(10):5915.

Jiao, Chunting, Lin Zhang, Xiaojie Su, Jiangshuai Huang, Zhenshan Bing, and Alois Knoll. 2023. Task-based compliance control for bottle screw manipulation with a dual-arm robot. *IEEE Transactions on Industrial Electronics* 71(2):1823–1831.

Johnston, Tim R. 2019. *Welcoming lgbt residents: A practical guide for senior living staff*. Routledge.

Jones, Susan L. 1996. The association between objective and subjective caregiver burden. *Archives of psychiatric nursing* 10(2):77–84.

Kane, Rosalie A, and Keren Brown Wilson. 1993. *Assisted living in the united states: A new paradigm for residential care for frail older persons?* American Association of Retired Persons.

Kemp, Candace L, Jason Lesandrini, Jennifer Craft Morgan, and Elisabeth O Burgess. 2021. The ethics in long-term care model: Everyday ethics and the unseen moral landscape of assisted living. *Journal of Applied Gerontology*.

Kemp, Charles C., Aaron Edsinger, Henry M. Clever, and Blaine Matulevich. 2022. The design of stretch: A compact, lightweight mobile manipulator for indoor human environments. In *2022 international conference on robotics and automation (icra)*, 3150–3157.

Khaksar, Weria, Diana Saplacan, Lee Andrew Bygrave, and Jim Torresen. 2023. Robotics in elderly healthcare: A review of 20 recent research projects. `2302.04478`.

King, Chih-Hung, Tiffany L Chen, Advait Jain, and Charles C Kemp. 2010. Towards an assistive robot that autonomously performs bed baths for patient hygiene. In *2010 ieee/rsj international conference on intelligent robots and systems*, 319–324. IEEE.

Klimesch, Anne, Alejandra Martinez-Pereira, Cheyenne Topf, Martin Härter, Isabelle Scholl, and Paulina Bravo. 2023. Conceptualization of patient-centered care in latin america: A scoping review. *Health Expectations* 26(5):1820–1831.

Kogan, Alexis Coulourides, Kathleen Wilber, and Laura Mosqueda. 2016. Person-centered care for older adults with chronic conditions and functional impairment: A systematic literature review. *Journal of the American Geriatrics Society* 64(1):e1–e7.

Kramer, Stephen C, Erika Friedmann, and Penny L Bernstein. 2009. Comparison of the effect of human interaction, animal-assisted therapy, and aibo-assisted therapy on long-term care residents with dementia. *Anthrozoös* 22(1):43–57.

Krauss, Nancy. 1998. *Characteristics of nursing home residents, 1996*. 99, US Department of Health and Human Services, Public Health Service, Agency.

Landis, J Richard, and Gary G Koch. 1977. The measurement of observer agreement for categorical data. *biometrics* 159–174.

Larsson, Niklas, and Lennart Molin. 2006. Rapid prototyping of user interfaces in robot surgery—wizard of oz in participatory design. In *Advances in information systems development*, 361–371. Springer.

Law, Mikaela, Ho Seok Ahn, Elizabeth Broadbent, Kathy Peri, Ngaire Kerse, Eve Topou, Norina Gasteiger, and Bruce MacDonald. 2021. Case studies on the usability, acceptability and functionality of autonomous mobile delivery robots in real-world healthcare settings. *Intelligent Service Robotics* 1–12.

Law, Mikaela, Craig Sutherland, Ho Seok Ahn, Bruce A MacDonald, Kathy Peri, Deborah L Johanson, Dina-Sara Vajsakovic, Ngaire Kerse, and Elizabeth Broadbent. 2019. Developing assistive robots for people with mild cognitive impairment and mild dementia: a qualitative study with older adults and experts in aged care. *BMJ open* 9(9):e031937.

Lee, Hee Rin, Selma Šabanović, Wan-Ling Chang, Shinichi Nagata, Jennifer Piatt, Casey Bennett, and David Hakken. 2017. Steps toward participatory design of social robots: mutual learning with older adults with depression. In *Proceedings of the 2017 acm/ieee international conference on human-robot interaction*, 244–253.

Lee, Hee Rin, Fei Sun, Tariq Iqbal, and Brenda Roberts. 2023. Reimagining robots for dementia: From robots for care-receivers/giver to robots for carepartners. In *Proceedings of the 2023 acm/ieee international conference on human-robot interaction*, 475–484.

Leonardi, Nicola, Marco Manca, Fabio Paternò, and Carmen Santoro. 2019. Trigger-action programming for personalising humanoid robot behaviour. In *Proceedings of the 2019 chi conference on human factors in computing systems*, 1–13.

Li, Junxin, and Davina Porock. 2014. Resident outcomes of person-centered care in long-term care: A narrative review of interventional research. *International journal of nursing studies* 51(10):1395–1415.

Li, Ruijiao, Mohammadreza A Oskoei, and Huosheng Hu. 2013. Towards ros based multi-robot architecture for ambient assisted living. In *2013 ieee international conference on systems, man, and cybernetics*, 3458–3463. IEEE.

Li, Toby Jia-Jun, Marissa Radensky, Justin Jia, Kirielle Singarajah, Tom M Mitchell, and Brad A Myers. 2019. Pumice: A multi-modal agent that learns concepts and conditionals from natural language and demonstrations. In *Proceedings of the 32nd annual acm symposium on user interface software and technology*, 577–589.

Lieberman, Henry, Fabio Paternò, Markus Klann, and Volker Wulf. 2006. End-user development: An emerging paradigm. In *End user development*, 1–8. Springer.

Lima, Julie C, Margot L Schwartz, Melissa A Clark, and Susan C Miller. 2020. The changing adoption of culture change practices in u.s. nursing homes. *Innovation in Aging* 4(3):igaa012. `https://academic.oup.com/innovateage/article-pdf/4/3/igaa012/33346457/igaa012.pdf`.

Lindsay, Stephen, Daniel Jackson, Guy Schofield, and Patrick Olivier. 2012. Engaging older people using participatory design. In *Proceedings of the sigchi conference on human factors in computing systems*, 1199–1208.

Lofland, John, and Lyn H Lofland. 1971. *Analyzing social settings*. Wadsworth Pub.

Luperto, Matteo, Javier Monroy, J. Raul Ruiz-Sarmiento, Francisco-Angel Moreno, Nicola Basilico, Javier Gonzalez-Jimenez, and N. Alberto Borghese. 2019. Towards long-term deployment of a mobile robot for at-home ambient assisted living of the elderly. In *2019 european conference on mobile robots (ecmr)*, 1–6.

Madan, Rishabh, Skyler Valdez, David Kim, Sujie Fang, Luoyan Zhong, Diego T Virtue, and Tapomayukh Bhattacharjee. 2024. Rabbit: A robot-assisted bed bathing system with multimodal perception and integrated compliance. In *Proceedings of the 2024 acm/ieee international conference on human-robot interaction*, 472–481.

Malle, Bertram F. 2016. Integrating robot ethics and machine morality: the study and design of moral competence in robots. *Ethics and Information Technology* 18(4):243–256.

Marques, Gonçalo. 2019. Ambient assisted living and internet of things. *Harnessing the Internet of everything (IoE) for accelerated innovation opportunities* 100–115.

McCormack, Brendan, and Tanya McCance. 2010. Person-centred nursing: theory, models and methods.

Médéric, Pascal, Viviane Pasqui, Frédéric Plumet, and Philippe Bidaud. 2004. Design of a walking-aid and sit to stand transfer assisting device for elderly people. In *Cism-iftomm int. symposium on robot design, dynamics and control (romansy'04)*.

Michaud, François, Patrick Boissy, Daniel Labonté, Simon Briere, Karine Perreault, H Corriveau, A Grant, M Lauria, R Cloutier, M-A Roux, et al. 2010. Exploratory design and evaluation of a homecare teleassistive mobile robotic system. *Mechatronics* 20(7):751–766.

Michaud, Francois, Patrick Boissy, Daniel Labonte, Helene Corriveau, Andrew Grant, Michel Lauria, Richard Cloutier, Marc-André Roux, Daniel Iannuzzi, and Marie-Pier Royer. 2007. Telepresence robot for home care assistance. In *Aaai spring symposium: multidisciplinary collaboration for socially assistive robotics*, 50–55. California, USA.

Miller, Hayley V, Kimberly Ward, and Sheryl Zimmerman. 2021. Implementation effectiveness of psychosocial and environmental care practices in assisted living. *Geriatric Nursing* 42(1):295–302.

Miller, Susan C, Margot L Schwartz, Julie C Lima, Renée R Shield, Denise A Tyler, Clara W Berridge, Pedro L Gozalo, Michael J Lepore, and Melissa A Clark. 2018. The prevalence of culture change practice in us nursing homes: Findings from a 2016/17 nationwide survey. *Medical Care* 56(12):985–993.

Mišeikis, Justinas, Pietro Caroni, Patricia Duchamp, Alina Gasser, Rastislav Marko, Nelija Mišeikienė, Frederik Zwilling, Charles de Castelbajac, Lucas Eicher, Michael Früh, et al. 2020. Lio-a personal robot assistant for human-robot interaction and care applications. *IEEE Robotics and Automation Letters* 5(4):5339–5346.

Mitchell, Elliot, and Lena Mamykina. 2021. From the curtain to kansas: Conducting wizard-of-oz studies in the wild. In *Extended abstracts of the 2021 chi conference on human factors in computing systems*, 1–6.

Moharana, Sanika, Alejandro E Panduro, Hee Rin Lee, and Laurel D Riek. 2019. Robots for joy, robots for sorrow: community based robot design for dementia caregivers. In *2019 14th acm/ieee international conference on human-robot interaction (hri)*, 458–467. IEEE.

Montgomery, Rhonda JV, Judith G Gonyea, and Nancy R Hooyman. 1985. Caregiving and the experience of subjective and objective burden. *Family relations* 19–26.

Morgan, Jennifer Craft, Kendra J Jason, Candace L Kemp, and Kallol Kumar Bhattacharyya. 2024. A collaborative approach to improving care outcomes for residents in assisted living. *Gerontology and Geriatric Medicine* 10.

Morgan, Stephanie, and Linda H Yoder. 2011. A concept analysis of person-centered care. *Journal of holistic nursing* 30(1):6–15.

Morris, Meg, Brooke Adair, Kimberly Miller, Elizabeth Ozanne, Ralph Hansen, Alan Pearce, Nick Santamaria, Luan Viega, Maureen Long, and Catherine Said. 2013. Smart-home technologies to assist older people to live well at home. *Journal of Aging Science*.

Mukai, Toshiharu, Shinya Hirano, Hiromichi Nakashima, Yo Kato, Yuki Sakaida, Shijie Guo, and Shigeyuki Hosoe. 2010. Development of a nursing-care assistant robot riba that can lift a human in its arms. In *2010 ieee/rsj international conference on intelligent robots and systems*, 5996–6001. IEEE.

Nani, Maria, Praminda Caleb-Solly, Sanja Dogramadzi, Tina Fear, and Herjan van den Heuvel. 2010. Mobiserv: an integrated intelligent home environment for the provision of health, nutrition and mobility services to the elderly. *4th Companion Robotics Workshop in Brussels*.

National Academies of Sciences, Engineering, and Medicine. 2022. *The national imperative to improve nursing home quality: Honoring our commitment to residents, families, and staff*. Washington, DC: The National Academies Press.

National Health Mission, Ministry of Health & family Welfare, Government of India. 2024. National quality assurance standards for public health facilities 2024. ISBN 978-93-82655-01-5.

Noury, Norbert. 2005. Ailisa: experimental platforms to evaluate remote care and assistive technologies in gerontology. In *Proceedings of 7th international workshop on enterprise networking and computing in healthcare industry, 2005. healthcom 2005.*, 67–72. IEEE.

Odabasi, Cagatay, Florenz Graf, Jochen Lindermayr, Mayank Patel, Simon D Baumgarten, and Birgit Graf. 2022. Refilling water bottles in elderly care homes with the help of a safe service robot. In *Proceedings of the 2022 acm/ieee international conference on human-robot interaction*, 101–109.

Odom, William, John Zimmerman, Scott Davidoff, Jodi Forlizzi, Anind K Dey, and Min Kyung Lee. 2012. A fieldwork of the future with user enactments. In *Proceedings of the designing interactive systems conference*, 338–347.

Omnibus Budget Reconciliation Act. 1987. Omnibus budget reconciliation act of 1987. Public Law 100-203.

Ostrowski, Anastasia K., Cynthia Breazeal, and Hae Won Park. 2021. Long-term co-design guidelines: Empowering older adults as co-designers of social robots. In *2021 30th ieee international conference on robot & human interactive communication (ro-man)*, 1165–1172.

Ostrowski, Anastasia K, Cynthia Breazeal, and Hae Won Park. 2022. Mixed-method long-term robot usage: Older adults' lived experience of social robots. In *2022 17th acm/ieee international conference on human-robot interaction (hri)*, 33–42. IEEE.

Pages, Jordi, Luca Marchionni, and Francesco Ferro. 2016. Tiago: the modular robot that adapts to different research needs. In *International workshop on robot modularity, iros*.

Park, Hae Won, Ishaan Grover, Samuel Spaulding, Louis Gomez, and Cynthia Breazeal. 2019. A model-free affective reinforcement learning approach to personalization of an autonomous social robot companion for early literacy education. In *Proceedings of the aaai conference on artificial intelligence*, vol. 33, 687–694.

Perkins, Bradford, Stephen A Kliment, J David Hoglund, Douglas King, and Eric Cohen. 2004. *Building type basics for senior living*, vol. 7. John Wiley & Sons.

Pettersson, John Sören, and Joe Siponen. 2002. Ozlab: a simple demonstration tool for prototyping interactivity. In *Proceedings of the second nordic conference on human-computer interaction*, 295–296.

Pew Research Center. 2014. Chapter 2. aging in the u.s. and other countries, 2010 to 2050. Accessed: 10-29-2021.

Pirhonen, Jari, Helinä Melkas, Arto Laitinen, and Satu Pekkarinen. 2020. Could robots strengthen the sense of autonomy of older people residing in assisted living facilities?—a future-oriented study. *Ethics and Information Technology* 22(2):151–162.

Polanyi, Michael, and Amartya Sen. 2009 [1966]. *The tacit dimension*. University of Chicago press.

Pollack, Martha E, Laura Brown, Dirk Colbry, Cheryl Orosz, Bart Peintner, Sailesh Ramakrishnan, Sandra Engberg, Judith T Matthews, Jacqueline Dunbar-Jacob, Colleen E McCarthy, et al. 2002. Pearl: A mobile robotic assistant for the elderly. In *Aaai workshop on automation as eldercare*, vol. 2002, 85–91.

Porfirio, David, Mark Roberts, and Laura M Hiatt. 2024. Goal-oriented end-user programming of robots. In *Proceedings of the 2024 acm/ieee international conference on human-robot interaction*, 582–591.

Porfirio, David, Allison Sauppé, Aws Albarghouthi, and Bilge Mutlu. 2020. Transforming robot programs based on social context. In *Proceedings of the 2020 chi conference on human factors in computing systems*, 1–12.

Porfirio, David, Laura Stegner, Maya Cakmak, Allison Sauppé, Aws Albarghouthi, and Bilge Mutlu. 2023. Sketching robot programs on the fly. In *Proceedings of the 2023 acm/ieee international conference on human-robot interaction*, 584–593.

Porfirio, David J, Laura Stegner, Maya Cakmak, Allison Sauppé, Aws Albarghouthi, and Bilge Mutlu. 2021. Figaro: A tabletop authoring environment for human-robot interaction. In *Proceedings of the 2021 chi conference on human factors in computing systems*, 1–15.

Powers, Bethel Ann. 2005. Everyday ethics in assisted living facilities: A framework for assessing resident-focused issues. *Journal of Gerontological Nursing* 31(1):31.

Quintana, Eduardo, and Jesus Favela. 2013. Augmented reality annotations to assist persons with alzheimers and their caregivers. *Personal and ubiquitous computing* 17(6):1105–1116.

Rabig, Judith, William Thomas, Rosalie A Kane, Lois J Cutler, and Steve McAlilly. 2006. Radical redesign of nursing homes: applying the green house concept in tupelo, mississippi. *The Gerontologist* 46(4):533–539.

Rashidi, Parisa, and Alex Mihailidis. 2013. A survey on ambient-assisted living tools for older adults. *IEEE Journal of Biomedical and Health Informatics* 17(3):579–590.

Robinson, Fraser, and Goldie Nejat. 2022. An analysis of design recommendations for socially assistive robot helpers for effective human-robot interactions in senior care. *Journal of Rehabilitation and Assistive Technologies Engineering* 9.

Robinson, Gretchen E, and Ann Gallagher. 2008. Culture change impacts quality of life for nursing home residents. *Topics in Clinical Nutrition* 23(2):120–130.

Rogers, Carl Ransom. 1995. *On becoming a person: A therapist's view of psychotherapy*. Houghton Mifflin Harcourt.

Rogers, Wendy A, Travis Kadylak, and Megan A Bayles. 2022. Maximizing the benefits of participatory design for human–robot interaction research with older adults. *Human Factors* 64(3):441–450.

Rosengren, Kristina, Petra Brannefors, and Eric Carlstrom. 2021. Adoption of the concept of person-centred care into discourse in europe: a systematic literature review. *Journal of Health Organization and Management* 35(9):265–280.

Šabanović, Selma, Wan-Ling Chang, Casey C Bennett, Jennifer A Piatt, and David Hakken. 2015. A robot of my own: participatory design of socially assistive robots for independently living older adults diagnosed with depression. In *International conference on human aspects of it for the aged population*, 104–114. Springer.

Saffari, Ehsan, Seyed Ramezan Hosseini, Alireza Taheri, and Ali Meghdari. 2021. "does cinema form the future of robotics?": a survey on fictional robots in sci-fi movies. *SN Applied Sciences* 3(6):655.

Sar, Kubra, and Pezhman Ghadimi. 2024. A web-interface based decision support system for optimizing home healthcare waste collection vehicle routing. *Logistics* 8(4):119.

Sather III, Richard, Mahsa Soufineyestani, Nabiha Imtiaz, and Arshia Khan. 2021. Assistive robots designed for eldery care and caregivers. *International Journal of Robotics and Control* 3(1).

Sauppé, Allison, and Bilge Mutlu. 2015. The social impact of a robot co-worker in industrial settings. In *Proceedings of the 33rd annual acm conference on human factors in computing systems*, 3613–3622.

Sawik, Bartosz, Sławomir Tobis, Ewa Baum, Aleksandra Suwalska, Sylwia Kropińska, Katarzyna Stachnik, Elena Pérez-Bernabeu, Marta Cildoz, Alba Agustin, and Katarzyna Wieczorowska-Tobis. 2023. Robots for elderly care: Review, multi-criteria optimization model and qualitative case study. *Healthcare* 11(9).

Scandurra, Isabella, and Marie Sjölinder. 2013. Participatory design with seniors: Design of future services and iterative refinements of interactive ehealth services for old citizens. *Medicine 2.0* 2(2).

Schaeffer, C, and T May. 1999. Care-o-bot-a system for assisting elderly or disabled persons in home environments. *Assistive technology on the threshold of the new millenium* 3.

Schoen, Andrew, Nathan White, Curt Henrichs, Amanda Siebert-Evenstone, David Shaffer, and Bilge Mutlu. 2022. Coframe: A system for training novice cabot programmers. In *2022 17th acm/ieee international conference on human-robot interaction (hri)*, 185–194. IEEE.

Schoenhofer, Savina O, Aimee van Wynsberghe, and Anne Boykin. 2019. Engaging robots as nursing partners in caring: nursing as caring meets care-centered value-sensitive design. *International Journal for Human Caring* 23(2):157–167.

Schroeter, Ch, Steffen Mueller, Michael Volkhardt, Erik Einhorn, Claire Huijnen, Herjan van den Heuvel, Andreas van Berlo, Andreas Bley, and H-M Gross. 2013. Realization and user evaluation of a companion robot for people with mild cognitive impairments. In *2013 ieee international conference on robotics and automation*, 1153–1159. IEEE.

Senft, Emmanuel, Michael Hagenow, Robert Radwin, Michael Zinn, Michael Gleicher, and Bilge Mutlu. 2021. Situated live programming for human-robot collaboration. In *Proceedings of the 2021 acm symposium on user interface and software technology*.

Senft, Emmanuel, Séverin Lemaignan, Paul E Baxter, Madeleine Bartlett, and Tony Belpaeme. 2019. Teaching robots social autonomy from in situ human guidance. *Science Robotics* 4(35):eaat1186.

SHAPES Guidelines. 2023. Shapes pan-european integrated care policy-making guidelines. Deliverable D3.4.

Sharma, Tanvi, Megan Bamford, and Denise Dodman. 2015. Person-centred care: an overview of reviews. *Contemporary nurse* 51(2-3):107–120.

Shield, Renée R., Jessica Looze, Denise Tyler, Michael Lepore, and Susan C. Miller. 2014. Why and how do nursing homes implement culture change practices? insights from qualitative interviews in a mixed methods study. *Journal of Applied Gerontology* 33(6):737–763. PMID: 24652888, `https://doi.org/10.1177/0733464813491141`.

Sixty-Ninth World Health Assembly. 2016. Strengthening integrated, people-centred health services. Document no. WHA69.24.

Smarr, Cory-Ann, Akanksha Prakash, Jenay M Beer, Tracy L Mitzner, Charles C Kemp, and Wendy A Rogers. 2012. Older adults' preferences for and acceptance of robot assistance for everyday living tasks. In *Proceedings of the human factors and ergonomics society annual meeting*, vol. 56, 153–157. Sage Publications Sage CA: Los Angeles, CA.

Somers, Sandra, and Wendy Thompson. 2008. *Caregiver's manual*. Glacier View Lodge.

Sorell, Tom, and Heather Draper. 2014. Robot carers, ethics, and older people. *Ethics and Information Technology* 16(3):183–195.

Spector, William D, and John A Fleishman. 1998. Combining activities of daily living with instrumental activities of daily living to measure functional disability. *The Journals of Gerontology Series B: Psychological Sciences and Social Sciences* 53(1):S46–S57.

Stasse, Olivier, Thomas Flayols, Rohan Budhiraja, Kevin Giraud-Esclasse, Justin Carpentier, Joseph Mirabel, Andrea Del Prete, Philippe Souères, Nicolas Mansard, Florent Lamiraux, et al. 2017. Talos: A new humanoid research platform targeted for industrial applications. In *2017 ieee-ras 17th international conference on humanoid robotics (humanoids)*, 689–695. IEEE.

Stegner, Laura, Yuna Hwang, David Porfirio, and Bilge Mutlu. 2024. Understanding on-the-fly end-user robot programming. In *Proceedings of the 2024 acm designing interactive systems conference*, 2468–2480.

Stegner, Laura, and Bilge Mutlu. 2022. Designing for caregiving: Integrating robotic assistance in senior living communities. In *Designing interactive systems conference*. DIS '22, New York, NY, USA: Association for Computing Machinery.

Stegner, Laura, Emmanuel Senft, and Bilge Mutlu. 2023. Situated participatory design: A method for in situ design of robotic interaction with older adults. In *Proceedings of the 2023 chi conference on human factors in computing systems*.

Sterns, Samantha, Susan C Miller, and Susan Allen. 2010. The complexity of implementing culture change practices in nursing homes. *Journal of the American Medical Directors Association* 11(7):511–518.

Stowers, Kimberly, Kevin Leyva, Gabriella M Hancock, and Peter A Hancock. 2016. Life or death by robot? *Ergonomics in Design* 24(3):17–22.

Strömberg, Hanna, Valtteri Pirttilä, and Veikko Ikonen. 2004. Interactive scenarios—building ubiquitous computing concepts in the spirit of participatory design. *Personal and Ubiquitous Computing* 8(3):200–207.

Su, Zhidong, Fei Liang, Ha Manh Do, Alex Bishop, Barbara Carlson, and Weihua Sheng. 2021. Conversation-based medication management system for older adults using a companion robot and cloud. *IEEE Robotics and Automation Letters* 6(2):2698–2705.

Subburaman, Rajesh, Dimitrios Kanoulas, Nikos Tsagarakis, and Jinoh Lee. 2023. A survey on control of humanoid fall over. *Robotics and Autonomous Systems* 166:104443.

Tanioka, Tetsuya, Marlaine C Smith, and Yueren Zhao. 2019. Framing the development of humanoid healthcare robots in caring science. *International Journal for Human Caring* 23(2).

Tatsch, Christopher Alexander Arend. 2020. *Route planning for long-term robotics missions*. West Virginia University.

Teller, Seth, Matthew R Walter, Matthew Antone, Andrew Correa, Randall Davis, Luke Fletcher, Emilio Frazzoli, Jim Glass, Jonathan P How, Albert S Huang, et al. 2010. A voice-commandable robotic forklift working alongside humans in minimally-prepared outdoor environments. In *2010 ieee international conference on robotics and automation*, 526–533. IEEE.

Thomas, Kali S, and Robert Applebaum. 2015. Long-term services and supports (ltss): A growing challenge for an aging america. *Public Policy & Aging Report* 25(2):56–62.

Thomas, William H. 1996. *Life worth living: How someone you love can still enjoy life in a nursing home: The eden alternative in action*. Publisher: VanderWyk&Burnham.

Trainum, Katie, Jiaying Liu, Elliott Hauser, and Bo Xie. 2024. Nursing staff's perspectives of care robots for assisted living facilities: Systematic literature review. *JMIR aging* 7:e58629.

Tseng, Shih-Huan, Feng-Chih Liu, and Li-Chen Fu. 2018. Active learning on service providing model: Adjustment of robot behaviors through human feedback. *IEEE Transactions on Cognitive and Developmental Systems* 10(3):701–711.

temi USA Inc. 2025. https://www.robotemi.com. Accessed: 3-31-2025.

Vanderelst, Dieter, and Jurgen Willems. 2020. Can we agree on what robots should be allowed to do? an exercise in rule selection for ethical care robots. *International Journal of Social Robotics* 12(5):1093–1102.

Vaquero, Tiago Stegun, Sharaf Christopher Mohamed, Goldie Nejat, and J Christopher Beck. 2015. The implementation of a planning and scheduling architecture for multiple robots assisting multiple users in a retirement home setting. In *Aaai workshop: Artificial intelligence applied to assistive technologies and smart environments*.

Vines, John, Mark Blythe, Stephen Lindsay, Paul Dunphy, Andrew Monk, and Patrick Olivier. 2012. Questionable concepts: Critique as resource for designing with eighty somethings. In *Proceedings of the sigchi conference on human factors in computing systems*, 1169–1178. CHI '12, New York, NY, USA: Association for Computing Machinery.

Vink, Peter, AS Imada, and Klaus J Zink. 2008. Defining stakeholder involvement in participatory design processes. *Applied ergonomics* 39(4): 519–526.

Viswanathan, Meera, Alice Ammerman, Eugenia Eng, Gerald Garlehner, Kathleen N Lohr, Derek Griffith, Scott Rhodes, Carmen Samuel-Hodge, Siobhan Maty, Linda Lux, et al. 2004. Community-based participatory research: Assessing the evidence: Summary. *AHRQ evidence report summaries*.

Wada, Kazuyoshi, Takanori Shibata, Tomoko Saito, Kayoko Sakamoto, and Kazuo Tanie. 2005. Psychological and social effects of one year robot assisted activity on elderly people at a health service facility for the aged. In *Proceedings of the 2005 ieee international conference on robotics and automation*, 2785–2790. IEEE.

Walker, Nick, Yu-Tang Peng, and Maya Cakmak. 2019. Neural semantic parsing with anonymization for command understanding in general-purpose service robots. In *Robot world cup*, 337–350. Springer.

Watson, Julie. 2019. Developing the senses framework to support relationship-centred care for people with advanced dementia until the end of life in care homes. *Dementia* 18(2):545–566.

Webster, Matt, Clare Dixon, Michael Fisher, Maha Salem, Joe Saunders, Kheng Lee Koay, and Kerstin Dautenhahn. 2014. Formal verification of an autonomous personal robotic assistant. In *2014 aaai spring symposium series*.

Webster, Matt, Clare Dixon, Michael Fisher, Maha Salem, Joe Saunders, Kheng Lee Koay, Kerstin Dautenhahn, and Joan Saez-Pons. 2016. Toward reliable autonomous robotic assistants through formal verification: A case study. *IEEE Transactions on Human-Machine Systems* 46(2):186–196.

Whitesides, George M. 2018. Soft robotics. *Angewandte Chemie International Edition* 57(16):4258–4273.

WHO. 2017. *Global action plan on the public health response to dementia 2017–2025*. World Health Organization.

Wik, Malin, and Akhona Khumalo. 2020. Wizardry in distributed participatory design. In *International conference on human-computer interaction*, 172–186. Springer.

Wiles, Janine, Annette Leibing, Nancy Guberman, Jeanne Reeve, and Ruth Allen. 2012. The meaning of "aging in place" to older people. *The Gerontologist* 52(3).

Winkle, Katie, Praminda Caleb-Solly, Ailie Turton, and Paul Bremner. 2018. Social robots for engagement in rehabilitative therapies: Design implications from a study with therapists. In *Proceedings of the 2018 acm/ieee international conference on human-robot interaction*, 289–297.

Winkle, Katie, Emmanuel Senft, and Séverin Lemaignan. 2021. Leador: A method for end-to-end participatory design of autonomous social robots. *Frontiers in Robotics and AI* 8.

Wong, Karen Lok Yi, Lillian Hung, Joey Wong, Juyoung Park, Hadil Alfares, Yong Zhao, Abdolhossein Mousavinejad, Albin Soni, and Hui Zhao. 2024. Adoption of artificial intelligence–enabled robots in long-term care homes by health care providers: scoping review. *JMIR aging* 7(1):e55257.

Wright, James. 2018. Tactile care, mechanical hugs: Japanese caregivers and robotic lifting devices. *Asian Anthropology* 17(1):24–39.

Yamazaki, Keiichi, Michie Kawashima, Yoshinori Kuno, Naonori Akiya, Matthew Burdelski, Akiko Yamazaki, and Hideaki Kuzuoka. 2007. Prior-to-request and request behaviors within elderly day care: Implications for developing service robots for use in multiparty settings. In *Ecscw 2007*, 61–78. Springer.

Yan, Fei, Abdullah M Iliyasu, and Kaoru Hirota. 2021. Emotion space modelling for social robots. *Engineering Applications of Artificial Intelligence* 100:104178.

Zimmerman, John, Jodi Forlizzi, and Shelley Evenson. 2007. Research through design as a method for interaction design research in hci. In *Proceedings of the sigchi conference on human factors in computing systems*, 493–502.

Zimmerman, Sheryl. 2001. *Assisted living: Needs, practices, and policies in residential care for the elderly*. JHU Press.

Zimmerman, Sheryl, and Philip D Sloane. 2007. Definition and classification of assisted living. *The Gerontologist* 47(suppl_1):33–39.

Zulas, A Leah, Aaron S Crandall, Maureen Schmitter-Edgecombe, and Diane J Cook. 2012. Caregiver needs from elder care assistive smart homes: Nursing assessment. In *Proceedings of the human factors and ergonomics society annual meeting*, vol. 56, 125–129. SAGE Publications Sage CA: Los Angeles, CA.