Examining Engagement and Motivation in a Conversational Robotic Exercise Coach for Older Adults

Rayna Hata

CMU-RI-TR-25-108

Dce 12, 2025

The Robotics Institute
School of Computer Science
Carnegie Mellon University
Pittsburgh, PA

Thesis Committee:
Aaron Steinfeld, *chair*
Reid Simmons
Jean Oh
Michelle Zhao

Submitted in partial fulfillment of the requirements for the Master of Science in Robotics degree.

Abstract

Exercise is essential for healthy aging, but motivation and adherence to exercise often decline with age, leading to a sedentary lifestyle. This challenge, along with an aging population, strains the ability of physical therapists and coaches to meet demand. In this paper, we introduce a conversational robotic exercise coach system to help address this demand. Our research aims to evaluate the acceptability of such agents among older adults, identify key design considerations for this demographic, and explore a method for assessing exercise motivation using natural conversations facilitated through Wizard-of-Oz. The system was tested in a user study with 10 participants aged 59 and above. Results show that participants had varied levels and types of engagement with the robot. Furthermore, participants with low motivation rated the exercise sessions highly, suggesting that the engaging, interactive agents can enhance exercise enjoyment. Lastly, we provide design recommendations for future autonomous coaches.

Acknowledgments

I am deeply grateful to my advisor, Aaron Steinfeld, for being an exceptional mentor and for believing in me, my research, and the ideas I bring forward. Your trust in my curiosity and your encouragement to pursue questions I genuinely care about have shaped how I approach research and how I understand myself as a researcher.

I am also thankful to Reid Simmons for serving as an unofficial advisor and a constant source of guidance. Your thoughtful advice and steady encouragement to think critically at every stage of a project have deeply influenced how I reason through problems and refine my work.

I am grateful to my committee members, Jean Oh and Michelle Zhao, for their insightful questions, constructive feedback during research talks, and thoughtful perspectives throughout this process. Your input challenged me in the best ways and helped strengthen this work.

My sincere thanks go to my collaborator, mentor, and friend, Roshni Kaushik. From research discussions to traveling together to everyday conversations, you have been a constant source of support and encouragement over the past two years.

I am thankful to my labmates in the TBD Lab for their collaboration, feedback, and camaraderie. Working alongside you made the lab a supportive and inspiring environment!

I am grateful to the undergraduate students I have worked with over the past two years for embracing robotics, exploring ambitious ideas, and building with curiosity and enthusiasm. Your energy and creativity continually reminded me why mentorship matters.

I am thankful to my friends in Pittsburgh for making this city feel like a second home. Your presence during both challenging and joyful moments, from quiet conversations to shared adventures, made this journey deeply meaningful.

Above all, I am grateful to my parents and my brother for their unwavering support throughout my life. I would not be the curious and driven person I am today without you. Thank you for believing in me, supporting my decision to pursue robotics, and encouraging me to follow what excites me most.

Funding

This work was supported by NSF Grant (AI-CARING) #2112633

Contents

List of Figures

List of Tables

Chapter 1

Introduction

Physical therapy and regular exercise sessions are especially beneficial for aging populations, as they promote both physical and mental wellness [6, 18, 48]. Studies have shown that older adults in assisted living facilities who participate in structured wellness programs experience reduced risk of falling and protection against functional decline [23]. However, exercise motivation and adherence often decline with age [41]. Prior work has found that older adults who are already active tend to prefer exercising with others [44], while those who are less active often require individualized routines and may prefer working one on one with an exercise coach [16].

The increasing number of older adults presents significant challenges for wellness professionals, especially as the number of available physical therapists continues to decline [13, 52]. This imbalance creates an opportunity for innovative solutions such as robotic exercise coaches to support aging adults in maintaining physical health and mobility. Robotic systems can offer consistent and personalized guidance, greater availability, and scheduling flexibility for older adults, while also reducing some of the burden on healthcare professionals. These systems have the potential to supplement the work of physical therapy providers and to benefit both individuals who are already motivated to exercise and those who prefer personalized support from a coaching system.

While these coaches can help supplement the demand placed on physical therapists, it is important to acknowledge that not all individuals who need to exercise will choose to do so, particularly as sources of exercise motivation shift with age. Younger individuals may be motivated by appearance or performance, while older adults often prioritize maintaining mobility, reducing pain, enhancing quality of life, or participating for social enjoyment [11, 33, 35, 44]. Given these differences in motivation and exercise frequency among older adults, there is a need to tailor robotic systems to the specific preferences, abilities, and expectations of this population rather than relying on generic exercise coaching designs. Systems that incorporate domain-specific support for older adults have the potential to promote healthier and more active lifestyles while also addressing the growing shortage of wellness professionals.

Conversational agents provide an additional opportunity to support exercise engagement by allowing systems to interact through natural dialogue. Conversation can reveal how motivated or prepared an older adult feels on a given day, and it can surface personal concerns that may influence participation. Beyond simply gathering information, conversational systems can create a more welcoming and supportive environment by offering companionship and reducing the sense of exercising alone. Prior research shows that social interaction plays a meaningful role in the lives of older adults, and socially assistive agents, including robots, can help reduce loneliness, foster trust, and encourage adherence to daily routines. When embedded in an exercise context, a conversational robot can assess motivation, offer tailored encouragement, and make the exercise experience feel more personal and engaging. These capabilities motivate our exploration of conversational interactions as a pathway to better support aging adults during physical activity.

In this work, we present a conversational robotic exercise coach to interact with aging adults.

To understand how aging adults choose to converse with an exercise coach, we developed a Wizard of Oz conversational system integrated with an existing robotic exercise coach platform. We conducted a user study to explore participants' motivation and engagement with the system and identified a set of design considerations for building an effective autonomous conversational agent that supports older adults during physical activity. The findings show the potential for conversational systems to promote the health and well-being of the aging population.

This study makes three main contributions:

1. Assessing the engagement levels and acceptance of a robotic system as an exercise coach.

2. Using conversational interactions to measure exercise motivation for aging adults.
3. Proposing design considerations for exercise systems designed for the aging adult population.

Chapter 2

Related Works

2.1 Robotic Exercise Coaching Systems

Socially Assistive Robots (SARs) provide support through social interaction and have become increasingly prominent in rehabilitation and exercise contexts. Embodied robots often evoke higher empathy, trust, and engagement than virtual agents [42, 46], and older adults consistently prefer physically embodied exercise coaches across enjoyableness, helpfulness, and social attraction metrics [19]. This advantage has been supported by later work showing that physical robots can improve exercise performance; for example, participants performed 69% of exercises correctly with a physical robot compared to 57% with a tablet-based virtual coach [37].

Robotic exercise systems have demonstrated strong potential for improving form, technique, and adherence. Coaches that provide continuous real-time feedback outperform systems that offer only end-of-exercise corrections [2], and multimodal feedback combining audio and visual cues can be especially effective. Advanced platforms integrating physiological monitoring and kinematic analysis have also shown success in supporting proper performance during exercise [38].

Personalization plays a central role in sustaining motivation and engagement. Adaptive robots that learn user preferences are perceived as more competent, trustworthy, and supportive than static or user-controlled systems [40]. Long-term clinical deployments further demonstrate the value of personalization, with a 2.5-year cardiac rehabilitation study reporting that 97% of participants recommended the personalized robotic coach [25]. Therapist-centered design work similarly highlights the importance of tailoring feedback and communication style to a patient's personality, motivation, and lifestyle [49], underscoring the need for exercise robots that combine performance monitoring with social attunement.

Yet, despite these advances, most robotic exercise coaching systems frame the robot primarily as an instructor that provides corrective feedback. Human-led exercise programs, by contrast, naturally incorporate social bonding, light conversation, encouragement, and emotional support as part of the therapeutic process. Current robotic systems rarely investigate companionship or conversational engagement as mechanisms for fostering adherence or increasing enjoyment. This gap motivates our work, which shifts the focus from purely corrective coaching toward understanding how social interaction and conversation with a robotic exercise companion can influence motivation and engagement for older adults.

2.2 Robots as Social Companions for Aging Adults

Beyond physical activity, Socially Assistive Robots have been explored extensively as social partners for older adults, particularly those at risk of social isolation. The rapid improvement of conversational systems, especially large language model based frameworks, has opened new opportunities for natural social interaction.

Lima et al. [31] conducted a five week study with 22 older adults interacting with a GPT-enhanced robot. Participants displayed significantly higher social engagement with the robot than with human facilitators, making 4.1 social comments on average compared to 2.3 with humans. The robot also elicited improved cognitive task descriptions, reduced anxiety, and greater trust and sociability.

Empathy and emotional responsiveness also play crucial roles in social robot acceptance. Abdollahi et al. [1] compared an empathetic robot to a non-empathetic version across three weeks. The empathetic robot used facial expression analysis and speech sentiment detection to adjust its dialogue. Engagement was significantly higher with the empathetic system, and participants expressed more positive facial expressions (45% compared to 26%).

Simple, consistent social interactions can have meaningful impact. In a 3.5-month deployment in an eldercare facility, Sabelli et al. [36] found that daily greetings, calling residents by name, and small talk significantly improved emotional wellbeing. Residents shared personal stories and concerns with the robot, reporting comfort in its non-judgmental presence.

These findings demonstrate that older adults respond positively to robots that provide companionship, emotional sensitivity, and meaningful conversation. However, most of this work focuses on sedentary or caregiver-patient interactions rather than on shared physical activity. Integrating social bonding into exercise interactions presents an opportunity to support both wellbeing and physical motivation.

2.3 Conversational Agents for Aging Adults

Conversational agents (CAs) designed for older adults are increasingly used to support social connection, daily routines, and health management. Prior work shows that these systems can empower both older adults and their care partners by expanding perceived support networks and reducing caregiving burden [53]. In home settings, some older adults engage in small talk with their conversational systems, form social bonds, and treat these agents as more than task-oriented tools. These interactions suggest that CAs can provide a sense of companionship in addition to instrumental assistance.

Beyond social interaction, CAs have also been explored as tools to support health-related behaviors among older adults. By offering reminders, encouragement, and structured guidance, conversational systems can help users manage medications, appointments, and physical activity routines. Their interactive nature allows them to deliver support in a more engaging and adaptive manner than traditional static interfaces. This is particularly relevant for older adults who may experience increased cognitive load when managing multiple health-related tasks.

More recently, conversational agents have been investigated specifically for promoting physical activity and exercise engagement in older adult populations [14, 32, 50]. These systems encourage regular physical activity through goal setting, feedback, reminders, and motivational dialogue. For example, Wiratunga et al. [50] demonstrated that chatbot-based coaching can effectively support older adults in increasing and sustaining physical activity by providing personalized encouragement and structured exercise guidance. Similar work shows that older adults are receptive to conversational systems that promote health behaviors when the interaction style is clear, supportive, and easy to understand [14, 32].

CAs have also been shown to reduce cognitive load and support daily task management. Older adults managing chronic conditions often feel overwhelmed by the need to remember medications, medical appointments, and ongoing health monitoring tasks [34]. Reminder-based conversational systems have been shown to help maintain adherence and reduce stress. Medication guidance is another key area where CAs have demonstrated promise. Azevedo et al. [3] showed that translating clinical information into patient-friendly explanations improved older adults' comprehension and recall. This is particularly important as medication adherence, similar to exercise adherence, tends to decline with age [21].

This body of work highlights the potential for conversational agents to play a meaningful role in the everyday lives of older adults. By combining practical support with social interaction, CAs can serve not only as tools for behavior change but also as companions that contribute to motivation, engagement, and overall well-being. These findings motivate the exploration of conversational agents as exercise support systems for aging adults, particularly when embedded within socially interactive and physically embodied platforms.

2.4 Applications of Conversational Agents in Other Domains

Conversational agents have also been broadly adopted across healthcare and educational settings. In learning environments, CAs have been shown to improve motivation, engagement, and academic performance [30], and they are used across a wide range of subjects and instructional formats [22, 24]. Beyond academic benefits, CAs can also reshape classroom dynamics by transforming the instructor role into a more collaborative and supportive facilitator [15], creating a more interactive and student-centered learning experience.

In healthcare, conversational systems have been used to support cognitive behavioral therapy, social skills development, and chronic disease self-management [8, 20, 45]. These systems provide accessible, personalized guidance that can supplement clinical care and encourage sustained engagement. These applications demonstrate the versatility of conversational agents and highlight their potential to support users across both educational and health-related domains.

Chapter 3

Methods

In this work, we explored the preferences of older adults for conversational interaction with a social robotic exercise coach to inform the design of future autonomous conversational exercise systems. We used an existing exercise coach robot [27] and implemented an additional Wizard of Oz conversation system. Although multiple types of data were collected, this thesis focuses specifically on conversational engagement.

3.1 Design of the Exercise Coach

Exercise coaches provide real time, contextually aware feedback as people exercise. To create a comparable environment, our robotic exercise coach needed to analyze participant movements in real time and deliver appropriate feedback. In our study, participants performed two upper body exercises: bicep curls and lateral raises. These movements were selected because they can be performed while seated and involve relatively simple form corrections compared to compound exercises such as squats or lunges.

We used a Quori robot [43][1], outfitted with an Orbbec Astra Mini[2] depth camera. Figure 3.1 shows the Quori platform used in this work.

Quori was developed and distributed by another research team [43] and has been used in prior research involving exercise and social interaction [28, 29]. The robot

[1] https://quori.org
[2] https://shop.orbbec3d.com/Astra-Mini-S

Figure 3.1: The Quori robot used in our study.

used the Mediapipe library to extract three dimensional joint positions from the camera feed. Repetitions were segmented by monitoring changes in relevant joint angles using gradients and thresholding [26]. After detecting a completed repetition, the system compared the motion to recorded demonstrations to evaluate both form and speed. Based on these evaluations, the robot selected verbal and nonverbal feedback to deliver to the participant.

The robot supported two feedback styles: firm and encouraging. Prior studies have shown that the feedback style an individual performs best with does not always align with the style they report enjoying most [28]. Building on this insight, the current work explores whether people engage differently with a robot that adopts their stated style preference. Previous work [28] detailed how exercise evaluations were mapped to specific verbal phrases, facial expressions, and movements for each style. Table 3.1 provides examples of both verbal and nonverbal feedback associated with these styles.

3.2 Design of the Conversation System

The conversational system was a central component of the study, designed to engage participants before and during exercise while providing explanations, motivational prompts, and opportunities for interaction. The system used a Wizard of Oz setup in

Table 3.1: Examples of verbal and nonverbal feedback for the two feedback styles from [28]

	Firm		Encouraging	
Evaluation	**Verbal**	**Nonverbal**	**Verbal**	**Nonverbal**
Last 2 reps slow	Try to speed up	50% sad, lean forward slightly	Nice job, can you speed up a little on the next few?	50% sad, lean forward slightly less than firm
Last 2 reps low range of motion	Focus on getting a full range of motion in your elbows	50% sad, lean forward slightly	You are doing great, try to get a full range of motion in your elbows.	50% sad, lean forward slightly less than firm
Last 2 reps good speed, previous 2 were slow	Nice speed, keep going	60% happy, small upward arms, small backward torso	Nice job, great speed!	90% happy, large upward arms, large backward torso

which two researchers operated the dialogue. One researcher triggered a set of pre-programmed phrases that introduced the robot, described the structure of the session, and asked motivation related questions. A second researcher used a supplementary typing interface to generate real-time responses whenever participants asked questions that were not included in the pre-programmed options.

All spoken output was produced using the Google Text-to-Speech API[3]. The system converted text into MP3 audio files, which were played through the robot to create the appearance of autonomous speech.

Although this conversational platform could have been delivered through a virtual or computer based system, prior work demonstrates that physical embodiment meaningfully shapes how users engage with an agent. Interactions with embodied robots tend to elicit greater engagement, attention, and instructional comprehension compared to virtual avatars [4, 39, 47]. These findings motivated the choice to embed the conversational system within a physical robot for this study.

[3]https://cloud.google.com/text-to-speech

3.3 Procedure

3.3.1 Participants

We recruited ten aging adults between the ages of 59 and 94 (mean 77.4, SD 11.2), seven identifying as female and three as male. Eight participants were recruited from a local assisted living facility through word of mouth and an introductory meet-and-greet session, and two participants were recruited through a university participant pool. Eight of the ten participants reported that they had never interacted with a robot before. All study procedures were approved by our Institutional Review Board. Participants provided informed consent, including consent for video and audio recording, and received $10 for their participation.

3.3.2 Location and Layout

The first study location was the common room of a senior assisted living facility. The robot was positioned in a corner, and the participant was seated approximately five feet away, facing the robot to ensure clear camera capture. The researchers sat to the left of the robot, out of the camera's view but still visible to the participant.

The second location was a university lab space. The placement of the robot and participant mirrored the assisted living facility setup. However, in this setting, the researchers sat behind the participant and were concealed behind a barrier to remain out of the camera's view.

Figure 3.2 shows the study setup in the second location.

3.3.3 Introduction, Intake, and Assessment Conversations

Upon arrival, participants were guided to their seat and positioned so they remained fully within the camera frame. After providing informed consent, they were greeted by the robot, which said:

- Welcome and thank you for taking the time to be part of this research study. My name is Quori. How are you today?

The robot then continued with simple follow up questions, such as:

Figure 3.2: Study setup with the participant facing the robot.

- Before I explain the exercises, I would like to ask you a few questions. How old are you?

The wording and order of these questions were informed by a physical therapy expert specializing in older adults. The expert emphasized that early conversational cues, such as responses to "How are you?", often provide insight into a person's readiness or motivation to exercise. Guided by this feedback, we incorporated three motivation related questions derived from the Locus of Causality Exercise Scale (LCES) [5], grounded in self determination theory [17]:

Q1 On a scale of 1 to 10, how would you rate your energy level today?

Q2 On a daily basis, is exercise something you choose to do?

Q3 In general, do you feel like someone else is making you exercise, such as a doctor or family member?

After the motivation questions, the robot asked participants to select their preferred feedback style. It introduced the options by saying:

- I want to be the best coach I can be for you, so I want to understand how you like to be coached. For example, when you make a mistake, I could give you feedback that sounds like, "Amazing effort, let us aim for full range next time."

> Or I could say, "Focus on improving your range, keep pushing." Do you think you prefer the first way or the second way?

Half of the participants experienced their preferred style in the first round of exercises and the remaining half experienced it in the second round. This ordering was chosen based on prior findings that the style participants report preferring does not always align with the style they perform best with [28].

The robot then introduced the structure of the exercise session:

- You will perform two rounds with four sets each. The first two sets will be bicep curls and the next two will be lateral raises. Each set will be for forty seconds. Please do the exercises at your own pace. In between each set there will be a rest period. Please look at the screen next to you to see how to perform the exercises.

After this introduction, participants completed a brief intake survey.

3.3.4 Intake Survey

Participants completed an intake survey based on items from the RoSAS scale [12], rating their perceptions of the robot's intelligence, understandability, friendliness, awkwardness, and competence on a seven point scale. The statements were:

- I understood the robot well during the introduction.
- I think the robot understood me well during the introduction.
- I think the robot responded in a timely manner.
- I thought the robot was friendly.
- I thought the robot was awkward.
- I thought the robot was competent.
- I thought the robot was intelligent.
- I thought the robot explained the exercises well.
- I thought the robot was compassionate and understanding.

3.3.5 Exercise Rounds

Participants completed two rounds of exercises. Each round consisted of four forty five second sets: two sets of bicep curls followed by two sets of lateral raises. Each set was followed by a forty five second rest period. Before and after every set, the robot asked participants to report their pain level using the Wong Baker Faces pain scale [51]:

- Please choose the face that best shows your pain after that set.
- Please choose the face that best shows your pain after resting.

3.3.6 Exercise Surveys

Following each exercise round, participants completed a survey derived from the Godspeed questionnaire [7] and items used in prior work [28]. They rated the robot on eleven attributes: lively, interactive, responsive, friendly, kind, pleasant, competent, intelligent, strict, motivational, and corrective.

After completing both rounds, participants filled out a comparison survey indicating whether the robot in the first round felt more, less, or equally lively, interactive, responsive, friendly, kind, pleasant, competent, intelligent, strict, motivational, or corrective. These items used a seven point scale, with four indicating no perceived difference between the two rounds.

Chapter 4

Results

We performed two types of analysis on the data collected to measure the engagement level of the participants as well as the effectiveness of the adapted motivation questions. First, we conducted a reflective thematic analysis [9, 10] on the audio transcripts to understand how people interacted with the conversational exercise coach [9, 10]. During the coding analysis process of this step, we aimed to categorize and understand the types of conversations the participants were having with the robot. This helped us identify patterns in how the participants interacted with the robot and the nature of their responses. Second, we analyzed the survey responses, which included 7-point scale items, and compared these quantitative results to the conversational answers provided by the participants when asked about their motivation to exercise. This dual approach allowed us to gain a deeper understanding of the participants' engagement and motivation levels. Out of the 10 participants in the study, we had to exclude one participant due to their difficulty in understanding both the robot and the researcher. This communication barrier made it challenging to ensure effective engagement and accurate data collection, leading to the removal of their data from the study.

4.1 Robot Engagement

While coding the transcripts, we identified three types of conversations participants had with the robot.

1. Answer Engagement

2. Confusion-Related Engagement
3. Social Engagement

Answer engagement refers to the times that the participants answered the questions that the system directly asked them. Questions that the participants saw were the questions asked during the intake and the pain level questions asked before and after each exercise set. We found that most gave one-word answers to the questions asked by the robot and did not engage further with the questions. For example, when asked *"How are you?"* by the robot, most participants would answer with *"I'm good"* or *"Fine."*

Confusion-related engagement refers to the questions or statements of confusion that the participants expressed during the session. We found that participants who had difficulty with hearing in general often had a harder time understanding the robot. They would typically respond with phases such as *"What?", "I can't understand", "I'm sorry?"*, or *"what was the question?"* Additionally, the pace at which the robot spoke sometimes created challenges, leading to instances in which participants could not comprehend what the robot said. In such cases, the researchers would step in and speak on behalf of the robot to ensure clarity and maintain engagement.

We also found that there were instances where the participants needed clarification on on the exercises after the explanation during the intake and also during the sets. One participant responded to the system after the explanation by saying *"Could you repeat the routine again? How many do you want me to do and how many sets?"* During the exercise sets, some participants would ask *"What am I going to do now?"* or *"Am I doing the right thing?"*

Social engagement refers to two types of conversations that participants had with the robot. The first type includes discussions on topics not directly related to the current exercise session. The second type involves responses to the feedback the robot provided that were not in the form of questions, such as comments or affirmations related to the feedback. Examples of this type of engagement include saying thanks to the robot when given feedback or verbally acknowledging that they understood what the robot said to them by answering *"Okay"* or *"Thank you."* In some participants' cases, they also provided personal information about themselves or made jokes throughout the session. Notably, multiple participants mentioned the hospital in their comments, saying *"I'm halfway there? Sounds like I went to the hospital"* and *"I just thought it said I'm in a hospital."*

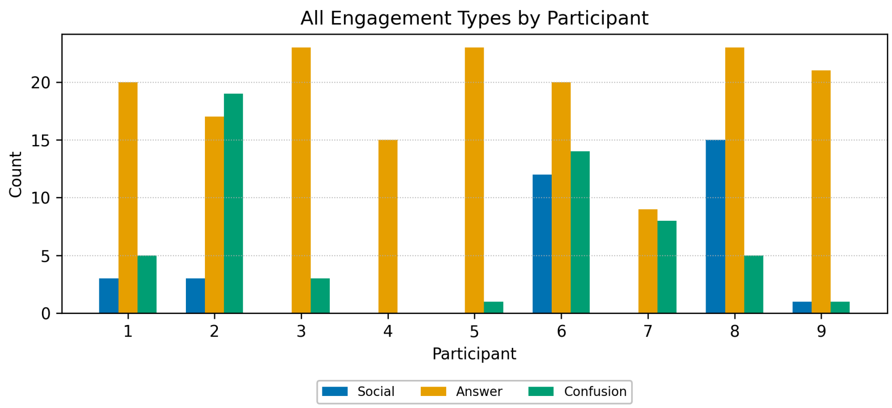

Figure 4.1: Number of engagement instances of each type for each participant

Figure 4.1 presents a bar chart illustrating the number of instances each participant exhibited across the three different conversational engagement categories. All participants were asked the same number of questions. However, some participants struggled to understand the questions, resulting in either non-responses or non-verbal answers, such as nodding when researchers pointed to different faces on the pain scale. Of the 23 total questions asked of each person, participants answered an average of 19.

A closer look at the graph reveals that Participant 6 demonstrated a higher level of social engagement (12 instances) but also had more instances of confusion (14 instances) than the average. Participant 8 also exhibited a high level of social engagement but experienced fewer instances of confusion. Both participants had a higher number of answer engagements than the average. In contrast, Participant 2 had a high number of confusion instances (19) and a lower number of answer engagements (17) than the average. Some participants, such as Participants 1, 3, 4, 5, and 9, showed an overall low level of engagement aside from simply answering the questions asked by the robot.

We also examined whether the number of social engagements varied between sessions where participants experienced their preferred coaching style and those where they did not. The results showed no apparent difference in social engagement between these conditions. If participants chose to engage socially, they typically responded in a similar manner to the feedback being given by the system by saying *"Thank you"* or *"Okay"*.

4.2 Exercise Motivation

In addition to assessing motivation through conversational questions, we quantified participants' exercise motivation using the Locus of Causality Exercise Scale (LCES). To compute an overall motivation score, responses to the second and third items were reverse coded to ensure directional consistency, and the three items were then averaged. Higher average scores indicate greater intrinsic motivation toward exercise.

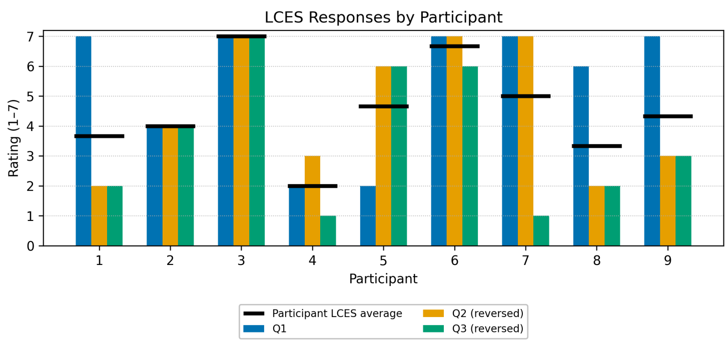

Figure 4.2: Locus of Causality Exercise Scale (LCES) responses and participant averages

Figure 4.2 shows individual participant responses to each LCES item as well as their average score. Overall, most participants agreed with the statement that they exercise because they like to. However, several participants scored lower on the reverse coded items, indicating that they viewed exercise as something they felt obligated to do rather than something they freely chose. Participants 1, 4, 8, and 9 scored lower on the second item, suggesting that exercise felt more like an obligation. Participant 7 showed a similar pattern.

To better understand how conversational motivation aligned with standardized measures, we compared participants' LCES scores with how they responded to the robot's verbal motivation questions. When speaking with the robot, most participants stated that they chose to exercise and did not feel that an external person was forcing them to do so. Despite this, some participants' LCES scores reflected lower intrinsic motivation.

For several participants, conversational responses closely matched their LCES scores. Participants 3 and 6 told the robot that they chose to exercise and that exercise did not feel like a burden. This alignment was reflected in their high LCES averages, indicating strong intrinsic motivation. On the opposite end of the spectrum, Participant 8 told the robot that they did not enjoy exercising and that exercise felt like a burden. Their LCES average was also low at 3.33, below the neutral midpoint of 4, reflecting lower intrinsic motivation.

In contrast, some participants showed a partial mismatch between their conversational responses and their LCES scores. Participants 1, 2, and 9 told the robot that they chose to exercise and that exercise did not feel like a burden. However, their LCES averages were closer to the midpoint of the scale, around 4. These scores suggest moderate or mixed motivation. In these cases, the conversational responses did not provide additional insight into potential barriers or external pressures related to exercise, even though the survey results suggested lower intrinsic motivation.

One participant demonstrated a clear mismatch between conversational responses and survey scores. Participant 4 told the robot that they chose to exercise, yet their LCES score was low, indicating low intrinsic motivation. This discrepancy highlights a difference between how participants may present motivation conversationally versus how they report it in a more private, survey-based format.

For some, conversational measures of motivation and standardized questionnaires do not always capture the same information.

4.3 Other Survey Data

We saw no apparent trends in the other participant ratings. For the sake of completeness, Table 4.1 shows the average LCES score, intake rating survey average, and exercise rating survey average for each participant. The intake average was calculated by first reversing the score for the awkwardness question and then taking the average of all the scores. The same method was applied to the exercise survey. All scores were on a scale of 1 to 7, with 7 being the highest possible rating. Participants were asked to complete the same exercise survey twice—once after experiencing each coaching style. To assess the overall rating of the robot, we averaged the scores from both surveys, rather than analyzing the ratings based on individual coaching styles.

Table 4.1: LCES (motivation) survey, Intake (perception of the robot's conversation and introduction before the exercise session), and Exercise Coach (perception of the robot after both exercise rounds) averages

Participant ID	**LCES Avg.**	**Intake Avg.**	**Exercise Coach Avg.**
1	3.7	5.2	5.0
2	4.0	3.7	6.1
3	7.0	6.6	6.9
4	2.0	6.3	5.8
5	4.7	7.0	4.8
6	6.7	2.0	6.9
7	5.0	5.8	6.1
8	3.3	7.0	7.0
9	4.3	6.2	6.8

In the intake survey, most participants rated the experience highly with 7 out of the 9 participants (P1, P3, P4, P5, P7, P9) scoring the robot higher than a 4. The lowest score rating was 2/7 shown by participant 6 and the highest score rating was 7/7 shown by participants 5 and 8. In the exercise session survey, participants also rated the robot positively, with all participants scoring it higher than 4. The lowest score was 5/7, given by participant 1, and the highest was 7/7, given by participant 8.

4.4 Themes

Following the coding process of the reflexive thematic analysis, we identified two themes to explain how motivation, engagement, and the perception of the robot and its conversational abilities are interconnected.

4.4.1 Theme 1: Low Motivation, High Robot Rating

We observed that some participants rated the robot highly even when their self-reported exercise motivation was low. For example, P4 exhibited low motivation on the LCES survey, yet verbally told the robot that they liked to exercise. When asked whether exercise was something they chose to do, P4 responded *"Yes,"* and when asked whether they felt external pressure to exercise, they responded *"No."* Despite this low motivation score, P4 rated the robot positively, giving the intake interaction a score of 6.3/7 and the exercise interaction an average score of 5.8/7.

A similar pattern was observed for P8, who had a low LCES score of 3.3/7 and verbally expressed that they do not choose to exercise and do not exercise often. When asked by the robot whether exercise was something they chose to do, P8 responded *"No."* Despite this low motivation, P8 rated both the intake and exercise interactions with the robot very highly, assigning an average score of 7/7 on both surveys.

P8 also demonstrated a high level of engagement with the robot, frequently asking questions and thanking the robot when it provided positive feedback on their exercise form. Notably, P8 had the highest number of social engagement instances among all participants, even though they reported low intrinsic motivation to exercise.

Participants like P8 highlight the potential role of social interaction and enjoyment in robotic exercise coaching. Even when older adults report low motivation to exercise, exercising with a socially engaging robot may be perceived as enjoyable and may encourage continued participation. For older adults, initiating exercise can be a critical first step toward increasing motivation, and external factors such as enjoyment and positive interaction with a robot may help support that process.

4.4.2 Theme 2: Initial Confusion, Later Enjoyment

Some participants displayed confusion early in the session but still reported enjoyment later on. For example, P2 exhibited a high level of confusion-related engagement (Figure 4.1), frequently having difficulty understanding what the robot was saying and reporting an average level of motivation. The participant often asked for clarification using phrases such as *"What?"* or *"I can't/don't understand."* At one point, the participant turned to the researchers and directly stated, *"I can't tell what she is saying."* Similar expressions of confusion were observed across multiple participants and often resulted in the robot repeating its statements or requiring the researcher to repeat them on the robot's behalf. Despite these challenges, P2 still rated the exercise session highly.

P6 showed a similar pattern. This participant was highly motivated to exercise, with an LCES score of 6.7/7, but experienced difficulty understanding the robot during the intake session, leading to a low intake survey rating of 2/7. Of the 14 instances in which P6 asked a clarifying question or expressed confusion, 6 occurred during the intake interaction. The participant particularly struggled with understanding spoken questions from the robot. For example, when asked which coaching style they preferred, they responded, *"What is it? It's push-ups?"*

Despite this initial confusion, P6 rated their interaction with the robot during the exercise rounds highly and engaged socially throughout the session. The participant frequently made lighthearted remarks, often joking about their performance or age by saying, *"Pretty good for 94."* During one round, they commented, *"I can do this all day."* They also made playful remarks during specific exercises, such as *"I am throwing rocks over my head"* during bicep curls and *"Tweet tweet, tweet tweet"* or *"If I get too fast, I fly"* during lateral raises. When these comments were not acknowledged by the robot or researchers, P6 often repeated them, suggesting a desire for social engagement and response. Overall, P6 rated the exercise interaction highly, with an average score of 6.9/7.

While initial confusion sometimes negatively affected early impressions of the robot, it did not prevent older adults from enjoying exercising with a robotic system. Participants continued to report positive exercise experiences even when they experienced difficulty understanding the robot's speech. This suggests that enjoyment and engagement can persist despite interaction challenges.

At the same time, these findings point to clear opportunities for improvement. Addressing sources of confusion, such as unclear phrasing, speech pacing, and limited ability to rephrase or clarify instructions, would likely improve the overall interaction experience. Importantly, the presence of confusion highlights the need to more carefully consider age-related communication needs.

In the discussion, we examine how these observations relate to population-specific design considerations for older adults, including hearing differences, processing speed, and the need for adaptive and multimodal communication strategies.

Chapter 5

Discussion

As the aging population continues to grow, so does the demand for physical therapists and exercise coaches. In this work, we explored the use of a conversational robotic exercise coach designed to interact with older adults and examined key considerations for designing such systems. Our goals were to evaluate the acceptability of a conversational exercise robot, understand how older adults naturally interact with an exercise coach, and identify design considerations that better support this population. To do so, we implemented a Wizard of Oz system that enabled natural conversational interaction during exercise sessions and allowed us to assess motivation in context.

Using reflexive thematic analysis, we identified three primary types of conversational engagement with the robot: answer-related engagement, confusion-related engagement, and social engagement. Answer-related engagement was the most common type of interaction. Most participants responded directly to the robot's questions, such as reporting pain levels or answering intake prompts, but typically did not elaborate beyond what was asked. This suggests that many older adults may take a more reactive role in conversation during exercise sessions unless explicitly prompted otherwise.

Confusion-related engagement was the second most common type. Several participants expressed difficulty understanding the robot, often asking for clarification or indicating that they could not hear what was said. Participants with hearing challenges, such as P2 and P6, frequently used phrases like *"What?", "I cannot understand"*, or *"What was the question?"*. P2, in particular, often required statements to be repeated or clarified and at one point turned to the researchers and stated, "I cannot tell what she is saying." P6 similarly experienced substantial difficulty during the intake session, misunderstanding basic questions and responding with comments such as *"What is it? It is push-ups?"*. These moments highlight how hearing limitations and the robot's fixed speech delivery contributed to confusion throughout the interaction.

Social engagement was the least common type of interaction, but when it occurred, it offered important insight into how older adults may relate to an exercise coach. Participants such as P6 and P8 frequently thanked the robot, acknowledged feedback, or incorporated humor into the session. P6 made playful remarks such as *"Pretty good for 94"* and *"If I get too fast, I fly"*, often repeating them when they were not acknowledged. P8 also showed persistent social engagement, asking additional questions and responding verbally to compliments like *"Nice job."* These individual differences suggest that while some older adults are naturally inclined to socially engage with a robot, others remain primarily task-focused.

A discrepancy emerged when comparing conversational responses about motivation with participants' LCES survey scores. Several participants verbally stated that they chose to exercise or enjoyed exercising, yet their LCES results indicated lower autonomous motivation. Participants 4 and 8 provide clear examples. Both told the robot that they chose to exercise, but their LCES scores suggested that exercise felt more obligatory than intrinsically motivated. This discrepancy indicates that spoken responses during a social interaction may not always reflect internal motivational states. Social desirability, discomfort expressing low motivation aloud, or differences in how questions are interpreted conversationally versus on a survey may all play a role.

Theme 1, low motivation paired with high robot ratings, was most clearly demonstrated by Participants 4 and 8. Despite low LCES scores, both participants rated the robot highly and appeared engaged during the session. Participant 8, in particular, showed the highest level of social engagement and rated the robot 7 out of 7 on both the intake and exercise surveys. These cases suggest that a supportive and enjoyable robotic coach may positively influence the exercise experience even for individuals with low intrinsic motivation.

Theme 2 captured participants who initially experienced confusion but later reported enjoyment. Participants 2 and 6 exemplify this pattern. Participant 2 displayed repeated confusion-related engagement during the intake session but ultimately rated the overall experience positively. Participant 6 provided the lowest intake rating due to difficulty understanding the robot, yet rated the exercise experience 6.9 out of 7 and demonstrated high social engagement during the workout. These examples suggest that early interaction challenges do not necessarily prevent older adults from enjoying exercising with a robotic system.

Because this study involved a single interaction session, some positive evaluations may reflect a novelty effect. Longer-term studies are needed to determine whether engagement patterns, perceptions, and motivation change as participants become more familiar with the robot over time.

5.1 Design Considerations

Based on the thematic analysis, participant feedback, and researcher observations, we identified several design considerations for future autonomous exercise coaches designed for older adults. These considerations reflect recurring challenges observed across participants, particularly related to hearing differences, cognitive load during exercise, and the need for supportive and adaptive communication.

5.1.1 Ability to Rephrase

Many instances of confusion, including those observed for Participants 2 and 6, stemmed from difficulty understanding the robot's phrasing. The Wizard of Oz setup relied on fixed speech, which limited the robot's ability to rephrase or simplify statements in real time. Because confusion-related engagement was the second most common interaction type, future systems should support dynamic rephrasing, simplified alternatives, and partial explanations. Advances in large language models offer a promising approach for enabling real-time adaptation of robot dialogue to improve clarity.

5.1.2 Differences Between Conversational and Survey-Based Motivation

Participants such as Participants 4 and 8 verbally stated that they chose to exercise, while their LCES scores indicated lower autonomous motivation. This mismatch suggests that conversational responses may be influenced by social norms or a desire to respond positively when interacting with a social agent. Systems that attempt to infer motivation from conversation alone should be cautious and consider integrating conversational cues with behavioral data or longitudinal trends rather than relying on single intake responses.

5.1.3 Conversations Beyond Exercise

Although most participants did not initiate conversation beyond answering questions, individuals such as Participants 6 and 8 demonstrated the potential value of social interaction during exercise. These participants joked, commented on their performance, and responded enthusiastically to feedback. Their social engagement appeared to contribute to positive perceptions of the robot and the exercise experience. This suggests that future systems may need to take a more proactive role in initiating light social interaction. Longitudinal work is needed to examine whether early social engagement supports sustained motivation and adherence over time.

5.1.4 Population-Specific Speech and Accessibility Needs

Challenges experienced by participants such as Participants 2 and 6 were closely tied to hearing differences and difficulty processing synthesized speech. These issues were common in our sample and should be treated as core design constraints for systems intended for older adults. Adjustable speech features such as slower speaking rates, clearer articulation, longer pauses, and volume control are important. Additional modalities, including on-screen text or captions, can further support comprehension and reduce reliance on auditory cues alone. Designing for accessibility and variability in hearing and processing speed is essential for creating effective and inclusive robotic exercise coaches.

Chapter 6

Future Work

There are several promising directions that could be explored in future work. These suggestions build on the insights from this preliminary study and point toward ways the system could be expanded, refined, and evaluated more thoroughly.

One direction involves improving the communication abilities of the system. Participants noted moments when the robot was difficult to hear or understand. Future versions of the platform should include multimodal communication tools that support different sensory needs. For example, a screen that displays captions during the robot's speech would provide a secondary channel for following instructions. Adjustable speech settings, such as volume and pace control, may also help participants who benefit from slower or clearer speech during physical activity.

Another possible direction is to move beyond the WoZ setup used in this study. While manual control is useful for exploring user expectations, it limits the flexibility of the interaction. An automated system powered by a large language model could offer more adaptive behavior, such as rephrasing instructions, responding to confusion, and maintaining a more natural conversational rhythm. This type of system could adjust its dialogue in real time based on user needs and support more fluid interactions.

Future work may also consider expanding the social and motivational capabilities of the robot. Because the participants in this study interacted with the system only once, their reactions may have been shaped by novelty or unfamiliarity. Multi session longitudinal studies could help researchers understand how motivation and engagement evolve once novelty decreases. These longer interactions may also reveal how users come to view the robot, whether as a partner, a coach, or something else. Insights from repeated sessions could inform how the system supports users across different stages of exercise engagement.

Additional work could also examine how the robot might recognize and respond to user states such as fatigue, hesitation, or frustration. Integrating multimodal sensing, including speech patterns, timing, facial expressions, or physiological information, may allow the system to offer more personalized support. For example, if a user appears tired, the robot could slow the pace or provide more supportive dialogue. If a user seems highly engaged, the robot could introduce variation or a challenge to maintain interest.

Future systems may also benefit from richer social behaviors that go beyond task focused instructions. The brief interactions in this study may not have created enough time for all participants to feel comfortable sharing personal information or engaging in casual conversation. However, the few participants who did engage socially suggest that there is potential value in exploring how social connection might influence motivation during exercise. Incorporating features such as small talk, personal goal setting, routine check ins, or reflective prompts could help build rapport and trust. These elements may play an important role in long term adherence to exercise routines.

These future directions look at how different social robot capabilities could be leveraged to increase motivation and support exercise adherence in older adults. Continued exploration in these areas may lead to more engaging, adaptable, and effective exercise coaching systems.

Chapter 7

Conclusion

This thesis explored how adults engage with a conversational exercise robot during physical activity, with a focus on understanding the social and motivational qualities that shape these interactions. While much of the prior work in robotic exercise coaching has centered on performance monitoring, corrective feedback, and physical embodiment, far less is known about how people naturally communicate with a robot during exercise and how this communication influences motivation. This preliminary study provides an early look at the conversational dynamics that emerge in this setting and offers insights that can guide the development of more adaptive and socially aware robotic exercise companions.

The findings from this work show that participants were willing to speak with the robot and some attempted to treat it as a social partner. Many participants responded to the robot's questions, expressed acknowledgment cues, and made conversational comments related to their comfort, enjoyment, or confusion. These behaviors suggest that even a simple, non-autonomous conversational system can evoke social responses during exercise. At the same time, several challenges were observed that limited smoother interaction. Participants sometimes struggled to understand the robot, experienced difficulty engaging in back-and-forth conversation, or expressed confusion about the robot's phrasing or timing. These moments show both the promise and the limitations of early-stage systems in supporting socially grounded exercise interactions.

This work also demonstrates that motivation during robot-guided exercise is shaped by more than task performance or instruction delivery. Some participants expressed interest in conversations beyond encouragement and exercise feedback, suggesting that the social dimension of exercise coaching may be just as important as the physical or instructional dimension. These findings align with research on human-led exercise programs, where social bonding and interpersonal connection contribute to long-term adherence. Translating similar qualities into robotic systems offers an opportunity to support users not only through corrective feedback but also through shared social presence.

The study also revealed several system-level limitations that point to clear opportunities for improvement. The fixed Wizard of Oz setup prevented real time rephrasing or adjustment of dialogue, which contributed to confusion and occasionally disrupted conversational flow. Some participants had trouble hearing the robot or following its speaking pace. Others felt uncertain about how much they were expected to talk, which influenced the spontaneity of their responses. Addressing these limitations will require systems that are more flexible, transparent, and sensitive to user needs in real time.

Conversational exercise robots hold potential as engaging and socially meaningful partners during physical activity. They also show that meaningful interaction depends on the robot's ability to adapt, clarify, connect socially, and respond to user cues. While this work focused on a one session preliminary study, it lays the foundation for more extensive work that examines how these relationships evolve over time. Future systems could incorporate real-time rephrasing, multimodal sensing, adaptive personality modeling, and long-term conversational support to create a more responsive and motivating coaching experience. Longer-term studies would make it possible to observe changes in motivation once the novelty of the robot decreases and to explore how users build familiarity, trust, and connection across repeated interactions.

In summary, this thesis contributes early evidence that conversational engagement plays a meaningful role in robot-guided exercise and provides initial guidance for designing systems that support both motivation and social connection. Understanding how users communicate with a robot during physical activity allows us to move beyond narrow task based coaching models toward more holistic and human-centered approaches. By exploring the intersection of physical activity, social interaction, and conversational technology, this work shows the potential for exercise companions that are not only instructive but also socially supportive, approachable, and motivating.

Bibliography

[1] Hojjat Abdollahi, Mohammad H. Mahoor, Rohola Zandie, Jarid Siewierski, and Sara H. Qualls. Artificial emotional intelligence in socially assistive robots for older adults: A pilot study. *IEEE Transactions on Affective Computing*, 14(3): 2020–2032, 2022. 2.2

[2] Omri Avioz-Sarig, Samuel Olatunji, Vardit Sarne-Fleischmann, and Yael Edan. Robotic system for physical training of older adults. *International Journal of Social Robotics*, 13(5):1109–1124, 2021. 2.1

[3] Renato F. L. Azevedo, Dan Morrow, James Graumlich, Ann Willemsen-Dunlap, Mark Hasegawa-Johnson, Thomas S. Huang, Kuangxiao Gu, Suma Bhat, Tarek Sakakini, Victor Sadauskas, et al. Using conversational agents to explain medication instructions to older adults. In *AMIA Annual Symposium Proceedings*, volume 2018, page 185. American Medical Informatics Association, 2018. 2.3

[4] Wilma A. Bainbridge, Justin W. Hart, Elizabeth S. Kim, and Brian Scassellati. The benefits of interactions with physically present robots over video-displayed agents. *International Journal of Social Robotics*, 3:41–52, 2011. 3.2

[5] Bangor University. The locus of causality for exercise scale (lce), 2024. URL `http://exercise-motivation.bangor.ac.uk/lce/lcemain.php`. 3.3.3

[6] Anne Barnett, Ben Smith, Stephen R. Lord, Mandy Williams, and Adrian Baumand. Community-based group exercise improves balance and reduces falls in at-risk older people: A randomised controlled trial. *Age and Ageing*, 32(4): 407–414, 2003. 1

[7] Christoph Bartneck, Dana Kulić, Elizabeth Croft, and Susana Zoghbi. Measurement instruments for the anthropomorphism, animacy, likeability, perceived intelligence, and perceived safety of robots. *International Journal of Social Robotics*, 1(1):71–81, 2009. 3.3.6

[8] Abdullah Bin Sawad, Bhuva Narayan, Ahlam Alnefaie, Ashwaq Maqbool, Indra Mckie, Jemma Smith, Berkan Yuksel, Deepak Puthal, Mukesh Prasad, and A. Baki Kocaballi. A systematic review on healthcare artificial intelligent conversational agents for chronic conditions. *Sensors*, 22(7):2625, 2022. 2.4

[9] Virginia Braun and Victoria Clarke. Using thematic analysis in psychology. *Qualitative Research in Psychology*, 3(2):77–101, 2006. 4

[10] David Byrne. A worked example of braun and clarke's approach to reflexive thematic analysis. *Quality & Quantity*, 56(3):1391–1412, 2022. 4

[11] Paul G. Campbell, Domhnall MacAuley, Evelyn McCrum, and Alun Evans. Age differences in the motivating factors for exercise. *Journal of Sport and Exercise Psychology*, 23(3):191–199, 2001. 1

[12] Colleen M Carpinella, Alisa B Wyman, Michael A Perez, and Steven J Stroessner. The robotic social attributes scale (rosas): Development and validation. In *Proceedings of the 2017 ACM/IEEE International Conference on Human-Robot Interaction*, pages 254–262, 2017. 3.3.4

[13] John D. Childs, Laurence N. Benz, Andre Arellano, April A. Briggs, and Michael J. Walker. Challenging assumptions about the future supply and demand of physical therapists in the united states. *Physical Therapy*, 102(1): pzab239, 2022. 1

[14] Jessie Chin, Kelly Quinn, Naoko Muramatsu, and David Marquez. A user study on the feasibility and acceptance of delivering physical activity programs to older adults through conversational agents. In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, volume 64, pages 33–37. SAGE Publications Sage CA: Los Angeles, CA, 2020. 2.3

[15] Chih-Yueh Chou, Tak-Wai Chan, and Chi-Jen Lin. Redefining the learning companion: The past, present, and future of educational agents. *Computers & Education*, 40(3):255–269, 2003. 2.4

[16] Ellen Costello, Marcia Kafchinski, JoEllen Vrazel, and Patricia Sullivan. Motivators, barriers, and beliefs regarding physical activity in an older adult population. *Journal of Geriatric Physical Therapy*, 34(3):138–147, 2011. 1

[17] Edward Deci and Richard Ryan. Self-determination theory: A macrotheory of human motivation, development, and health. *Canadian Psychology / Psychologie Canadienne*, 49, 2008. doi: 10.1037/a0012801. 3.3.3

[18] Loretta DiPietro. Physical activity in aging: Changes in patterns and their relationship to health and function. *The Journals of Gerontology Series A: Biological Sciences and Medical Sciences*, 56(suppl_2):13–22, 2001. 1

[19] Juan Fasola and Maja J. Matarić. A socially assistive robot exercise coach for the elderly. *Journal of Human-Robot Interaction*, 2(2):3–32, 2013. 2.1

[20] Kathleen Kara Fitzpatrick, Alison Darcy, and Molly Vierhile. Delivering cognitive behavior therapy to young adults with symptoms of depression and anxiety using a fully automated conversational agent (woebot): A randomized controlled trial.

JMIR Mental Health, 4(2):e7785, 2017. 2.4

[21] Walid F. Gellad, Jerry L. Grenard, and Zachary A. Marcum. A systematic review of barriers to medication adherence in the elderly: Looking beyond cost and regimen complexity. *The American Journal of Geriatric Pharmacotherapy*, 9(1):11–23, 2011. 2.3

[22] David Griol, Jesús García-Herrero, and José M Molina. The educagent platform: Intelligent conversational agents for e-learning applications. In *Ambient Intelligence-Software and Applications: 2nd International Symposium on Ambient Intelligence (ISAmI 2011)*, pages 117–124. Springer, 2011. 2.4

[23] Janine Hatch and Michelle M. Lusardi. Impact of participation in a wellness program on functional status and falls among aging adults in an assisted living setting. *Journal of Geriatric Physical Therapy*, 33(2):71–77, 2010. 1

[24] Neil T Heffernan. Web-based evaluations showing both cognitive and motivational benefits of the ms. lindquist tutor. In *Artificial Intelligence in Education*, pages 115–122, 2003. 2.4

[25] Bahar Irfan, Nathalia Céspedes, Jonathan Casas, Emmanuel Senft, Luisa F. Gutiérrez, Mónica Rincon-Roncancio, Carlos A. Cifuentes, Tony Belpaeme, and Marcela Múnera. Personalised socially assistive robot for cardiac rehabilitation: Critical reflections on long-term interactions in the real world. *User Modeling and User-Adapted Interaction*, 33(2):497–544, 2023. 2.1

[26] Roshni Kaushik. *Personalized Context-aware Multimodal Robot Feedback*. PhD thesis, Carnegie Mellon University, 2025. 3.1

[27] Roshni Kaushik and Reid Simmons. Effects of feedback styles on performance and preference for an exercise coach. In *2024 33rd IEEE International Conference on Robot and Human Interactive Communication (RO-MAN)*, pages 1516–1523. IEEE, 2024. 3

[28] Roshni Kaushik and Reid Simmons. Effects of feedback styles on performance and preference for an exercise coach. In *2024 33rd IEEE International Conference on Robot and Human Interactive Communication (RO-MAN)*, pages 1516–1523. IEEE, 2024. (document), 3.1, 3.1, 3.3.3, 3.3.6

[29] Roshni Kaushik, Rayna Hata, Aaron Steinfeld, and Reid Simmons. Choosing robot feedback style to optimize human exercise performance. In *2025 20th ACM/IEEE International Conference on Human-Robot Interaction (HRI)*, pages 658–666. IEEE, 2025. 3.1

[30] Alice Kerry, Richard Ellis, and Susan Bull. Conversational agents in e-learning. In *International Conference on Innovative Techniques and Applications of Artificial Intelligence*, pages 169–182. Springer, 2008. 2.4

[31] Maria R. Lima, Amy O'Connell, Feiyang Zhou, Alethea Nagahara, Avni Hulyalkar, Anura Deshpande, Jesse Thomason, Ravi Vaidyanathan, and Maja Matarić. Promoting cognitive health in elder care with large language model-powered socially assistive robots. In *Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems*, pages 1–22, 2025. 2.2

[32] Tiffany Christina Luo, Adrian Aguilera, Courtney Rees Lyles, and Caroline Astrid Figueroa. Promoting physical activity through conversational agents: mixed methods systematic review. *Journal of Medical Internet Research*, 23(9):e25486, 2021. 2.3

[33] Keyvan Molanorouzi, Selina Khoo, and Tony Morris. Motives for adult participation in physical activity: Type of activity, age, and gender. *BMC Public Health*, 15(1):66, 2015. 1

[34] Daniel G. Morrow, H. Chad Lane, and Wendy A. Rogers. A framework for design of conversational agents to support health self-care for older adults. *Human Factors*, 63(3):369–378, 2021. 2.3

[35] Yael Netz and Shulamith Raviv. Age differences in motivational orientation toward physical activity: An application of social-cognitive theory. *The Journal of Psychology*, 138(1):35–48, 2004. 1

[36] Alessandra Maria Sabelli, Takayuki Kanda, and Norihiro Hagita. A conversational robot in an elderly care center: An ethnographic study. In *Proceedings of the 6th International Conference on Human-Robot Interaction*, pages 37–44, 2011. 2.2

[37] Nicole Salomons, Tom Wallenstein, Debasmita Ghose, and Brian Scassellati. The impact of an in-home co-located robotic coach in helping people make fewer exercise mistakes. In *2022 31st IEEE International Conference on Robot and Human Interactive Communication (RO-MAN)*, pages 149–154. IEEE, 2022. 2.1

[38] Emanuel Nunez Sardinha, Mohammadhadi Sarajchi, Kyle Xu, Maria Insuasty Pineda, Carlos Cifuentes, and Marcela Múnera. Real-time feedback on older adults' exercise: A socially assistive robot coaching system. In *2024 IEEE-RAS 23rd International Conference on Humanoid Robots (Humanoids)*, pages 730–737. IEEE, 2024. 2.1

[39] Kelly Satterfield, Victor Finomore, Vincent Mancuso, Joseph Lyons, Ewart de Visser, Kerstin Haring, Sarah Pruznick, Ariana Mosley, and Gregory Funke. Robot knows best? a comparison of compliance with human and robotic coaches. In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, volume 63, pages 406–407. SAGE, 2019. 3.2

[40] Sebastian Schneider and Franz Kummert. Comparing robot and human guided personalization: Adaptive exercise robots are perceived as more competent and trustworthy. *International Journal of Social Robotics*, 13(2):169–185, 2021. 2.1

[41] Karen A. Schutzer and B. Sue Graves. Barriers and motivations to exercise in older adults. *Preventive Medicine*, 39(5):1056–1061, 2004. 1

[42] Stela H. Seo, Denise Geiskkovitch, Masayuki Nakane, Corey King, and James E. Young. Poor thing! would you feel sorry for a simulated robot? a comparison of empathy toward a physical and a simulated robot. In *Proceedings of the Tenth Annual ACM/IEEE International Conference on Human-Robot Interaction*, pages 125–132, 2015. 2.1

[43] Andrew Specian, Ross Mead, Simon Kim, Maja Matarić, and Mark Yim. Quori: A community-informed design of a socially interactive humanoid robot. *IEEE Transactions on Robotics*, 38(3):1755–1772, 2021. 3.1, 3.1

[44] Crystal N Steltenpohl, Michael Shuster, Eric Peist, Amber Pham, and Joseph A Mikels. Me time, or we time? age differences in motivation for exercise. *The Gerontologist*, 59(4):709–717, 2019. 1

[45] Hiroki Tanaka, Hideki Negoro, Hidemi Iwasaka, and Satoshi Nakamura. Embodied conversational agents for multimodal automated social skills training in people with autism spectrum disorders. *PLOS ONE*, 12(8):e0182151, 2017. 2.4

[46] Joshua Wainer, David J. Feil-Seifer, Dylan A. Shell, and Maja J. Matarić. The role of physical embodiment in human-robot interaction. In *ROMAN 2006 - The 15th IEEE International Symposium on Robot and Human Interactive Communication*, pages 117–122. IEEE, 2006. 2.1

[47] Joshua Wainer, David J. Feil-Seifer, Dylan A. Shell, and Maja J. Matarić. Embodiment and human-robot interaction: A task-based perspective. In *RO-MAN 2007 - The 16th IEEE International Symposium on Robot and Human Interactive Communication*, pages 872–877. IEEE, 2007. 3.2

[48] Siobhan M. White, Thomas R. Wójcicki, and Edward McAuley. Physical activity and quality of life in community dwelling older adults. *Health and Quality of Life Outcomes*, 7:1–7, 2009. 1

[49] Katie Winkle, Praminda Caleb-Solly, Ailie Turton, and Paul Bremner. 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*, pages 289–297, 2018. 2.1

[50] Nirmalie Wiratunga, Kay Cooper, Anjana Wijekoon, Chamath Palihawadana, Vanessa Mendham, Ehud Reiter, and Kyle Martin. Fitchat: conversational artificial intelligence interventions for encouraging physical activity in older adults. *arXiv preprint arXiv:2004.14067*, 2020. 2.3

[51] Donna Lee Wong and Connie Morain Baker. Wong-baker faces pain rating scale. *Pain Management Nursing*, 2012. 3.3.5

[52] Rita Wong, Corrie J. Odom, and John O. Barr. Building the physical therapy workforce for an aging america. *Journal of Physical Therapy Education*, 28(2): 12–21, 2014. 1

[53] Tamara Zubatiy, Kayci L Vickers, Niharika Mathur, and Elizabeth D Mynatt. Empowering dyads of older adults with mild cognitive impairment and their care partners using conversational agents. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*, pages 1–15, 2021. 2.3