Social Buddy or Exercise Coach? Exploring Older Adults' Preferences for System Personality in Exercise Support

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***Abstract*—Regular exercise is vital for health and independence in older adulthood, yet motivation and adherence remain challenging. Socially aware AI systems can help by tailoring interaction styles to user needs. We compare two system personalities: a *social buddy* offering companionship and a *coach* providing structure and feedback. In a preliminary study, older adults exercised with both personalities across multiple sessions. Preferences shifted over time, with many favoring the coach by week two, though participants also expressed a desire for flexibility. RoSAS scores showed growing perceptions of warmth, competence, and comfort as participants adapted to the systems. Furthermore, open-ended feedback revealed that participants did not want to be constrained to a single personality type but instead desired flexibility, with the ability to blend characteristics depending on their current needs and states. These results highlight the value of adaptive systems that balance social support with directive coaching.**

***Index Terms*—Adaptive systems, exercise adherence, system personality, older adults, longitudinal interaction, cooperative intelligence, social support, human–AI interaction**

I. Introduction

Regular physical activity is essential for maintaining health and independence in later life, yet many older adults struggle with exercise adherence [1]. Factors such as declining motivation, lack of social support, and reduced perceived need often contribute to lower engagement in physical activity. As a result, there is growing interest in the use of socially aware AI systems to help encourage, motivate, and sustain exercise behaviors among older adults.

Prior research has explored different system roles in exercise contexts, ranging from directive coaching styles that provide structured guidance, to more socially oriented roles that emphasize companionship and encouragement. However, little is known about how older adults perceive and respond to distinct system personalities over repeated interactions. In particular, the contrast between a social buddy personality (SBP), which emphasizes empathy, casual interaction, and companionship, and an exercise coach personality (ECP), which emphasizes authority, structure, and directive feedback, remains underexplored.

In this preliminary work, we investigate older adults' preferences and experiences when exercising with AI systems that adopt these two distinct personalities. Specifically, we ask three research questions: (1) Do older adults prefer to exercise with a social buddy type system or an exercise coach type system? (2) Do their preferences change over time as they become more familiar with the system? and (3) Does exercising with either type of system personality motivate older adults to continue returning for future exercise sessions?

By addressing these questions, our goal is to contribute insights into how socially aware systems can foster cooperative intelligence, respect social norms, and leverage both verbal and nonverbal cues to support long-term exercise engagement and promote healthy aging within the target older adult population.

II. Related Works

A. Robot Exercise Coaching Systems

Socially Assistive Robots have shown considerable promise in exercise coaching applications, mainly due to the benefits of having a physical embodiment. Fasola and Matarić [2] conducted a study specifically investigating a physical versus virtual robot in a healthcare scenario, finding that participants showed a strong preference for a physically embodied robot across multiple metrics of enjoyableness, helpfulness, and social preference. This preference for physically embodied robots has been validated in other studies, like Salomons et al. [3], demonstrating that participants with a physical robot performed 69% of the exercises correctly compared to 57% with a virtual tablet-based system.

The effectiveness of robotic exercise coaches is significantly influenced by the feedback style and interaction with the participant. Avioz-Sarig et al. [4] found that continuous feedback throughout exercise sessions resulted in higher success rates (80%) compared to discrete feedback at the end of each exercise (64%). Their study also showed that combining audio-visual feedback was most effective for the participants, compared to the feedback styles individually. Supporting these

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findings, Sardinha et al. [5] implemented a multimodal system that provided real-time corrective feedback while monitoring heart rate zones, demonstrating a successful implementation of a robotic exercise system with both physiological and kinematic monitoring.

Personalization is also a critical factor in motivating and engaging participants to be consistent with attending exercise sessions. Schneider and Kummert [6] found that adaptive robots that learned user preferences were perceived as significantly more competent and trustworthy than user-controlled adaptable robots. Irfan et al. [7] conducted a 2.5-year clinical evaluation on personalized robots for cardiac rehabilitation. The findings showed that the personalization features were perceived positively, with 97% of the participants recommending the system.

Studies on robotic exercise coaching systems have demonstrated the effectiveness of physical embodiment, real-time exercise correction, and personalized feedback. However, they primarily focus on trainer-trainee relationships where the robot functions solely as an instructor to perform the exercises. With traditional human-led exercise sessions naturally incorporating social bonding between instructors and participants as part of the therapeutic process, current robotic systems have not explored how social companionship can serve as a motivational mechanism. Our social-centered approach differs by positioning companionship as a driving factor for sustained engagement with exercise sessions, rather than relying on instructional feedback and performance monitoring.

B. Robots as Social Companions for Aging Adults

Beyond exercise coaching, Socially Assistive Robots have demonstrated significant potential as social companions for aging adults, a population that regularly experiences social isolation. The rapid improvement of conversational agents, particularly through large language models, has emerged as a promising approach to enhancing social interaction.

Lima et al. [8] conducted a 5-week study with 22 older adults using a GPT-4o-powered robot where participants engaged in cognitive tasks, such as picture description and semantic fluency exercises. Participants were significantly more socially engaged during robot sessions compared to human-administered sessions, making an average of 4.1 social comments with the robot compared to 2.3 with human administrators. The study also demonstrated significant improvements in cognitive tasks, and participants were able to provide more detailed descriptions with fewer assisting prompts. Participants showed a decrease in anxiety and increased trust, sociability, and perceived usefulness.

Researchers have also experimented with the therapeutic potential of empathetic robot companions with emotion recognition capabilities. Abdollahi et al. [9] compared an empathetic and non-empathetic version of a robot in a three-week study with 10 older adults. The empathetic version was equipped with multimodal emotion recognition using both facial expressions and speech sentiment analysis to adjust dialogue according to the user's emotional state. The results showed clear benefits of emotional intelligence in robotic embodiments, with significantly higher engagement with the empathetic version. Participants also expressed more positive facial expressions with the empathetic version (45% compared to 26%).

Simple and consistent social interactions have been shown to be remarkably effective for robot acceptance as a social companion by older adults. Sabelli et al. [10] developed a teleoperated conversational robot placed in an elderly care home for 3.5 months. They found that basic social behaviors like daily greetings, calling people by their names, and engaging in daily conversation had a significant positive impact on emotional well-being. The robot was widely accepted, and users would often share personal matters with the robot, finding relief in its non-judgmental responses.

These studies have established the therapeutic potential of socially interactive robots for older adults through cognitive engagement, emotional support, and conversational companionship. However, they primarily focus on sedentary activities with caregiver-patient models. Our research builds on these findings by integrating physical activity as a shared bonding experience that strengthens human-robot relationships. With the rise of conversational capabilities enabled by modern LLM technology, we can facilitate social connections naturally through collaborative physical engagement and meaningful dialogue.

III. Methods

In this work, we investigated older adults' preferences for exercising with either a social buddy-type robot or a coach-type robot. We used the Pepper robot to deliver personalized interactions throughout a longitudinal four-week study. Participants were invited to return weekly for up to four sessions and were free to withdraw at any time.

Each session consisted of three parts: an introduction, Round 1 (R1) of the exercise, and Round 2 (R2) of the exercise. Participants completed a short survey between each part. During both exercise rounds, participants performed two sets of bicep curls and two sets of lateral raises, each lasting 40 seconds with a 40-second rest interval between sets.

The study employed a within-subjects design. All participants experienced the same introductory interaction, followed by randomized exposure to both robot personalities across the two exercise rounds. Half of the participants interacted with the social buddy robot first, while the other half began with the coach-type robot. This design allowed us to compare preferences and experiences across conditions within the same individuals.

1) Participants: We conducted a pilot user study with a target population of aging adults over the age of 60 years, involving a total of $n = 3$ participants. All of the participants identified as female and their ages ranged from 61 to 80. The participants were recruited via a local participant pool and by via word of mouth to complete the study at our university.

This research was approved by our Institutional Review Board. All participants gave informed consent for the research, including video and audio recordings during the study. The participants who participated in the study at our university were given $20 for their time for each session to compensate for the parking cost of parking at our university.

2) Location and Layout: The pilot study was conducted in a laboratory space at our university. In this setting, the robot was positioned approximately five feet in front of the participant, directly facing them to ensure optimal visibility for the camera recordings. Researchers were seated behind the participant and remained out of view, concealed behind a barrier to minimize distractions and maintain a natural interaction environment.

A. Speech Generation

During the introduction session and the exercise round with the social coach robot, participants were able to engage in spoken conversation with the robot.

Upon arrival, each participant was equipped with a RODE Wireless Go II microphone, which was clipped onto their shirt to capture their speech. The participant's speech was transcribed in real time using the AWS Transcribe service. Once the system detected that the participant had begun speaking, it transcribed their utterance continuously until a silence threshold of two seconds was met, signaling the end of the input.

The transcribed text was then processed using GPT-4o to generate an appropriate response. This response was sent to the robot and delivered through the robot's onboard speakers.

Although the Pepper robot has built-in speech-to-text capabilities, we opted to use an external microphone and AWS Transcribe to obtain clearer recordings of participant speech. Additionally, this setup streamlined the process by allowing direct transmission of the participant's text to the computer for GPT-based response generation, reducing communication overhead.

1) Introduction, Intake, and Assessment Conversations: Upon arrival, participants were greeted by the researchers and escorted to a designated seat, strategically positioned to ensure they remained within the camera frame throughout the session. Once seated, participants were presented with the consent form and provided informed consent.

When the participant was ready to begin, the robot initiated the session by delivering a greeting. The greeting was generated using a LLM but followed a consistent structure across participants. An example of a first-session greeting was:

> "Hello, I'm Pepper, your exercise robot. How are you today?"

For subsequent sessions, the greeting was slightly modified to reflect the ongoing relationship, for example:

> "Hello! It's nice to see you again. How are you?"

After the participant responded, the robot asked a series of questions to assess their motivation levels. These questions were adapted from prior work based on self-determination theory [11]. Participants were asked the following:

Q1 On a scale of 1–10, 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 your doctor or a family member?

Once the participants answered the questions, the robot went on to explain the exercise session. Once it was done, it asked the participants if they had any questions about the exercise session. If the participants answered "yes", the conversation would continue until the system determined that they were ready to start. When the LLM returned the spoken responses, it also returned a boolean determining if the participant was ready to start the exercise session. Once the system determined that they were ready, it would ask the participants to fill out the survey rating the introduction session.

B. Social Robot Personality

During the Social Buddy Personality (SBP) session, the robot conversed with participants in a manner similar to the introductory session. The social session began when the participant used the wake word "ready," prompting the robot to start the conversation with:

> "Let's do some bicep curls. Got anything fun planned for the day?"

The conversation was then continued using a large language model (LLM), guided by a predefined range of allowed topics specified in the prompt.

During the exercises, the robot actively participated alongside the participant, performing the same movements and resting during designated rest periods.

C. Exercise Coach Personality

During the Exercise Coach Personality (ECP) session, participants received both verbal and non-verbal feedback from the robot. Unlike in the SBP condition, the robot did not perform the exercises alongside the participant.

The robot's feedback styles were adapted from prior work [12] and were designed to learn and adapt to the participant's coaching preferences, balancing between an encouraging and a more directive (strict) coaching style. The robot provided real-time feedback on the participant's performance, but no LLMs were deployed during this session, and the robot did not listen to participant's speech.

D. Study Survey

After each segment (Introduction, Round 1, and Round 2), participants were asked to complete a survey. The survey was based on the Robotic Social Attributes Scale (RoSAS) [13], which measures three key dimensions: *Warmth*, *Competence*, and *Discomfort* on a Likert scale of 1-7.

In addition, participants were asked two comprehension questions: whether they felt they understood the system well, and whether they felt the system understood them well. Participants were also asked to rate whether they perceived the system as motivational, strict, and corrective (each assessed through separate items).

The survey also included open-ended questions, where participants could describe aspects they liked about the round they experienced and suggest changes they would prefer. Finally, at the end of each session, participants were asked to indicate whether they preferred the first personality or the second personality overall.

IV. Preliminary Results

Our preliminary findings suggest that participants' preferences evolved over time. During the first week, most participants did not express a clear preference between the two system personalities. By the second week, however, participants began to show stronger preferences, with the majority favoring the exercise coach personality overall. Several participants noted that the coach personality felt more purposeful in an exercise context, while the social buddy personality sometimes felt unnecessary. For example, one participant commented, "It feels weird to converse with a robot," and another remarked, "It's distracting to talk while exercising."

At the same time, open-ended responses revealed more nuanced perspectives. Rather than preferring one personality exclusively, participants expressed a desire for systems that could flexibly combine elements of both styles. For instance, Participant 1 (P1) explained that her preference depended on her fatigue level: when she was not tired, she appreciated a more conversational and chatty interaction, whereas when she felt fatigued, she preferred the stricter and more directive approach of the coach.

Participants also offered suggestions for improving the system behaviors. Several noted that while the exercise coach personality provided verbal instructions and corrective feedback, it did not physically demonstrate the exercises alongside them in the way the social buddy personality did. Participants indicated that combining demonstration with coaching feedback would make the system more engaging and supportive.

In addition to these personality preferences, we observed longitudinal shifts in how participants perceived and interacted with the system itself. Early in the study, participants often responded too quickly to system prompts, leading to communication breakdowns where the system either failed to hear them or responded incorrectly. Participant 3 (P3), in particular, expressed frustration during these moments and rated the system poorly on the RoSAS, strongly agreeing with negative descriptors such as *awful* and *awkward*. However, as participants gained more experience, they adapted their interaction styles, and the system responses improved. By the end of the study, participants' survey responses reflected more positive overall impressions of the system.

RoSAS scores further illustrate these shifts. On the *Warmth* dimension, participants consistently rated the social buddy personality higher, aligning with its design to emphasize empathy and friendliness. On the *Discomfort* dimension, we observed a clear longitudinal trend: while initial ratings reflected unease and awkwardness, these ratings shifted toward more positive perceptions over time. Finally, on the *Competence* dimension, both personalities were rated similarly, suggesting that participants viewed the two system types as equally capable in carrying out the exercise tasks.

Overall, these findings suggest that older adults' perceptions of socially aware systems are not static but develop through repeated interaction. Frustration and perceived awkwardness of the robot progressed to more positive perceptions as participants became accustomed to the system. Importantly, preferences were shaped not only by personality type but also by contextual factors such as fatigue and expectations for demonstration versus instruction. This shows the importance of designing adaptive systems that can dynamically balance more social interactions with corrective feedback to better support motivation and long-term engagement in exercise.

V. Conclusion and Future Works

This work explored how older adults perceive and respond to socially aware exercise systems with different personality types, focusing on the contrast between a social buddy style and an exercise coach style. Our preliminary results suggest that preferences evolve over time: while initial impressions were often neutral or even negative, participants developed stronger preferences by the second week, with many favoring the coach personality in structured exercise contexts. At the same time, open-ended feedback revealed that participants did not want to be constrained to a single personality type but instead desired flexibility, with the ability to blend characteristics depending on their current needs and states (e.g., fatigue level). These findings emphasize the importance of designing adaptive systems that can dynamically shift between different interaction styles to support long-term engagement.

Our ongoing study at an assisted living facility will provide further insights into how these personality dynamics play out in more naturalistic and longitudinal settings. In future work, we plan to investigate adaptive methods that allow the system to adjust its personality in real time based on contextual cues, such as the user's physical state, affect, or expressed preferences. Another promising direction is to allow participants themselves to guide or select the interaction style, either by explicitly choosing a mode at the start of a session or by influencing the system's adaptation over time.

Finally, our results highlight the value of examining longitudinal effects in socially aware AI systems. While single-session studies capture initial impressions, repeated interactions reveal how users adapt to the system and how perceptions of warmth, competence, and discomfort shift with experience. We see this as a crucial step toward the design of exercise systems that not only motivate older adults to engage in physical activity but also foster sustainable, trust-based relationships that encourage long-term adoption and motivation to exercise.

References

[1] K. A. Schutzer and B. S. Graves, "Barriers and motivations to exercise in older adults," *Preventive medicine*, vol. 39, no. 5, pp. 1056–1061, 2004.

[2] J. Fasola and M. J. Matarić, "A socially assistive robot exercise coach for the elderly," *Journal of Human-Robot Interaction*, vol. 2, no. 2, pp. 3–32, 2013.

[3] N. Salomons, T. Wallenstein, D. Ghose, and B. 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)*. IEEE, 2022, pp. 149–154.

[4] O. Avioz-Sarig, S. Olatunji, V. Sarne-Fleischmann, and Y. Edan, "Robotic system for physical training of older adults," *International journal of social robotics*, vol. 13, no. 5, pp. 1109–1124, 2021.

[5] E. N. Sardinha, M. Sarajchi, K. Xu, M. I. Pineda, C. Cifuentes, and M. Munera, "Real-time feedback on older adults exercise: A socially assistive robot coaching system," pp. 730–737, 2024.

[6] S. Schneider and F. Kummert, "Comparing robot and human guided personalization: adaptive exercise robots are perceived as more competent and trustworthy," *International Journal of Social Robotics*, vol. 13, no. 2, pp. 169–185, 2021.

[7] B. Irfan, N. Céspedes, J. Casas, E. Senft, L. F. Gutiérrez, M. Rincon-Roncancio, C. A. Cifuentes, T. Belpaeme, and M. Múnera, "Personalised socially assistive robot for cardiac rehabilitation: Critical reflections on long-term interactions in the real world: B. irfan et al." *User Modeling and User-Adapted Interaction*, vol. 33, no. 2, pp. 497–544, 2023.

[8] M. R. Lima, A. O'Connell, F. Zhou, A. Nagahara, A. Hulyalkar, A. Deshpande, J. Thomason, R. Vaidyanathan, and M. 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*, 2025, pp. 1–22.

[9] H. Abdollahi, M. H. Mahoor, R. Zandie, J. Siewierski, and S. H. Qualls, "Artificial emotional intelligence in socially assistive robots for older adults: a pilot study," *IEEE Transactions on Affective Computing*, vol. 14, no. 3, pp. 2020–2032, 2022.

[10] A. M. Sabelli, T. Kanda, and N. Hagita, "A conversational robot in an elderly care center: an ethnographic study," in *Proceedings of the 6th international conference on Human-robot interaction*, 2011, pp. 37–44.

[11] J. Edmunds, N. Ntoumanis, and J. L. Duda, "Adherence and well-being in overweight and obese patients referred to an exercise on prescription scheme: A self-determination theory perspective," *Psychology of Sport and Exercise*, vol. 8, no. 5, pp. 722–740, 2007.

[12] R. Kaushik, R. Hata, A. Steinfeld, and R. Simmons, "Choosing robot feedback style to optimize human exercise performance," in *2025 20th ACM/IEEE International Conference on Human-Robot Interaction (HRI)*, 2025, pp. 658–666.

[13] C. M. Carpinella, A. B. Wyman, M. A. Perez, and S. J. Stroessner, "The robotic social attributes scale (rosas) development and validation," in *Proceedings of the 2017 ACM/IEEE International Conference on human-robot interaction*, 2017, pp. 254–262.