Opportunities to Talk, Negotiate, and Laugh: Robot Behaviors That Shape Repeated Interactions in Groups of Older Adults

Sarah Gillet*
KTH Royal Institute of Technology
Stockholm, Sweden

Yujing Zhang*
KTH Royal Institute of Technology
Stockholm, Sweden

Donald McMillan
Stockholm University
Stockholm, Sweden

Nicole Salomons
Imperial College
London, UK

Iolanda Leite
KTH Royal Institute of Technology
Stockholm, Sweden

Abstract

Feeling socially connected is important for personal well-being, yet many older adults report increasing loneliness and decreasing social connections. We explored how robots and their behaviors can support group interactions and foster social participation among older adults in a community center setting over repeated interactions. We developed a semi-autonomous collaborative and discussion-based variant of the game "With Other Words" for groups of three to four older adults and two robots. A facilitator robot (Furhat) mediated discussions using gaze and verbal support, while a guesser robot (Misty) attempted to guess the words that group members described 'with other words'. We invited 34 older adults aged 65+ to play the game in groups of three or four, three times over two to five weeks. An explorative mixed-method analysis, combining quantitative metrics with Ethnomethodological Conversation Analysis (EMCA), shows that robot gaze and verbal behaviors as well as negotiations around "wrangling" the guesser robot encouraged participation in the game. Further, verbal supporting behaviors elicited shared laughter but also led to breakdowns. While no direct significant improvement in social connectedness was observed, this work contributes to our understanding of how robot behaviors might shape interactions among older adults.

CCS Concepts

• **Human-centered computing** → *Empirical studies in collaborative and social computing*; **User studies**.

Keywords

Group Human-Robot Interaction, Older Adults, Interaction-Shaping

ACM Reference Format:
Sarah Gillet, Yujing Zhang, Donald McMillan, Nicole Salomons, and Iolanda Leite. 2026. Opportunities to Talk, Negotiate, and Laugh: Robot Behaviors That Shape Repeated Interactions in Groups of Older Adults. In *Proceedings of the 21st ACM/IEEE International Conference on Human-Robot Interaction (HRI '26), March 16–19, 2026, Edinburgh, Scotland, UK*. ACM, New York, NY, USA, 11 pages. https://doi.org/10.1145/3757279.3785637

*Both authors contributed equally to this research.

HRI '26, Edinburgh, Scotland, UK

ACM ISBN 979-8-4007-2128-1/2026/03
https://doi.org/10.1145/3757279.3785637

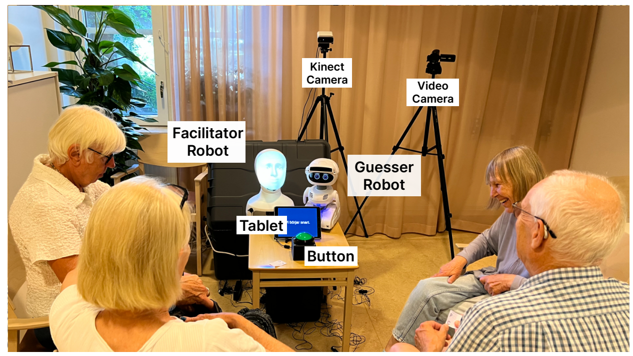

Figure 1: Study setup. Two-robot word-guessing game with three to four older adults in a community center. The facilitator robot (left) supports the discussion; the guesser robot (right) guesses words after participants' description. Images shown with consent.

1 Introduction

Social connectedness is important for individual well-being [28, 86]. It has been shown to slow cognitive decline [66, 68], increase emotional well-being [39], improve physical health [61] and even life expectancy [34]. Yet, older adults can face challenges, such as reduced mobility, and fewer opportunities for social interactions [35, 55], which hinder social connections. The 2015 WHO report on aging and health highlights the importance of providing opportunities for social participation for the aging population [62]. Our work explores how robots can facilitate human-human contact among older adults, supporting their need for social participation.

Prior work has demonstrated that robots can support and shape interactions among people [21, 36]. For example, non-verbal behaviors such as gaze have been found to shape conversational roles [52], provide turn-taking cues [75], or balance participation [18]. Verbal robot scaffolding behaviors have been shown to support creative storytelling [2] or parent-child social interactions [10, 27].

Despite these promising results, studies of how robots can shape interactions among people in real-world environments and beyond the novelty effect are scarce. Exceptions include school-based experiments supporting inclusion of newly arrived [20] or visually impaired [54] children, or in-home studies showing that robots can enhance parent–child conversations [10]. Closely related work [8, 64] showed that robots in older adults' community spaces can serve as a conversation facilitator increasing connectedness and bonds. Yet, which robot behaviors can support small group interactions among older adults over repeated interactions remains underexplored.

This paper investigates how robots can support groups of older adults in real-world settings, over repeated interactions. We engaged groups of older adults in a word-guessing game supported by a semi-autonomous dual-robot system. The facilitator robot guided the discussions using gaze and verbal support behaviors inspired by prior work [12, 18, 64]. The guesser robot played a key role by guessing words from participants' descriptions.

Though no significant increase of social connectedness observed, our mixed-method analysis confirms the effectiveness of robots supporting group interactions over repeated interactions for groups of older adults. We find that negotiations around "wrangling" the guesser robot and supporting gaze and verbal behavior encourage individuals' participation in group interactions. Verbal supporting behaviors often coincided with laughter. Whereas shared laughter can positively affect social interactions and connections [16, 73], our Ethnomethodological Conversation Analysis (EMCA) indicates that a robot's verbal participation in a group interaction is still challenging and should be used carefully. By using games and deploying our robot system in local community centers, we created genuine opportunities for social participation bridging the gap between laboratory research and real-world applications.

2 Background and Related Work

We position this study within existing HRI literature that investigates how robots can shape group processes and support older adults. In addition, we detail related works that motivate the non-verbal and verbal support strategies chosen for the facilitator robot.

Robots Supporting Older Adults. Prior HRI work with older adults focuses mostly on individual support [3, 17, 44] or general companionship [8, 29, 85]. In particular, researchers showed emotional benefits through robots like PARO [8]. Recently, researchers started to explore how robots can be part of group activities. For example, Louie et al. [47] integrated robots to facilitate a memory game for engagement and performance. Hebesberger et al. [30] examined robots in walking group therapy, reporting increased motivation, cohesion, and mood. Other related work identified factors influencing elderly social inclusion [9, 78], emphasizing the need for person-centered design, careful use of communal spaces, and accommodations for cognitive and sensory impairments [63, 64].

In this paper, we aim to advance prior insights for HRI working with older adults by deploying a facilitator robot that actively supports interactions between people in a real-world setting.

Robots in Groups. Research on groups has become increasingly important in HRI [56, 72, 74], e.g., how groups perceive or act toward them [11]. Other prior work demonstrated that robots can support and shape interactions between people [21, 36]. For example, robots can strengthen cohesion and performance [60], foster empathy [31], and promote inclusion and connectedness among newly-arrived [20] and visually-impaired children [54] and adults [81].

Related works explored verbal [27, 40] and non-verbal behaviors to support a group, e.g., through gaze [18, 52], gestures [20, 31, 67] or movement and lights [54]. **Gaze** has been shown effective in different ways. Mutlu et al. showed how gaze shapes conversational roles [52]. Gillet and Cumbal et al. showed [18] that adaptive gaze

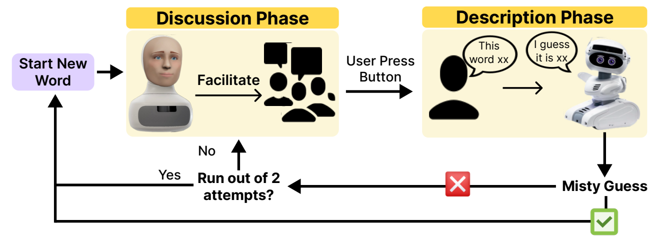

Figure 2: Flow of the game play. One game round has a discussion and a description phase and ends with the guess.

behaviors can mediate participation imbalance and Skantze et al. demonstrated that gaze can yield the turn [75].

Different from individual interactions, robots interacting with groups need to further decide whom they gaze at or speak to. Related work often either addresses a fixed participant [52] or focuses on supporting the least active participant [18, 20, 54, 84]. Given the insights from prior work, we designed the gaze behaviors of the facilitator robot to *gaze toward the least active participant*.

Scaffolding and Robots' Verbal Support. Scaffolding is defined as immediate and adaptive support during problem-solving to sustain participation, engagement, and effective communication [40, 41, 88]. In HRI, robots' verbal scaffolding support mediates interaction. For example, a robot's verbal scaffolding targeted to promote children's learning [27] or parents' reading behavior [10] could promote inclusion and richer social interaction among parents and children. For older adults, tailoring support to their cognitive and behavioral characteristics is important [7, 26]. Prior work explored scaffolding to help older adults adapt to unfamiliar activities [78], like robot's think-aloud supported cognitively impaired older adults in coding. Scaffolding, like engaging emotion [47] and creating error space [2], has also been applied to conversation-centered studies to improve engagement. For example, Otake-Matsuura et al. [65] explored a robot "assigning speaking time" for older adults' group training.

Building on these, we integrated the *verbal scaffolding* of shared memory and think-aloud to support group communication among older adults, aiming to sustain participation, balance group dynamics, and strengthen engagement across repeated interactions.

3 The Task: A Robot-Supported Collaborative Variant of the With Other Words Game

We designed a collaborative version of the original word-guessing game Med Andra Ord ("With Other Words") previously used in HRI studies [13, 18, 19]. The goal of the game is to describe a given word without using it so that a guesser can guess the word. As in prior work, we also use a robot as the guesser – the guesser robot. We further use a facilitator robot whose task will be detailed below.

We structured the game into rounds with two distinct phases to accommodate groups of three to four people. As shown in Fig. 2, participants first enter the *discussion phase* after the word is given on the tablet. Participants discuss and decide on the description together. In the *description phase*, participants describe the word to the guesser robot, which attempts to guess. Players receive a new word either after a correct guess or two incorrect guesses.

During the discussion, the facilitator robot guides the group through the gameplay, demonstrates active listening and encourages discussion and participation verbally and through gaze as detailed in Sec. 3.1. The guesser robot closes its eyes and lifts its arms during the discussion to indicate that it is not seeing or hearing the word. This behavior serves to give the impression of a genuine attempt to guess after the participants' description. To wake the guesser robot, participants press a centrally located button.

We selected target words from the highest difficulty category of the original pocket version of the game for the study to ensure the target words would warrant discussion, for example, "Suspension Bridge" or "Passionfruit". We prepared different sets of words to ensure that participants would not play the same words again.

Guess Generation. We fixed the rounds in which the robot would guess correctly due to the strong emotions that especially correct guesses elicited to ensure a comparable experience across groups[1].

Robot Platforms. We used Furhat [1] as the facilitator robot and Misty [77] as the guesser[2]. To improve accessibility [6] and better support mild hearing impairments, Furhat used a low-pitched Swedish male voice ("Erik", Acapela Group), and Misty's fixed female Swedish voice was adjusted to a low pitch (0.75). Furhat used the facial appearance "Titan" due to its robotic appearance.

3.1 Behaviors of the Facilitator Robot

The facilitator robot functioned as guide and discussion supporter. We developed supporting behaviors inspired by prior work that showed that robot **gaze behavior** can influence turn-taking [52, 75] and encourage participation [18]. The robot performed **reactive gaze** to demonstrate active listening, i.e., by turning to the speaker, and **proactive gaze** to encourage participation in the discussion. When the group was silent for at least 1 s, the facilitator robot proactively gazed at the participant with the *lowest* speaking share in the current discussion phase. For all gaze, we set the minimum gaze length to 1 s to avoid rapid and irritating robot movements.

We included **verbal supporting utterances** to encourage think-aloud and the sharing of personal experience, known to deepen interpersonal connections [64]. These were built according to a fixed structure: A brief statement about the given word, name of targeted participant, a question/ encouragement to think aloud, or instruction to share a memory (e.g."I noted that passionfruit is sweet and sour. Anders, have you ever used passionfruit to make a dessert? Please share a memory that can help us to find a good description for the word."). We pregenerated twenty such utterances using ChatGPT-4o (prompt in supplementary materials B) following criteria that (a) it should be suitable for older adults, (b) encourage memory sharing or think aloud, and (c) start with a detail from the robot's perspective. Per game word, we selected eight for each think aloud and sharing based on their fit to the rules.

3.1.1 Intervention Strategies. We define an intervention by the facilitator robot as the collection of multimodal supporting behaviors toward one target person within a discussion phase. Given the possible combinations of **gaze** and **verbal support**, participants could experience the following three interventions: (a) *Gaze only.* The facilitator robot **proactively gazed** at the target at least once. (b) *Verbal only* The facilitator robot provided **verbal support** to the target at least once. (c) *Gaze + Verbal* The robot proactively gazed at the target *and* provided verbal support at least once.

Outside of this behavior, the facilitator robot gazed at speaking participants. It could deliver interventions to multiple participants in one discussion phase. For example, it could gaze proactively at one participants and verbally support another.

3.1.2 Guiding the Interaction. The facilitator robot also guided participants through the game. We added guiding behavior in response to difficulties encountered in pilot experiments. After a guess, the facilitator robot made a transition statement. It repeated the guessed words and commented positively on the group interaction. For example, after a wrong guess, the facilitator could say: "That was really tough. It said [guessed word], but that was wrong. Everyone fails sometimes. Let's get back to the discussion and think about what information we could add!". After a correct guess, it might say: "Correct. It said [guessed word], I really liked how we supported each other and found good hints together." Transition utterances were randomly sampled from a pregenerated list of utterances. In addition, the facilitator robot would remind participants after 2.5 minutes of discussion to move to the description phase to avoid participants getting stuck on one particular word.

3.2 Autonomy and the Role of the Wizard

We developed a semi-autonomous system in which both the reactive and proactive gaze behaviors of the facilitator robot, as well as the behaviors of the guesser robot, were fully autonomous. In addition, the guiding behaviors of the facilitator were triggered autonomously after the guesser robot had guessed a word.

A wizard took control over the verbal supporting utterances described in Sec. 3.1. The wizard selected the target of the facilitator robot's verbal support and the most relevant utterance among a random selection of five from the pregenerated list. The wizard was instructed to select a participant who was not very active and could benefit from verbal support, to support each participant at least once, and to avoid addressing the same participant twice in a row. After selection, the facilitator robot waited for a pause in the discussion of at least 0.5 s to intervene. If there was no pause before moving to the description phase, the utterance was dropped.

4 Method

In this section, we detail the experimental procedure and our participant pool and provide an overview of the measurements and analysis methods used.

4.1 Experiment Design

We designed the experiment to investigate how different robots and behaviors would affect groups of older adults in real-world settings over repeated interactions.

4.1.1 Recruitment. We recruited local community centers through a newsletter and discussed study details with the management.

[1]For example, we fixed the robot to guess the first word on the second attempt, the second word on the first attempt, and to fail on the third word. In successful rounds, the guesser robot was given the correct word. In failed rounds, a desktop-hosted LLM (DeepSeek-V2 [14]) selected the best alternative from list based on participant's description. This list was generated by ChatGPT-4o and filtered for errors.

[2]We decided for Furhat and Misty during pilot studies which showed that older adults had problems understanding/hearing other robot platforms, e.g., the Nao robot

The management emailed out information or recruited participants directly. An information meeting for interested participants was held at three of four participating centers. Most participants signed up during these meetings, the rest by phone or email after.

4.1.2 Participants. 34 participants (25F, 9M) were recruited from the 4 local community centers[3]. Participants were aged 65+ years, with two being 65–69, ten being 70–74, seven being 75–79, nine being 80–84, four being 85–89 and two being 90+. Groups were assigned by staff in three centers, with participants randomly assigned by researchers in the fourth. All participants were invited to take part in three trials. In total, we ran 25 sessions with three (9 sessions) to four (16 sessions) participants. All participants completed one session, 31 participants completed two, and 26 participants completed three. People dropped out because of scheduling conflicts or personal preference. Those taking part in the same session may have participated in a different numbers of session before. Participants never played the same word twice. There were 2 - 21 days ($M = 8.96, SD = 4.66$) between sessions for individual participants.

4.1.3 Procedure. Participants were informed about the study and the data collected during the information meeting. Prior to the first trial, they provided written consent and demographic information. Before each trial, participants filled a pre-experiment questionnaire.

Chairs were set up so that all participants could see both robots and reach the button (Fig. 1). The experimenter explained the game and the roles of each robot and fitted each participant with an individual close-talk mic. Participants were informed that the experimenter would be in the room to help in case of technical problems but sit in the back. The robots introduced themselves and repeated the instructions. Participants then played for a minimum of 20 minutes, after which the facilitator robot announced the end of the game. The experimenter invited the participants to spread out in the available space away from the robots for more privacy for the post-experiment questionnaire which had questions about perceived social connectedness with other participants during the interaction [46], and general perception of social connectedness[42]. We also asked about participants' familiarity with other participants [82] and their relation to the community center. Participants received a gift card valued approx. 10.5 $ (100 SEK) as a thank you after each trial. The study was approved by the Swedish Ethical Review Authority (ID: 2025-01783-01).

4.2 Analysis

4.2.1 Quantitative Analysis. We collected subjective and objective measures from each session.

Subjective measures. Participants filled questionnaires before and after each trial. Demographic information (*age*, *gender* identity, *previous experience with robots*) was collected before the first trial. The following will detail the remaining subjective measures.

Social Connectedness Measured prior to every first trial and also in the post-experiment questionnaire using the Social Connectedness scale [42] to explore if the deployed robot system could improve social connectedness over repeated trials.

[3]Public institutions for older adults (65+). Two (24p) open to older adults living in the neighborhood and a connected elderly home. The two other centers (10p) are exclusively for those living in the connected elderly home.

Social connection in interaction Measured in the post-experiment questionnaire using the UBC State Social Connection Scale [46] to understand how connected participants felt during the interaction. The goal was to explore whether repeated trials could help participants feel connected during the interaction.

Familiarity among participants Measured every time participants met in a new group using self-reported familiarity [82] by asking participants to rank other participants between Strangers and Best Friends on a seven-point scale. Further, we asked participants how often they met other participants outside of the community center (five-point scale from never to very often). We normalized scores to a [0,1] range and average over the two questions.

Two native speaker of Swedish with high proficiency in English translated questionnaires from English to Swedish and from Swedish to English. Differences between the English original and the translations from Swedish were discussed among the two native speakers and one researcher to decide on the questionnaire translations which we provide in the supplemental material A.

Objective measures We used automatically extracted speech activity through Voice Activity Detection (VAD) from individual close-talk microphones to extract the utterances of individual participants during the discussion. For each discussion phase ph within a game and participant p, we collected time t of behaviors for intervention *int* as $\mathrm{int}_p^{\mathrm{ph}} : \{t_0, ...t_n\}$ where n denotes the total number of gaze or verbal supporting behaviors toward p in discussion phase ph. To collect and compare data before and after an intervention, we calculated the time of the intervention as the time of the last supporting behavior $t_{\mathrm{int}_p^{\mathrm{ph}}} = max(\mathrm{int}_p^{\mathrm{ph}})$. By using the time of the last behavior, we ensure that the measurements after robot intervention are not further influenced by robot behavior.

The overall time participants speak is dependent on the group and the word being discussed. Therefore, we focus on relative speech share per participant p_j, relative to other participants, with $\mathrm{sp}_j^{\mathrm{share},w} = sp_j^w / \sum_{i \in P} sp_i^w$, where w is the time window of interest.

Time of measurement: before intervention. We measure speech share *before intervention* as the share of speech that the target j of the intervention had from the start of the phase until the intervention: $\mathrm{sp}_j^{\mathrm{share},w_{\mathrm{before}}}$ where w_{before} describes the window of time from the start of the phase to $t_{\mathrm{int}_p^{\mathrm{ph}}}$.

Time of measurement: after intervention. We measure speech share *after intervention* as the share of speech that the target j of the intervention had directly after the intervention until the end of the discussion phase: $\mathrm{sp}_j^{\mathrm{share},w_{\mathrm{after}}}$ where w_{after} describes the window of time from $t_{\mathrm{int}_p^{\mathrm{ph}}}$ to the end of the phase.

Difference in speech share. We measure the *change in speech share* by calculating $\mathrm{sp}_j^{\mathrm{share},w_{\mathrm{after}}} - \mathrm{sp}_j^{\mathrm{share},w_{\mathrm{before}}}$

Note that we extract data separately for individual targets even if parallel interventions occur within one discussion phase.

4.2.2 Qualitative Analysis. Qualitative analysis was used to gain deeper insight into the human-human interactions that occur based on the robots and their behaviors. We observed patterns of general behaviors toward the robots. We review the moments of interaction in which the facilitator robot spoke or participants interacted with

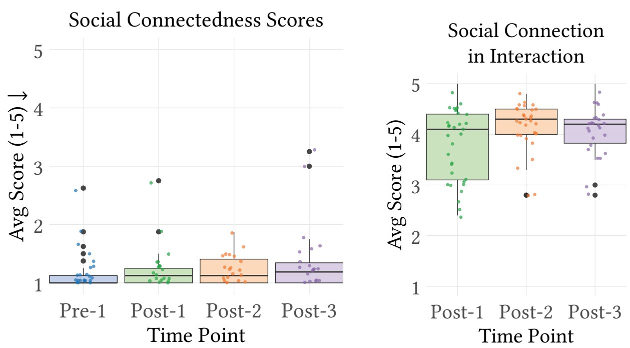

Figure 3: Boxplots of the Social Connectedness Scale (left, ↓ low values indicate high connectedness) and Social Connection in Interaction Scale (right) across different trials.

the guesser robot either through pressing the button or talking about/to it after the guess.

We used *video coding* to extract three frequently appearing patterns we observed during initial data review. **Laughter** coinciding with when facilitator robot spoke. Participants **talking over** the facilitator robot, or **stopping their own speech and waiting** for the facilitator robot. Lastly, we noticed that the pressing of the button was not consistent with who spoke in the description phase. Four annotators used ELAN (v7.0) [57] to code for the following:
Laughter. The annotator marked if laughter occurred while the facilitator robot spoke or during an answer to the robot's questions.
Overtalk. The annotator marked the moments in which participants talked at the same time as the facilitator robot.
Stop talking and wait. The annotator marked when participants stopped talking and waited for the facilitator robot to finish.
Pressing button and giving description. The annotator noted who pressed the button and who was describing the word.

Moments of facilitator speech and button press as well as speaking activity during the description were automatically extracted from the game logs and used to support video coding. The frequency of each code was counted and used to provide descriptive statistics (e.g., counts, percentages).

Through *Ethnomethodological Conversation Analysis (EMCA)*, we examined the practices of interacting with the robots. EMCA combines ethnography and video analysis with a focus on understandings of activities, cultures, and practice through video recordings [15, 48, 76]. One strength lies in uncovering taken-for-granted understandings embedded in the activity and the context [4, 32, 45, 51].

We present transcripts in a simplified Jeffersonian style [37], with overlapping speech enclosed in `[square brackets]`, elongated vowels with `co:lo:ns`, pauses with `(.)`, aligned screenshots with `*n` and actions described in *italics*. All transcripts were translated. The interested reader can find original transcripts in the supplementary material C.

5 Results

From the 25 sessions, we excluded 4 sessions due to errors either in the recording of the data or the behavior of the robot. In the remaining 21 sessions, we had 9 groups of three and 12 groups of

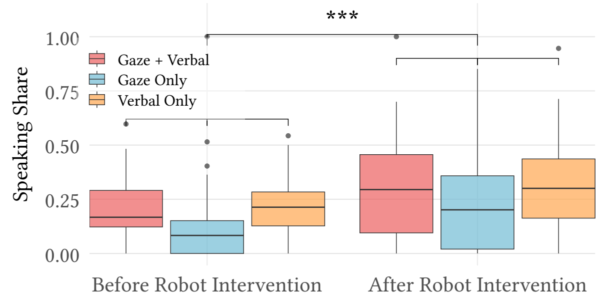

Figure 4: Boxplot of speech share before and after the facilitator robot's intervention, depending on intervention strategy.

four. We analyzed data from 22 participants in the first trial, 29 participants in the second trial and 24 participants in the third repeated trial. On average, groups played 10.1 discussion rounds (SD=2.47 rounds) and 6.2 different words (SD=1.16 words) in 22 minutes (SD=2.22 minutes). Participants reported an average familiarity of 0.61 (SD=0.31).

5.1 Quantitative Analysis

Our goal for this exploratory quantitative analysis is to examine the effect of the three variants of robot interventions on the verbal participation of participants, i.e., participants' speech share.

5.1.1 Social Connectedness and Social Connection. We fitted a linear mixed-effects model to examine the effect of trial number for each *Social Connectedness* and *Social Connection in Interaction* with random intercept for participant, group and center. We did not find any significant main effects. Results are visualized in Fig. 3. We note that participants were well socially connected before our intervention ($M = 1.155$, $SD = 0.33$ before first trial (Pre-1), Value = 1 implies highest social connectedness,)

5.1.2 Speaking Share and Robot Behavior. We analyze the speech share before and after as follows. First, we analyze the effect of intervention strategy on the repeated measure of speech share. Second, we examine the effects on change in speaking share and lastly explore the speech share with regard to an equal share baseline.

We fitted a linear mixed-effects model to examine the effects of intervention strategy, time of measurement, trial number and the interaction between intervention strategy and time of measurement, controlling for round number. We included random intercepts for participant, group, activity center, and the discussed target word. The analysis revealed significant main effects of intervention strategy, $F(2, 383.12) = 15.18, p < .001$, and time of measurement, $F(1, 345.02) = 32.02$, $p < .001$, while trial number, round number, and the interaction between intervention strategy and time were nonsignificant (all $ps > .79$). Post hoc Tukey-adjusted comparisons indicated that the *Gaze+Verbal* interventions were accompanied with higher speech share than the *Gaze only* intervention, $b = 0.09$, $SE = 0.02$, $t(369) = 3.90$, $p < .001$, $d = 0.53$, 95% CI $[-1.33, 2.39]$, and that speech share in the *Gaze only* intervention was lower than the *Verbal only* intervention, $b = -0.12$, $SE = 0.03$, $t(370) = -4.26$, $p < .001$, $d = -0.75$, 95% $CI[-3.14, 1.65]$. No significant difference

Table 1: Means and Standard Deviations of Speech Share by Intervention Strategies and Time of Measurement.

Intervention Strategy	Time	M	SD	n
Gaze+Verbal	Before	0.20	0.13	40
	After	0.31	0.24	40
Gaze only	Before	0.10	0.13	132
	After	0.23	0.21	132
Verbal only	Before	0.22	0.13	26
	After	0.33	0.24	26

emerged between *Gaze+Verbal* and *Verbal only* ($p = .56$). Additionally, speech share was significantly higher after the intervention ($M = 0.26$, $SD = 0.23$) compared to before ($M = 0.14$, $SD = 0.14$) across intervention strategies, $b = 0.12$, $SE = 0.02$, $t(335) = 5.66$, $p < .001$, $d = 0.71$, 95% CI $[-0.17, 1.59]$. Tab. 1 and Fig. 4 provides an overview of means and standard deviation before and after interventions.

To further understand the potential differences in effects between intervention strategies, we wanted to further ensure that differences in the before-intervention speech share did not influence the results. We fit a linear mixed-effects model to examine the effect of intervention strategy on the change in speech from before to after the intervention. We kept the random intercept from the above model. The analysis revealed no significant effect of intervention strategy, $F(2, 187.37) = 0.38$,$p = .685$.

In a group interaction, we assume perfect participation balance if all participants share speech equally, i.e., each participant speaks 33 % in groups of three and 25 % in groups of four. To evaluate if the interventions would lead to equal speech share, we ran a paired t-test to compare before and after the intervention speech share to the equal share baseline. We also added the speech share of participants who did not receive an intervention for comparison. In this case, we used speech share over the whole phase.

Participants who were not the target of an intervention shared significantly more speech share ($M = .33$) than expected equal speech share ($M = .27$), $t(192) = 4.61$, $p < .001$. In contrast, participants who received a *Verbal only* ($M = .22$ vs. baseline=.28), $t(25) = -2.50$, $p = .019$, *Gaze+Verbal* ($M = .20$ vs. baseline=.29), $t(39) = -4.11$, $p < .001$, or *Gaze only* ($M = .10$ vs. baseline=.28), $t(131) = -17.26$, $p < .001$, intervention shared significantly less than equal share before the intervention.

After the intervention, participants who received a *Gaze only* intervention shared still less than equal speech ($M = .23$ vs baseline=.28), $t(131) = -2.78$, $p = .006$. No significant differences from equal speech were observed for *Verbal only* or *Gaze+Verbal* ($ps > .31$).

5.2 Qualitative Analysis

5.2.1 Robot Verbal Behaviors and Reactions. In the 21 sessions, the facilitator robot provided 209 guiding (M per session = 10, SD=2.29) and 116 supporting behaviors (M=5.52, SD=1.94).

Laughter. We recorded laughter as reaction to a robot's verbal behavior 91 times (total 325). On average, 47.03 % (SD=16.25 %) of the verbal supporting behaviors and 18.39 % (SD=15.37 %) of the guiding behaviors coincided with laughter.

Overtalk. Groups overtalked parts of the facilitator robot's guiding utterances on average 21 % (SD=15.34 %) and parts of the verbal supporting utterances 5.75 % (SD=10.79 %).

Stopped Conversation. Participants stopped their conversation on average for 19.15 % (SD=14.86 %) of the guiding utterances and 37.20 % (SD=25.45 %) of the verbal supporting utterances.

5.2.2 EMCA. In this paper, the clips for analysis were informed by triangulation, employing the results of the video coding to pinpoint repeated and exceptional interactions. The first section, Understanding Laughter, draws on a corpus of identified laugher points within the video data adjacent to Furhat utterances. The second, Wrangling the Robot, focuses on points in the video data where the interaction with the Misty robot was initiated.

Understanding Laughter. In Fig. 5, we can see an example of the participation management carried out by the Furhat. Each time the same pattern was followed to attempt to reconfigure the participation framework [23].

These interjections were selected by the wizard but the Furhat waited until a pause in the conversation before speaking. The result was that Furhat's verbal behavior often entered the ongoing talk as disjunctive junctures [71] that abruptly changed the topic of conversation. When this happened, as can be seen in the example above, responses were brief or perfunctory. Longer or deeper engagement with the Furhat's questions would result in a context and topic shift in the conversation. By keeping their answers brief, participants displayed their orientation towards the progressivity of their own conversation as priority [80]. The brief answer is framed more for the benefit of the other participants, than to answer the robot's question. They used this to show accountability for the disruption attributed to them by name, while simultaneously downgrading the robot's status in the group. This pattern of dealing with interruptions can also be seen in the way adults handle interruptions from children [25] or even animals [58] where interjections are acknowledged but only minimally attended to.

The laughter at these points is more than an involuntary response to the funny robot. First, laughter was seen to be invited at two distinct points in the interaction. One being when the robot named the recipient, and the other when the recipient presented their answer. The first moment in which the robot sparked laughter can be seen as a social mitigation of the robot's awkward timing [38]. The recipient of the Furhat's verbal utterance needs to account for the robot entering the conversation out of sequence without a proper Transition Relevant Place (TRP) [69]. A breakdown in the progressivity occurs and the laughter serves as a way to soften this breakdown. At this point, the laughter also works to signal affiliation with the other participants instead of the robot [22]. The second laughter in the example occurs after the recipient provides a short or perfunctory response to the robot which could also be seen as a signal of affiliation. Participant C provides a dismissive response, just the word 'pear' elongated in a singsong tone, cuing the laughter. At this point the laughter is also part of structuring the turn-taking and serves as a topic closure signal [33] – everyone laughs marking the response as sufficient and providing a collective TRP to move back to the group's ongoing conversation.

Wrangling the Robot. With the two robots in this trial setup there were two different ways to interact with them, the facilitator robot


```
D: Yes, and it doesn't have to be shortcrust pastry, it can be any apple pie you like
   [but]
F:[I ] have read that shortcrust pastry is often served with custard or ice cream.
F: C***, do you have a favourite thing to eat with shortcrust pastry?
        [A, B, D turn to C - A, and B laugh lightly]
F: That could be a great tip.
C: pe::ar::
               [All laugh]
```

Figure 5: Laughter in Two Places. Images shown with consent.


```
C: If you will press it *1
B: Press, I don't want to go *2
A: Go..o[ooo] *3
D:       [Should] I pres[ss and *4 you answer]
A:                      [Go,  you Go]        yeah
```


```
A: (leans forward to press the button)*1
C:       (Gestures, pointing towards the button)*2/3
C:              You do it
```

Figure 6: Two examples of negotiations around button press. Images shown with consent.

Furhat – controlled by the wizard – asked questions and guided through the interaction. Here we take a closer look at interactions with the guesser robot Misty, which 'slept' during most of the trial only to be woken and interacted with by pressing a button.

Participation and interaction with the robots was carefully managed through 'robot wranglers.' Who pressed the button and talked to Misty was often not the same person, and as we see in these examples, it was *negotiated* in different ways within the group. Performing either of these actions didn't necessarily mean that a participant was taking on the 'wrangler' role at that time.

In Fig. 6 top, we see a negotiation around who should tell Misty the results of their discussions. Here A, C, and D are able to orient towards the button that will wake the robot. C gestures towards the button, bringing the action of waking the robot and presenting the guess as the topic of discussion, and verbally suggests that A do so. D gestures as well, pushing the button towards participant A, suggesting that they have shared ownership of the guess and that they be the one to speak to the robot. A waves away the offer, and D waves towards A, then hovers his hand over the button to convey that he will press the button and that A can talk to Misty – which is how the interaction proceeds. This sequence highlights how the material affordance of the button allowed participants to coordinate through embodied and laminated actions [24, 49]. Unlike Furhat, Misty was not continuously ratified as a participant, but was only conditionally made relevant through the summons–answer sequence of pressing the button [70]. The button served as a tangible shared object through which participation was managed, producing a more multimodal and distributed negotiation than in the purely verbal case. It also shows that even when the actions detected as being distributed among the groups, the role of the wrangler may not be. D initiated the negotiation around who should perform the actions, and frames the participation as the ratified speaker selector [23], managing the sequentiality of when and how the robot will be interacted with within the larger frame of the task [80]. This other-selection [43] re-asserts their role as the wrangler even if, programmatically, it may appear otherwise.

In Fig. 6 bottom, we see this in another form, here C was acting as the wrangler earlier in the task, yet at this point A bypasses C in performing the ratification of speaker selection towards B and pressing the button themselves. As the button press action becomes apparent, C gestures towards A, performing what might be seen as redundant other-selection which re-asserts their role as the one managing who should interact with the robot and when. This shows that the role of wrangler is not observable in single actions, but maintained interactionally through sequential positioning, embodied displays and ratification practices.

6 Discussion

This work explored how robots can support interactions among groups of older adults. We adapted a robot-supported word-guessing game to allow for discussion and interaction and developed the facilitator robot's behavior with the goal that every group member could take part in the activity.

Our mixed-method analysis shows that the robots and their behaviors can encourage participation through active interventions (*Verbal only*, *Gaze only* and *Verbal+Gaze*) and the need to "wrangle" the guesser robot. Our quantitative analysis can thereby confirm the effectiveness of the facilitator robot's behaviors with an increase in speech share by on average 12% from before to after the intervention with no difference between intervention strategies. Our qualitative analysis reveals the patterns of negotiation and encouragement that emerge around pressing the button and giving the description to the guesser robot, i.e., "wrangling" the guesser robot.

Gaze Behaviors. We designed the facilitator robot's supportive gaze to support the participant with the least speech share. Verbal supportive behaviors, on the contrary, were distributed more broadly among all participants. Still, we found that the increase in speech share did not differ between gaze and verbal behaviors despite the different target selection criteria. Interestingly, *Gaze only* interventions were twice (n=132) as likely as interventions with verbal support (n=40+26). Prior work has shown that gaze behaviors can be subtle in influencing the dynamics when human dyads interact with robots in lab [18, 52] or realistic settings [75]. Our results extend these prior works by showing that gaze behaviors are also effective in groups larger than dyads, in combination with supporting verbal behavior, and over repeated trials.

Verbal Support Behaviors and Laughter. We found that participants' speech share was not different from equal share after a verbal supporting behavior. Verbal utterances always ended with a question toward a named participant. Therefore, an increase in participation after the facilitator robot's question might be expected.

Participants, however, did not always react as expected to verbal robot behaviors. We found that participants partially overtalked 21% of guiding utterances and that supporting robot utterances led to laughter about half of the time. While not every laughter was observed as a shared laughter, shared laughter occurred in particular when the target of the intervention created a funny moment, as observable in Fig. 5 for the second laugh. These results suggest that verbal robot interventions can balance participation and invite shared laughter which may aid cognitive-emotional coordination [53], help maintain social ties [73], and foster cooperation [16]. Nevertheless, our EMCA analysis illustrates that the use of laughter in conversation is more complex than it first appears. The use of laughter as a topic-closing device, as mitigation for awkward interactions, or as a way to signal social affiliations that downgrade the robot interlocutor goes beyond laughter as a signal of enjoyment or the generation of empathy with a system (e.g., [5, 59]).

Overall, the facilitator robot's verbal behavior elicits a mixed picture where interventions are effective, but participants regularly talk over the robot and laugh at its expense. We conclude that verbal participation in group interaction is still challenging for robots and can lead to conversational breakdowns with unexpected outcomes. Yet some of these outcomes, such as shared downgrade of the robot to the other, might have a positive effect on group cohesion and identity [83]. When we are building interactions to support the overall human-human connection, the effectiveness of interventions, sometimes at the expense of the robot, could provide an interesting opportunity for future work [87].

Using Control. There has been a large body of work, as noted above, on the use of (social) robots to improve and better distribute discussion and collaboration among groups. Yet in close examination of the interactions with and around the Misty robot (see Sec. 5.2.2), we can see that this improvement is not only built by the actions of the robot – but through the resulting interpersonal negotiations that arise *due to* interactions with the robot. As such, while measuring the amount and timing of speech to the robot has shown an increase in participation, the way in which this participation is managed through defacto-wranglers allows us to look at participation through a different lens. It is important to understand and design for the role of wrangler, as intermediary between the group and the robot and something that will be negotiated – in a similar way as a temporary intermediary may be negotiated within a group to interact with an other yet without the robot participating in, responding to, or even pushing back and changing the results of this negotiation as a human would [50, 79]. This not only points to a requirement for different metrics to understand impacts of group-level interactions with agents, but to interactional levers that, through careful manipulation, hold the potential to perform values-based changes to group dynamics and participation [87].

This study focused on older adults, a population typically affected by declining abilities and reduced opportunities for social participation [35, 55]. The game and experimental setup were adapted to these challenges, for example by using low-pitched robot voices. Small group activities, such as playing cards or other games, are also a common for older adults at the local community centers we visited. Therefore, our study can provide insight into a robot's effects in ecologically valid real-world settings. Future work should explore further if our findings can extend to other age groups.

Limitations. Our study was accompanied by technical problems that stem from the regular transport of the setup from and to community centers. As reported, we excluded groups in which technical limitations strongly impacted robot behavior. Other technical issues, like a breakdown of the button or problems with the microphones, occurred evenly through sessions and do not compromise our results. Further, participants' scheduling constraints did not allow for all groups to experience repeated interactions, so that roughly half of the participants met different others during each trial. In addition, our results indicate that our participants were well socially connected before our experiments. Therefore, future work should further investigate whether robots can impact social connectedness over repeated trials. This study was explorative in its design and analysis. Whereas our results indicate strong effects of the robots on the group dynamics and the individual chance to participate over repeated interactions, future work should include controlled studies to further confirm our results.

7 Conclusion

This work provides an exploratory study that investigates how robots can act as effective facilitators in groups of older adult across repeated interactions while creating opportunities for meaningful social interaction in a real-world settings. Thirty-four participants played a word-guessing game in groups of three or four facilitated by two robots in their local community center. The facilitator robot used gaze and verbal support to facilitate the interactions and a guesser robot created opportunities for negotiation around who has the right to 'wrangle' the robot. Our results show that both gaze and verbal supporting robot behaviors can increase participation consistently over repeated interactions. Further, verbal support not only promoted contributions but also elicited social bonding behaviors, such as shared laughter. Our mixed-method analysis further highlights how laughter might have additional functions such as laughter at the robots expense which creates interesting avenues for future work.

Acknowledgments

We would like to thank Elias Värling and Filip Svebeck for their help coding the videos, Rebecca Stower for the help with the statistical analysis and the staff and administrators in the community centers as well as the Äldreförvaltning Stockholm for their support during this project. This research was supported by the Digital Futures Research Center at KTH Royal Institute of Technology.

References

[1] Samer Al Moubayed, Jonas Beskow, Gabriel Skantze, and Björn Granström. 2012. Furhat: A Back-Projected Human-Like Robot Head for Multiparty Human-Machine Interaction. In *Cognitive Behavioural Systems*. Vol. 7403. Springer Berlin Heidelberg, Berlin, Heidelberg, 114–130. Lecture Notes in Computer Science.

[2] Safinah Ali, Ayat Abodayeh, Zahra Dhuliawala, Cynthia Breazeal, and Hae Won Park. 2025. Towards Inclusive Co-creative Child-robot Interaction: Can Social Robots Support Neurodivergent Children's Creativity?. In *Proceedings of the 2025 ACM/IEEE International Conference on Human-Robot Interaction (HRI '25)*. IEEE Press, Melbourne, Australia, 321–330.

[3] Victor Nikhil Antony, Clara Jeon, Jiasheng Li, Ge Gao, Huaishu Peng, Anastasia K. Ostrowski, and Chien-Ming Huang. 2025. The Design of On-Body Robots for Older Adults. In *Proceedings of the 2025 ACM/IEEE International Conference on Human-Robot Interaction (HRI '25)*. IEEE Press, Melbourne, Australia, 589–598.

[4] Paul Atkinson and Lisa Morriss. 2017. On Ethnographic Knowledge. *Qualitative Inquiry* 23, 5 (June 2017), 323–331. doi:10.1177/1077800416655825

[5] Wilma A. Bainbridge, Justin W. Hart, Elizabeth S. Kim, and Brian Scassellati. 2011. The Benefits of Interactions with Physically Present Robots over Video-Displayed Agents. *International Journal of Social Robotics* 3, 1 (Jan. 2011), 41–52. doi:10.1007/s12369-010-0082-7

[6] Johnna Blair and Saeed Abdullah. 2020. It Didn't Sound Good with My Cochlear Implants: Understanding the Challenges of Using Smart Assistants for Deaf and Hard of Hearing Users. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 4, 4 (Dec. 2020), 118:1–118:27. doi:10.1145/3432194

[7] Katerina Cerna, Claudia Müller, Dave Randall, and Martin Hunker. 2022. Situated Scaffolding for Sustainable Participatory Design: Learning Online with Older Adults. *Proc. ACM Hum.-Comput. Interact.* 6, GROUP (Jan. 2022), 12:1–12:25. doi:10.1145/3492831

[8] Wan-Ling Chang and Selma Šabanović. 2015. Interaction Expands Function: Social Shaping of the Therapeutic Robot PARO in a Nursing Home. In *Proceedings of the Tenth Annual ACM/IEEE International Conference on Human-Robot Interaction (HRI '15)*. Association for Computing Machinery, New York, NY, USA, 343–350. doi:10.1145/2696454.2696472

[9] Hannah Chapman, Jennifer Bethell, Neha Dewan, Madalena P. Liougas, Gill Livingston, Katherine S. McGilton, and Andrew Sommerlad. 2024. Social Connection in Long-Term Care Homes: A Qualitative Study of Barriers and Facilitators. *BMC Geriatrics* 24, 1 (Oct. 2024), 857. doi:10.1186/s12877-024-05454-8

[10] Huili Chen, Yubin Kim, Kejia Patterson, Cynthia Breazeal, and Hae Won Park. 2025. Social robots as conversational catalysts: Enhancing long-term human-human interaction at home. *Science Robotics* 10, 100 (2025), eadk3307.

[11] Filipa Correia, Samuel F. Mascarenhas, Samuel Gomes, Patrícia Arriaga, Iolanda Leite, Rui Prada, Francisco S. Melo, and Ana Paiva. 2019. Exploring Prosociality in Human-Robot Teams. In *2019 14th ACM/IEEE International Conference on Human-Robot Interaction (HRI)*. 143–151. doi:10.1109/HRI.2019.8673299

[12] Dagoberto Cruz-Sandoval, Michele Murakami, Alyssa Kubota, and Laurel D. Riek. 2025. PODER: A Robot Programming Framework to Further Inclusion of People with Mild Cognitive Impairment in HRI Research. In *Proceedings of the 2025 ACM/IEEE International Conference on Human-Robot Interaction (HRI '25)*. IEEE Press, Melbourne, Australia, 599–609.

[13] Ronald Cumbal, Daniel Alexander Kazzi, Vincent Winberg, and Olov Engwall. 2022. Shaping unbalanced multi-party interactions through adaptive robot backchannels. In *Proceedings of the 22nd ACM International Conference on Intelligent Virtual Agents*. 1–7.

[14] DeepSeek-AI, Qihao Zhu, Daya Guo, Zhihong Shao, Dejian Yang, Peiyi Wang, Runxin Xu, Y. Wu, Yukun Li, Huazuo Gao, Shirong Ma, Wangding Zeng, Xiao Bi, Zihui Gu, Hanwei Xu, Damai Dai, Kai Dong, Liyue Zhang, Yishi Piao, Zhibin Gou, Zhenda Xie, Zhewen Hao, Bingxuan Wang, Junxiao Song, Deli Chen, Xin Xie, Kang Guan, Yuxiang You, Aixin Liu, Qiushi Du, Wenjun Gao, Xuan Lu, Qinyu Chen, Yaohui Wang, Chengqi Deng, Jiashi Li, Chenggang Zhao, Chong Ruan, Fuli Luo, and Wenfeng Liang. 2024. DeepSeek-Coder-V2: Breaking the Barrier of Closed-Source Models in Code Intelligence. doi:10.48550/arXiv.2406.11931 arXiv:2406.11931 [cs].

[15] Michael F. DeLand. 2021. Men and Their Moments: Character-driven Ethnography and Interaction Analysis in a Park Basketball Rule Dispute. *Social Psychology Quarterly* 84, 2 (June 2021), 155–176. doi:10.1177/01902725211004894

[16] Robin Dunbar and Marc Mehu. 2008. Naturalistic Observations of Smiling and Laughter in Human Group Interactions. *Behaviour* 145, 12 (2008), 1747–1780. doi:10.1163/156853908786279619

[17] Yuan Gao, Ngaire Kerse, Bruce MacDonald, and Elizabeth Broadbent. 2025. Using Social Robots to Enhance Cognitive Health in Older Adults with Mild Cognitive Impairment. In *Proceedings of the 2025 ACM/IEEE International Conference on Human-Robot Interaction (HRI '25)*. IEEE Press, Melbourne, Australia, 1841–1843.

[18] Sarah Gillet, Ronald Cumbal, André Pereira, José Lopes, Olov Engwall, and Iolanda Leite. 2021. Robot Gaze Can Mediate Participation Imbalance in Groups with Different Skill Levels. In *Proceedings of the 2021 ACM/IEEE International Conference on Human-Robot Interaction (HRI '21)*. Association for Computing Machinery, New York, NY, USA, 303–311. doi:10.1145/3434073.3444670

[19] Sarah Gillet, Maria Teresa Parreira, Marynel Vázquez, and Iolanda Leite. 2022. Learning Gaze Behaviors for Balancing Participation in Group Human-Robot Interactions. In *Proceedings of the 2022 ACM/IEEE International Conference on Human-Robot Interaction (HRI '22)*. IEEE Press, Sapporo, Hokkaido, Japan, 265–274.

[20] Sarah Gillet, Wouter van den Bos, and Iolanda Leite. 2020. *A Social Robot Mediator to Foster Collaboration and Inclusion among Children*. doi:10.15607/RSS.2020.XVI.103

[21] Sarah Gillet, Marynel Vázquez, Sean Andrist, Iolanda Leite, and Sarah Sebo. 2024. Interaction-Shaping Robotics: Robots That Influence Interactions between Other Agents. *J. Hum.-Robot Interact.* 13, 1 (March 2024), 12:1–12:23. doi:10.1145/3643803

[22] Phillip Glenn. 2003. *Laughter in Interaction*. Cambridge University Press.

[23] Erving Goffman. 1981. *Forms of Talk*. University of Pennsylvania Press.

[24] Charles Goodwin. 2000. Action and Embodiment within Situated Human Interaction. *Journal of Pragmatics* 32, 10 (Sept. 2000), 1489–1522. doi:10.1016/S0378-2166(99)00096-X

[25] Marjorie Harness Goodwin and Charles Goodwin. 1987. Children's Arguing. In *Language, Gender, and Sex in Comparative Perspective*, Susan Steele Susan Philips and Christine Tanz (Eds.). Cambridge University Press, Cambridge, Chapter 8, 200–248.

[26] Mitchell L. Gordon, Leon Gatys, Carlos Guestrin, Jeffrey P. Bigham, Andrew Trister, and Kayur Patel. 2019. App Usage Predicts Cognitive Ability in Older Adults. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems (CHI '19)*. Association for Computing Machinery, New York, NY, USA, 1–12. doi:10.1145/3290605.3300398

[27] Omer Gvirsman and Goren Gordon. 2024. Effect of Social Robot's Role and Behavior on Parent-Toddler Interaction. In *Proceedings of the 2024 ACM/IEEE International Conference on Human-Robot Interaction (HRI '24)*. Association for Computing Machinery, New York, NY, USA, 222–230. doi:10.1145/3610977.3634928

[28] Catherine Haslam, Tegan Cruwys, and S. Alexander Haslam. 2014. "The We's Have It": Evidence for the Distinctive Benefits of Group Engagement in Enhancing Cognitive Health in Aging. *Social Science & Medicine* 120 (Nov. 2014), 57–66. doi:10.1016/j.socscimed.2014.08.037

[29] Yugo Hayashi, Keita Kiuchi, Shigen Shimojo, Lisa Abe, and Emika Watanabe. 2025. A Comparative Study of Older and Younger Adults Using Solution-Focused Brief Therapy with an Active Listening Counseling Robot. In *Proceedings of the 2025 ACM/IEEE International Conference on Human-Robot Interaction (HRI '25)*. IEEE Press, Melbourne, Australia, 1337–1341.

[30] Denise Hebesberger, Tobias Koertner, Christoph Gisinger, Juergen Pripfl, and Christian Dondrup. 2016. Lessons Learned from the Deployment of a Long-Term Autonomous Robot as Companion in Physical Therapy for Older Adults with Dementia a Mixed Methods Study. In *2016 11th ACM/IEEE International Conference on Human-Robot Interaction (HRI)*. 27–34. doi:10.1109/HRI.2016.7451730

[31] Guy Hoffman, Oren Zuckerman, Gilad Hirschberger, Michal Luria, and Tal Shani Sherman. 2015. Design and Evaluation of a Peripheral Robotic Conversation Companion. In *Proceedings of the Tenth Annual ACM/IEEE International Conference on Human-Robot Interaction (HRI '15)*. Association for Computing Machinery, New York, NY, USA, 3–10. doi:10.1145/2696454.2696495

[32] Emily Hofstetter. 2024. A Novice Inquiry into Unique Adequacy. *Qualitative Research* 24, 1 (Feb. 2024), 81–98. doi:10.1177/14687941221132959

[33] Elizabeth Holt and Phillip Glenn. 2013. Studies of Laughter in Interaction. (2013), 1–312.

[34] Julianne Holt-Lunstad, Timothy B. Smith, and J. Bradley Layton. 2010. Social Relationships and Mortality Risk: A Meta-analytic Review. *PLOS Medicine* 7, 7 (July 2010), e1000316. doi:10.1371/journal.pmed.1000316

[35] Wiebren S. Jansen, Sabine Otten, Karen I. van der Zee, and Lise Jans. 2014. Inclusion: Conceptualization and Measurement. *European Journal of Social Psychology* 44, 4 (2014), 370–385. doi:10.1002/ejsp.2011

[36] Hifza Javed, Weinan Wang, Affan Bin Usman, and Nawid Jamali. 2024. Modeling interpersonal perception in dyadic interactions: towards robot-assisted social mediation in the real world. *Frontiers in Robotics and AI* 11 (2024). doi:10.3389/frobt.2024.1410957

[37] Gayle Jefferson. 1984. Transcript Notation. In *Structures of social action: studies in conversation analysis*, J. M. Atkinson and J. Heritage (Eds.). Cambridge University Press, Cambridge, ix–xvi.

[38] Gail Jefferson. 1985. On the Organization of Laughter in Talk about Troubles. In *Structures of Social Action*, J. MaxwellEditor Atkinson (Ed.). Cambridge University Press, Cambridge, 346–369.

[39] Keonhee Kim, Sangyoon Shin, Seungyeon Kim, and Euni Lee. 2023. The Relation Between eHealth Literacy and Health-Related Behaviors: Systematic Review and Meta-analysis. *Journal of Medical Internet Research* 25, 1 (Jan. 2023), e40778. doi:10.2196/40778

[40] Christopher Lange, Jamie Costley, and Seung Lock Han. 2016. Informal Cooperative Learning in Small Groups: The Effect of Scaffolding on Participation. *Issues in Educational Research* (May 2016).

[41] Martha Larkin. 2002. *Using Scaffolded Instruction To Optimize Learning. ERIC Digest*. Technical Report. ERIC Clearinghouse on Disabilities and Gifted Education,

Council for Exceptional Children, 1110 North Glebe Rd.

[42] Richard M. Lee and Steven B. Robbins. 1995. Measuring Belongingness: The Social Connectedness and the Social Assurance Scales. *Journal of Counseling Psychology* 42, 2 (1995), 232–241. doi:10.1037/0022-0167.42.2.232

[43] Gene H. Lerner. 2003. Selecting next speaker: The context-sensitive operation of a context-free organization. *Language in Society* 32, 2 (April 2003), 177–201. doi:10.1017/S004740450332202X

[44] Maria R. Lima, Maitreyee Wairagkar, Manish Gupta, Ferdinando Rodriguez y Baena, Payam Barnaghi, David J. Sharp, and Ravi Vaidyanathan. 2022. Conversational Affective Social Robots for Ageing and Dementia Support. *IEEE Transactions on Cognitive and Developmental Systems* 14, 4 (Dec. 2022), 1378–1397. doi:10.1109/TCDS.2021.3115228

[45] Oskar Lindwall and Gustav Lymer. 2014. Inquiries of the Body: Novice Questions and the Instructable Observability of Endodontic Scenes. *Discourse Studies* 16, 2 (April 2014), 271–294. doi:10.1177/1461445613514672

[46] Iris Lok and Elizabeth Dunn. 2023. The UBC State Social Connection Scale: Factor Structure, Reliability, and Validity. *Social Psychological and Personality Science* 14, 7 (Sept. 2023), 835–844. doi:10.1177/19485506221132090

[47] Wing-Yue Geoffrey Louie, Derek McColl, and Goldie Nejat. 2012. Playing a Memory Game with a Socially Assistive Robot: A Case Study at a Long-Term Care Facility. In *2012 IEEE RO-MAN: The 21st IEEE International Symposium on Robot and Human Interactive Communication*. 345–350. doi:10.1109/ROMAN.2012.6343777

[48] Christian Meier zu Verl and René Tuma. 2021. Video Analysis and Ethnographic Knowledge: An Empirical Study of Video Analysis Practices. *Journal of Contemporary Ethnography* 50, 1 (Feb. 2021), 120–144. doi:10.1177/0891241620973716

[49] Lorenza Mondada. 2019. Contemporary Issues in Conversation Analysis: Embodiment and Materiality, Multimodality and Multisensoriality in Social Interaction. *Quo Vadis, Pragmatics?* 145 (May 2019), 47–62. doi:10.1016/j.pragma.2019.01.016

[50] Lorenza Mondada. 2025. Maximizing participation while preserving the normative order of the service: The autonomy and porosity of service encounters. *Discourse Studies* 27, 4 (Aug. 2025), 565–589. doi:10.1177/14614456241292723 Publisher: SAGE Publications.

[51] Lisa Morriss. 2016. Dirty Secrets and Being 'Strange': Using Ethnomethodology to Move beyond Familiarity. *Qualitative Research* 16, 5 (Oct. 2016), 526–540. doi:10.1177/1468794115598194

[52] Bilge Mutlu, Toshiyuki Shiwa, Takayuki Kanda, Hiroshi Ishiguro, and Norihiro Hagita. 2009. Footing in Human-Robot Conversations: How Robots Might Shape Participant Roles Using Gaze Cues. In *Proceedings of the 4th ACM/IEEE International Conference on Human Robot Interaction (HRI '09)*. Association for Computing Machinery, New York, NY, USA, 61–68. doi:10.1145/1514095.1514109

[53] Jorge Navarro, Raquel Del Moral, and Pedro C. Marijuán. 2016. Laughing Bonds: A Multidisciplinary Inquiry into the Social Information Processes of Human Laughter. *Kybernetes* 45, 8 (Sept. 2016), 1292–1307. doi:10.1108/K-02-2016-0026

[54] Isabel Neto, Filipa Correia, Filipa Rocha, Patricia Piedade, Ana Paiva, and Hugo Nicolau. 2023. The Robot Made Us Hear Each Other: Fostering Inclusive Conversations among Mixed-Visual Ability Children. In *Proceedings of the 2023 ACM/IEEE International Conference on Human-Robot Interaction (HRI '23)*. Association for Computing Machinery, New York, NY, USA, 13–23. doi:10.1145/3568162.3576997

[55] Loveday Newman, Charlotte Stoner, and Aimee Spector. 2021. Social Networking Sites and the Experience of Older Adult Users: A Systematic Review. *Ageing & Society* 41, 2 (Feb. 2021), 377–402. doi:10.1017/S0144686X19001144

[56] Massimiliano Nigro, Emmanuel Akinrintoyo, Nicole Salomons, and Micol Spitale. 2025. Social Group Human-Robot Interaction: A Scoping Review of Computational Challenges. In *Proceedings of the 2025 ACM/IEEE International Conference on Human-Robot Interaction (HRI '25)*. IEEE Press, Melbourne, Australia, 468–478.

[57] Nijmegen. 2025. ELAN. Max Planck Institute for Psycholinguistics, The Language Archive.

[58] Stefan Norrthon and Jenny Nilsson. 2025. Human Affiliative Responses to Companion Animal Vocalizations. *Language & Communication* 101 (March 2025), 1–14. doi:10.1016/j.langcom.2024.12.011

[59] Raquel Oliveira, Patrícia Arriaga, Minja Axelsson, and Ana Paiva. 2021. Humor–Robot Interaction: A Scoping Review of the Literature and Future Directions. *International Journal of Social Robotics* 13, 6 (Sept. 2021), 1369–1383. doi:10.1007/s12369-020-00727-9

[60] Raquel Oliveira, Patrícia Arriaga, and Ana Paiva. 2021. Human-Robot Interaction in Groups: Methodological and Research Practices. *Multimodal Technologies and Interaction* 5, 10 (Oct. 2021), 59. doi:10.3390/mti5100059

[61] Anthony D. Ong and Jason C. Allaire. 2005. Cardiovascular Intraindividual Variability in Later Life: The Influence of Social Connectedness and Positive Emotions. *Psychology and Aging* 20, 3 (2005), 476–485. doi:10.1037/0882-7974.20.3.476

[62] World Health Organization. 2015. *World report on ageing and health*. World Health Organization.

[63] Anastasia K. Ostrowski, Cynthia Breazeal, and Hae Won Park. 2022. Mixed-Method Long-Term Robot Usage: Older Adults' Lived Experience of Social Robots. In *2022 17th ACM/IEEE International Conference on Human-Robot Interaction (HRI)*. 33–42. doi:10.1109/HRI53351.2022.9889488

[64] Anastasia K. Ostrowski, Daniella DiPaola, Erin Partridge, Hae Won Park, and Cynthia Breazeal. 2019. Older Adults Living With Social Robots: Promoting Social Connectedness in Long-Term Communities. *IEEE Robotics & Automation Magazine* 26, 2 (June 2019), 59–70. doi:10.1109/MRA.2019.2905234

[65] Mihoko Otake-Matsuura, Seiki Tokunaga, Kumi Watanabe, Masato S. Abe, Takuya Sekiguchi, Hikaru Sugimoto, Taishiro Kishimoto, and Takashi Kudo. 2021. Cognitive Intervention Through Photo-Integrated Conversation Moderated by Robots (PICMOR) Program: A Randomized Controlled Trial. *Frontiers in Robotics and AI* 8 (April 2021), 633076. doi:10.3389/frobt.2021.633076

[66] Brea L Perry, William R McConnell, Siyun Peng, Adam R Roth, Max Coleman, Mohit Manchella, Meghann Roessler, Heather Francis, Hope Sheean, and Liana A Apostolova. 2022. Social Networks and Cognitive Function: An Evaluation of Social Bridging and Bonding Mechanisms. *The Gerontologist* 62, 6 (Aug. 2022), 865–875. doi:10.1093/geront/gnab112

[67] Tuan Vu Pham, Thomas H Weisswange, and Marc Hassenzahl. 2024. Embodied mediation in group ideation–a gestural robot can facilitate consensus-building. In *Proceedings of the 2024 ACM Designing Interactive Systems Conference*. 2611–2632.

[68] Judith L Poey, Jeffrey A Burr, and J Scott Roberts. 2017. Social Connectedness, Perceived Isolation, and Dementia: Does the Social Environment Moderate the Relationship Between Genetic Risk and Cognitive Well-Being? *The Gerontologist* 57, 6 (Nov. 2017), 1031–1040. doi:10.1093/geront/gnw154

[69] Harvey Sacks, Emanuel A. Schegloff, and Gail Jefferson. 1974. A Simplest Systematics for the Organization of Turn-Taking for Conversation. *Language* 50, 4 (1974), 696–735.

[70] EMANUEL A. SCHEGLOFF. 1968. Sequencing in Conversational Openings. *American Anthropologist* 70, 6 (Dec. 1968), 1075–1095. doi:10.1525/aa.1968.70.6.02a00030

[71] EMANUEL A. SCHEGLOFF and HARVEY SACKS. 1973. Opening up Closings. *Semiotica* 8, 4 (1973), 289–327. doi:doi:10.1515/semi.1973.8.4.289

[72] Eike Schneiders, EunJeong Cheon, Jesper Kjeldskov, Matthias Rehm, and Mikael B. Skov. 2022. Non-Dyadic Interaction: A Literature Review of 15 Years of Human-Robot Interaction Conference Publications. *J. Hum.-Robot Interact.* 11, 2 (Feb. 2022), 13:1–13:32. doi:10.1145/3488242

[73] Sophie K. Scott, Nadine Lavan, Sinead Chen, and Carolyn McGettigan. 2014. The Social Life of Laughter. *Trends in Cognitive Sciences* 18, 12 (Dec. 2014), 618–620. doi:10.1016/j.tics.2014.09.002

[74] Sarah Sebo, Brett Stoll, Brian Scassellati, and Malte F. Jung. 2020. Robots in Groups and Teams: A Literature Review. *Proc. ACM Hum.-Comput. Interact.* 4, CSCW2 (Oct. 2020), 176:1–176:36. doi:10.1145/3415247

[75] Gabriel Skantze. 2017. Predicting and Regulating Participation Equality in Human-robot Conversations: Effects of Age and Gender. In *Proceedings of the 2017 ACM/IEEE International Conference on Human-Robot Interaction (HRI '17)*. Association for Computing Machinery, New York, NY, USA, 196–204. doi:10.1145/2909824.3020210

[76] Robin James Smith. 2024. Fieldwork, Participation, and Unique-Adequacy-in-Action. *Qualitative Research* 24, 1 (2024), 60–80. doi:10.1177/14687941221132955

[77] Srivatsan Srinivasan. 2019. Misty-A Development Platform for Socially Assistive Robots [Student's Corner]. *IEEE Robotics & Automation Magazine* 26, 2 (June 2019), 103–105. doi:10.1109/MRA.2019.2910420

[78] Laura Stegner, Emmanuel Senft, and Bilge Mutlu. 2023. Situated Participatory Design: A Method for In Situ Design of Robotic Interaction with Older Adults. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*. 1–15. arXiv:2302.00588 [cs] doi:10.1145/3544548.3580893

[79] Tanya Stivers. 2001. Negotiating Who Presents the Problem: Next Speaker Selection in Pediatric Encounters. *Journal of Communication* 51, 2 (June 2001), 252–282. doi:10.1111/j.1460-2466.2001.tb02880.x

[80] TANYA STIVERS and JEFFREY D. ROBINSON. 2006. A Preference for Progressivity in Interaction. *Language in Society* 35, 3 (2006), 367–392. doi:10.1017/S0047404506060179

[81] Sarah Strohkorb Sebo, Ling Liang Dong, Nicholas Chang, and Brian Scassellati. 2020. Strategies for the Inclusion of Human Members within Human-Robot Teams. In *Proceedings of the 2020 ACM/IEEE International Conference on Human-Robot Interaction*. ACM, Cambridge United Kingdom, 309–317. doi:10.1145/3319502.3374808

[82] Sarah Strohkorb Sebo, Margaret Traeger, Malte F. Jung, and Brian Scassellati. 2018. The Ripple Effects of Vulnerability: The Effects of a Robot's Vulnerable Behavior on Trust in Human-Robot Teams. *Proceedings of the 2018 ACM/IEEE International Conference on Human-Robot Interaction - HRI '18* February (2018), 178–186. doi:10.1145/3171221.3171275

[83] Henri Tajfel, Michael Billig, Robert Bundy, and Claude Flament. 1971. Social Categorization and Inter-Group Behavior. *European Journal of Social Psychology* 1 (April 1971), 149–178. doi:10.1002/ejsp.2420010202

[84] Hamish Tennent, Solace Shen, and Malte Jung. 2019. Micbot: a peripheral robotic object to shape conversational dynamics and team performance. In *2019 14th*

ACM/IEEE International Conference on Human-Robot Interaction (HRI). IEEE, 133–142.

[85] K. Wada, T. Shibata, T. Saito, and K. Tanie. 2003. Effects of Robot Assisted Activity to Elderly People Who Stay at a Health Service Facility for the Aged. In *Proceedings 2003 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS 2003) (Cat. No.03CH37453)*, Vol. 3. 2847–2852 vol.3. doi:10.1109/IROS.2003.1249302

[86] Xingmin Wang. 2016. Subjective well-being associated with size of social network and social support of elderly. *Journal of Health Psychology* 21, 6 (2016), 1037–1042. doi:10.1177/1359105314544136 PMID: 25104778.

[87] Katie Winkle, Donald McMillan, Maria Arnelid, Katherine Harrison, Madeline Balaam, Ericka Johnson, and Iolanda Leite. 2023. Feminist Human-Robot Interaction: Disentangling Power, Principles and Practice for Better, More Ethical HRI. In *Proceedings of the 2023 ACM/IEEE International Conference on Human-Robot Interaction (HRI '23)*. Association for Computing Machinery, New York, NY, USA, 72–82. doi:10.1145/3568162.3576973

[88] David Wood, Jerome S. Bruner, and Gail Ross. 1976. The Role of Tutoring in Problem Solving. *Journal of Child Psychology and Psychiatry* 17, 2 (1976), 89–100. doi:10.1111/j.1469-7610.1976.tb00381.x

Received 2025-09-30; accepted 2025-12-01