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Seriously, What Did One Robot Say to the Other? Being Left out From Communication by Robots Causes Feelings of Social Exclusion

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Abstract

While humans actually need some overt communication channel to transmit information, be it verbally or nonverbally, robots could use their network connection to transmit information quickly to other robots. This raises the question how this covert robot-robot communication is perceived by humans. The current study investigates how transparency about communication happening between two robots affects humans' trust in and perception of these robots as well as their feeling of being included/excluded in the interaction. Three different robot-robot communication styles were analyzed: silent, robotic language, and natural language. Results show that when robots transmit information in a robotic language (beep sounds) this leads to lower trust and more feelings of social exclusion than in the silent (i.e., covert) or natural language conditions. Results support the notion that humans are over-sensitive to signs of ostracism which seems to be detected in this style of overt but nonhuman robot-robot communication.

Keywords: robot-robot interaction, social exclusion, ostracism, trust

Introduction

With robots on the move to enter our work-related lives, human-robot interactions that involve multiple communicating robots could soon be a relevant and common situation. When looking into human-robot interaction, especially robots and humans interacting

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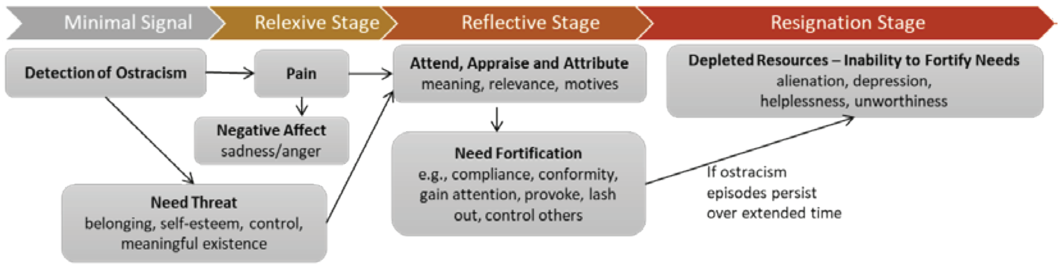
in groups—most research so far concentrated on how group dynamics unfold in human-robot mixed groups and how robots can intervene in a positive way for instance to moderate conflicts between the humans or to include all group members. For instance, robots were successfully used to positively intervene and moderate working team conflicts (Martelaro et al., 2015) as well as conflicts between children (Shen et al., 2018). Moreover, robots can shape conversational dynamics for equal consideration of all group members' contributions during a discussion (Tennent et al., 2019). This need to positively intervene or moderate already exemplifies that sometimes individuals might experience conflicts in HRI groups, that they might feel largely ignored or excluded by other group members—potentially also robot group members as has recently been discussed by Rosenthal-von der Pütten and Abrams (2020). Consequently, the question arises how robots should communicate with each other, not only when humans interact with them directly, but also in the presence of observing humans who might be affected by the robots' behavior. While humans need some overt communication channel to transmit information, be it verbally or nonverbally, robots could use their network connection to transmit information quickly to other robots. This raises the question how this *covert* robot-robot communication is perceived by humans and especially whether humans feel excluded when robots use non-humanlike communication styles.

Theoretical Background

Humans have a fundamental need to belong; thus, having and maintaining good and long-lasting relationships with others is central to humans (Baumeister & Leary, 1995). Social exclusion threatens these crucial relationships with severe consequences for the affected individuals. Social exclusion is defined "as events and situations that signal a lack of social connections with others" and thus includes ostracism, devaluation, and social rejection (cf. Kawamoto et al., 2015, p. 1). People who experienced social exclusion show a variety of negative tendencies as they become aggressive, defensive, and self-defeating (e.g., make less rational, healthy choices; Twenge & Baumeister, 2004), uncooperative and unhelpful (e.g., help experimenter less after a mishap; Twenge et al., 2007), perform worse on tasks such as intellectual tests (Twenge & Baumeister, 2004), and show decreased self-regulation (e.g., give up early when confronted with a frustrating task; Baumeister et al., 2005). Social exclusion has also been shown to be related to decreased mental health (Nolan et al., 2003) and reduced survival rates (Holt-Lunstad et al., 2010). Individuals can experience interpersonal or intergroup social exclusion, the former targeting them as individuals and the latter as members of some outgroup. When experiencing social exclusion, individuals undergo several intra- and interpersonal processes. According to Williams' Temporal-Need-Threat-Model (Williams, 2009, cf. Figure 1), social exclusion causes a reflexive social pain response (activating similar brain regions as physical pain, cf. Eisenberger & Lieberman, 2004; Eisenberger et al., 2003) accompanied with negative affect (e.g., sadness, anger) and triggers threats to four fundamental needs: belonging, self-esteem, control over one's social environment, and meaningful existence. In a reflective stage, individuals' attention is directed to the social exclusion episode, and they reflect on its meaning and relevance. This may lead to coping responses such as compliance and conformity (to regain belongingness/self-esteem) or attracting attention, provoking, and attempts of controlling others (control/recognition)

FIGURE 1 Temporal-Need-Threat Model by Williams, 2009



to fortify the threatened needs. Persistent exposure to social exclusion over time consumes the resources necessary to motivate the individual to fortify threatened needs. Eventually, this leads to resignation, alienation, helplessness, and depression.

Humans tend to over-detect social exclusion. Empirical studies have shown that rational or logical characteristics of the social exclusion episode do not appear to moderate the detection of it. For instance, people felt ostracized when the source of ostracism were algorithms (Zadro et al., 2004). This hypersensitivity to social exclusion has its reason: the cost of perceiving social exclusion when it is not actually occurring (false alarm) is lower than the cost of a miss (not detecting that exclusion is happening). Thus, humans are extremely likely to detect social exclusion also in interactions with (especially anthropomorphized) artificial agents and experience and engage in the described reflexive and reflective processes. Indeed, first studies have shown that humans react sensitively to social rejection and social exclusion by robots. After playing a game of *Connect 4*, participants were informed by a humanoid robot that it would not like to see them again. Participants reported significantly reduced self-esteem relative to receiving no feedback or social acceptance (robot would like to see them again; Nash et al., 2018). Intentions for future use were not affected. Erel and colleagues (2021) implemented a robotic Cyberball game where participants played with two nonhumanoid robots. The robots either included (33% of ball tosses with three players), over-included (75% of tosses), or excluded (10% of tosses) the human player. Excluded participants reported lowered mood and experienced ostracism expressed via threatened needs, including control, belonging, and meaningful existence. In post-interaction interviews, many reported to feel "rejected," "ignored," and "meaningless." Fraune and Šabanović (2014) explored whether humans feel excluded when robots were exchanging information using beep sounds instead of natural language while participants were waiting for the experimenter of an unrelated study. Participants did not report differences in feeling excluded. However, participants might not have experienced the robots to be related to them in any way, thus, not experiencing a situation of social exclusion. This might be different if it were clear from the situational context that the two robots were communicating about the human(s) in the room.

Similar to findings in HHI, research in HRI and HMC has shown that social attributes such as perceived warmth, competence, or trustworthiness positively affect evaluations of and interactions with robots as well as usage intentions (Carpinella et al., 2017; A. Edwards et al., 2020; C. Edwards et al., 2021; Schaefer et al., 2012). A robot's ability to send social cues via its appearance, functionality, or behavior was identified as a crucial factor impacting this social perception (Duffy, 2003; Hegel, 2012; Schaefer et al., 2012).

Moreover, the communication style of AI systems has been found influential. For instance, in higher education courses in natural and social science students were more willing to accept an AI instructor-based education when the AI instructor is relational rather than functional in its communication style (Kim et al., 2020). How messages are formulated by robots are also important for the robot's evaluation regarding social attributes (e.g., A. Edwards et al., 2020). Since communication between robots in nonhuman language offers less opportunity to send clear social cues or to convey a communication style, such communication situations could lead not only to feelings of social exclusion, but also to decreased evaluations of the robots' social attributes.

In order to explore the socio-psychological effects of different styles of robot-robot communication, we created a scenario in which participants observed two robots interact and exchange information about a human. The robots were responsible for running an assessment center session of a human applicant during her application process, which participants could see in videos included in our online study. Communication styles varied in transparency (i.e., the amount of information provided about the content of the robots' conversation and thereby about how they function, behave, and reach decisions). The robots were either communicating covertly via their wireless network directly transmitting information from one robot to the other without making any sounds, or they communicated overtly, either in natural language or using a robotic language (beeps and clicks).

As argued above, we assume that communication in natural language offers more opportunity to send social cues (and for the user to perceive social cues) potentially positively influencing its social perception (Duffy, 2003; Hegel, 2012; Schaefer et al., 2012). Robots communicating silently or in robotic language, however, provide less or unfamiliar social cues assumingly leading to less favorable social perception. Moreover, the content of the robot-robot communication is not understandable in the silent and robotic language condition, potentially leading to lower trust in these conditions. Thus, we hypothesize:

> **H1:** Participants will trust the robots more (H1a) and perceive them as warmer (H1b), more competent (H1c), and less discomforting (H1d) in the natural language condition compared to the robotic language condition and silent condition.

Prior research provides evidence that humans experience social exclusion episodes when a robot directly rejected them (Nash et al., 2018) or when they were being left out of a game with two robotic players (Erel et al., 2021). Since our participants in the silent and robotic language conditions are not able to follow the robots' conversation they presumably will feel socially excluded. Hence, we hypothesize:

> **H2:** Participants will experience higher social exclusion when observing the robots on the robotic language condition (H2a) and silent condition (H2b) compared to the natural language condition.

Moreover, we want to explore whether the type of nonhumanlike robot-robot communication has an influence on humans' perception of the robots, their (dis)trust, and their feeling of social exclusion. We thus ask:

RQ1: Are human observers affected differently by a covert (silent) and a non-understandable overt (robotic language, e.g., beep sounds) communication style?

Method

Experimental Design

The present study is an online study consisting of an instruction followed by three short videos showing a human-robot interaction scenario in an assessment center (cf. procedure). The study followed a 3×1 between-subject design, with *transparency of robot-to-robot communication* as independent variable, operationalized through three different communication styles used by the two robots in the second video presented during the study. The following three conditions were compared:

Silent Communication. The robots exchange information covertly via their network. They do not explicitly acknowledge that information had been shared between them since they merely stand in front of each other without moving. In this condition, no overt interaction or communication is used.

Communication in Robotic Language. The robots overtly exchange information using a robot-like language which consists of nonlinguistic, stereotypical robot sounds, such as beeps and clicks. Additionally, the robots used human-like gestures and take turns in the nonlinguistic utterances emphasizing the impression of a conversation.

Communication in Natural Language. The robots overtly exchanged information using natural human language allowing the participants to understand everything they are saying. The robots update each other on the application process, transfer information about the applicants' performance, and point out what the following step in the procedure will be. While speaking with each other, the robots applied the same timing of turn-taking, conversation proportions, and human-like gestures as in the Robotic Language condition (cf. https://osf.io/hjm2t/ for transcript of utterances and the full videos as well as for the anonymized data set).

Stimulus Material

For the videos we used two humanoid robots from Aldebaran. While Pepper greets and guides applicants as well as discusses test results, Nao is responsible for conducting tests. Pepper is approximately 120 cm high and mobile in our setting (cf. Figure 2, picture on the right) while Nao is considerably smaller and placed stationary on a table next to the applicant (cf. Figure 2, picture on the left).

Procedure

Participants were randomly distributed to one of the three conditions. On the first page of the survey, participants were informed about the upcoming task, data protection, and their right to withdraw from the study at any time. They verified that they were above 18 years and gave informed consent by clicking on the start button. Participants first provided demographic data (gender, age, occupation) and were asked to describe pre-experiences with robots if applicable. Next, participants were asked about their negative attitudes toward robots (Negative Attitudes toward Robots Scale, Nomura et al., 2006) and their affinity for technology (Affinity for Technology Interaction Scale, Franke et al., 2019; cf. section measures).

Afterward, instructions explained the scenario the participants would take part in. To help put themselves in the position of the situation and identify with the role of the applicant in the video, they were informed about the German software development company GDQ-Technologies where they applied for an open position in the management of the development department. GDQ-Technologies invited them to an interview and an Assessment-Centre, which would be performed by two robots. The full instruction was:

> Please put yourself in the shoes of an applicant who is interested in an open position in a large German high-tech company called GDQ-Technologies. This is an important position in the management of the software development department.
>
> Your tasks as part of the management team would be:
>
> - Cooperation with software developers
> - Management of the development process
> - Coordination of the quality inspection of new software
>
> You applied with your résumé and were then invited to the GDQ-Technologies assessment center for an interview and to test your suitability. When you get there, a robot greets you, introduces itself by the name "Pepper," and explains that it will guide you through the entire application process. He will then accompany you to an office where you will be interviewed, and a few aptitude tests will be carried out.
>
> After you have been told that you did this well, Pepper leads you to another room where you should take another psychological test. Because of its abilities, it is part of the job of a second robot called "Nao" to conduct the test with you.

Participants were informed that they would now see one part of the assessment center in three videos. First, they would see a video (the same video in all conditions) of the Nao robot performing a psychological attention and stress test with the applicant. After that, participants read a short instruction that Pepper re-entered the room to pick up the applicant for the rest of the application process. Afterward, participants experienced one of the three experimental videos observing the two robots communicate silently, in robotic language, or natural language, depending on the condition they were assigned to. Following this, written explanations informed participants that they would receive some personal feedback about their performance, which could be seen in the third video which was the same for all conditions (cf. Figure 2).

Immediately following this last video, participants completed questionnaires assessing their perception of the robots (trust, competence, warmth, and discomfort) and whether they experienced social exclusion during the communication between the two robots.

FIGURE 2 Manipulation Was Included in the Second Video in Which the Robots Communicated Silently (Covertly via Their Network), in Robotic Language (Overtly Using Beeps and Clicks) or in Natural Language (Overtly Using Natural Language and Gestures).

At the end of the survey, the manipulation check was performed, and participants could respond to open-ended questions regarding the interaction (cf. section measures). Finally, participants were debriefed.

Measures

Dependent Variables

Trust. Participants' trust in the robots was measured using the Trust in Automated Systems Survey by Jian et al. (2000). This scale is unique in that it measures both trust and distrust as polar opposites along a single dimension rather than simple unidimensional trust as, for instance, it is the case in the Trust Perception Scale HRI (Schaefer, 2016). Moreover, the latter scale is regarded as less adequate since it also includes items that are measuring social perceptions regarding competence and warmth, thereby potentially mixing too many concepts into one (very long) scale. The Trust in Automated Systems Survey, however, is short and delivers separate values for the trust and distrust dimensions. The items sampling distrust, for instance, measure the perception of the automation's deceptive nature or the likelihood of harmful outcomes if it is used (for a discussion of trust measurements see also Kohn et al., 2021). The 12 items were slightly adapted exchanging the "system" with "robots" and were rated on a 7-point Likert scale from "strongly agree" to "strongly disagree" (e.g., "The robots are deceptive," Distrust Cronbach's alpha = .778; M = 3.10, SD = 0.138; Trust Cronbach's alpha = .805; M = 4.05, SD = 0.62).

ROSAS. We captured participants' views on the robots' social properties for each robot individually using the 18-item Robotic Social Attributes Scale (RoSAS) by Carpinella et al. (2017). For each robot, participants were asked to complete the full inventory with the three sub-scales warmth (items: feeling, happy, organic, compassionate, social, emotional; Pepper Cronbach's alpha = .862, M = 3.15, SD = 1.50; Nao Cronbach's alpha = .901, M = 3.11, SD =1 .62), competence (items: knowledgeable, interactive, responsive, capable, competent, reliable; Pepper Cronbach's alpha = .873, M = 5.62, SD = 1.63; Nao Cronbach's alpha = .885, M = 5.61, SD = 1.67), and discomfort (items: awkward, scary, strange, awful, dangerous, aggressive; Pepper Cronbach's alpha = .776, M = 3.14, SD = 1.48; Nao Cronbach's alpha = .856, M = 2.87, SD = 1.72). Participants responded on a 9-point Likert scale ranging from "definitely not associated" to "definitely associated."

Social Exclusion. In order to capture whether participants felt socially excluded during the conversation between the robots, we created five ad-hoc items rated on a 5-point Likert scale (Cronbach's alpha = .842, *M* = 2.73, *SD* = 1.15; items: While the two robots were interacting . . . " . . . I felt uncomfortable," " . . . I felt nervous," " . . . I had the feeling that the robots were talking about me," " . . . I felt excluded," " . . . I felt that the robots don't want me to know what they are talking about").

Moderating Variables

Previous HRI research has shown that negative attitudes toward robots might have a moderating effect on interaction with and perception of robots (Nomura et al., 2006; Sanders et al., 2017). Moreover, Franke et al. (2019) argue that affinity for technology is a key personal resource for successful interaction with technology. It might, therefore, affect how participants engage in and perceive the interaction with robot technology. Consequently, we assume affinity for technology and negative attitudes toward robots may have impacts on trust in robots and social perception.

Negative Attitudes Toward Robots. To measure participants' general negative attitudes toward robots, we employed the Negative Attitudes toward Robots Scale (NARS) created by Nomura et al. (2006). The 14 items on the three subscales were rated on a 5-point Likert scale ranging from "I do not agree at all" to "I completely agree" (S1—Negative attitude toward situations of interaction with robots, six items, Cronbach's alpha = .741, *M* = 2.15, *SD* = 0.73; S2—Negative attitude toward social influence of robots, five items, Cronbach's alpha = .681, *M* = 3.00, *SD* = 0.78; S3—Negative attitude toward emotions in interaction with robots, three items, Cronbach's alpha = .612, *M* = 3.39, *SD* = 0.85).

Affinity for Technology. We captured participants' general affinity for technology using the Affinity for Technology Interaction Scale (ATI) from Franke et al. (2019) consisting of nine items which are measured using a 6-point Likert scale from "completely disagree" to "completely agree" (e.g., "I like testing the functions of new technical systems"; Cronbach's alpha = .947, *M* = 3.69, *SD* = 1.23).

Open-Ended Questions and Manipulation Check. For data cleansing purposes we included two test statements to verify that participants' answers matched the conditions they were assigned to asking (i) "Could you hear that the robots were communicating with each other in the second video?" (yes/no) and (ii) "Did you understand what the robots were talking about in the second video?" Following the manipulation check participants had to answer open-ended questions asking whether and if yes, which kind of information was exchanged between the robots. Answers were checked for plausibility. Twenty-one participants gave a deviant answer from their assigned condition (e.g., stating that they could understand what the robots were saying although in the "silent" condition). However, their answers to open-ended questions proved they misinterpreted the question (i.e., thinking it referred to the robots talking in general in the three videos). Hence their data remained in the data set.

Participants

The study was advertised among university students and via social networking sites such as Facebook and Instagram. In total, 183 volunteers took part. The data cleansing procedure yielded 176 participants (71 male, 103 female, 2 diverse) with a mean age of 34.7 (*SD*

TABLE 1 Distribution of Participants Across Conditions

	Silent	Robotic	Natural	Total
Male	23	19	29	71
Female	33	38	32	103
Diverse	0	0	2	2
Total	**56**	**57**	**63**	**176**

= 13.49; range = 18–72 years, based on 176 participants). Seventy-two were employed, 20 self-employed, 73 students, 1 retired, 4 university lecturers, 2 people in an apprenticeship, 2 were stay-at-home parents. Table 1 shows the distribution of participants across conditions.

Results

Testing Assumptions for ANOVA and ANCOVA

All dependent variables were tested for homogeneity of variance. Levene's tests were not significant except for the Trust subscale. Kolmogorov-Smirnov tests indicated for all dependent variables that data was not normally distributed (see Appendix for values of skew and kurtosis). Since visual inspection showed that the skewness was equal between groups for Trust and Distrust, Competence (Nao & Pepper), and Discomfort (Nao & Pepper) this violation of normality can be ignored for these variables (cf. Field & Wilcox, 2017). However, Warmth (Nao & Pepper) as well as Social Exclusion shows different skewness between conditions. As a result, we will perform Kruskal-Wallis tests instead of ANOVAS when assumptions are not met. For the planned ANCOVAS, the assumption of homogeneity of regression slopes was violated for Discomfort (Pepper) for the ATI score, for Competence (Nao) for NARS-S1, and for most dependent variables except Discomfort (Nao & Pepper) and Social Exclusion for NARS-S2. Homogeneity of regression slopes was given for all dependent variables for NARS-S3. The covariates are independent of the manipulation effect, meaning there is no interaction between the covariates (ATI, NARS-S1, NARS-S2, NARS-S3) and the independent variable.

(Dis)Trust

To test whether participants trusted the robots more in the natural language condition compared to the robotic language condition and silent condition (H1a), we calculated a Kruskal-Wallis tests. There was a significant effect of communication style on trust, $H(2) = 7.05$, $p = .029$. Post-hoc tests (all Bonferroni corrected) revealed that the robotic language significantly elicited lower trust than the natural language ($U = 1312$, $p = .011$, $r = -.23$), while there were no significant differences between natural language and silent ($U = 1514$, $p = .183$, $r = -.12$) and no difference between silent and robotic language or robotic ($U = 1335$, $p = .134$, $r = -.14$).

The same analysis was performed with the subscale distrust. There was a significant effect of communication style on distrust, $H(2) = 11.34$, $p = .003$. Post-hoc tests (all

Bonferroni corrected) revealed that the robotic language significantly elicited higher distrust than the natural language ($U = 1163$, $p < .001$, $r = -.31$), while there were no significant differences between natural language and silent ($U = 1506$, $p = .169$, $r = -.15$) and no difference between silent and robotic language or robotic ($U = 1255$, $p = .050$, $r = -.18$).

Robot Perception

To test whether participants evaluated the robots as warmer (H1b), more competent (H1c), and less discomforting (H1d) in the natural language condition compared to the robotic language condition and silent condition, we calculated Kruskal-Wallis tests for warmth (Nao & Pepper) and ANCOVAs for competence and discomfort (Nao & Pepper). There were no significant effects for warmth, competence, and discomfort. However, for both Nao and Pepper, we found the tendency that participants perceived them as more discomforting in the robotic language condition (cf. Table 2 for descriptives); Pepper, $F(2,174) = 2.662$, $p = .073$, ${}_p\eta^2 = .030$; Nao, $F(1,174) = 2.926$, $p = .056$, ${}_p\eta^2 = .033$. Post-hoc tests (all Bonferroni corrected) were not significant. From the covariates, the subscale "S1—Negative attitude toward situations of interaction with robots" was significantly related to discomfort for Pepper, $F(1,175) = 10.899$, $p = .001$, and to discomfort for Nao, $F(1, 175) = 14.903$, $p < .001$.

Social Exclusion

To test whether participants experience higher social exclusion when observing the robots on the robotic language condition (H2a) and silent condition (H2b) compared to the natural language condition, we calculated a Kruskal-Wallis tests. There was a significant effect

TABLE 2 Mean Values and Standard Deviations for Dependent Variables Across Conditions

	Silent	Robotic	Natural	Total
	M (SD)	*M (SD)*	*M (SD)*	*M (SD)*
Trust*	4.31 (1.10)	4.07 (.99)	4.54 (1.33)	4.31 (1.17)
Distrust*	3.06 (1.10)	3.47 (1.09)	2.80 (1.07)	3.10 (1.11)
Social Exclusion*	2.16 (0.92)	3.81 (0.84)	2.24 (0.85)	2.73 (1.15)
Perception of Pepper				
Warmth	3.16 (1.40)	2.96 (1.33)	3.32 (1.73)	3.15 (1.50)
Competence	5.66 (1.64)	5.53 (1.52)	5.66 (1.74)	5.62 (1.63)
Discomfort	3.05 (1.40)	3.44 (1.67)	2.94 (1.35)	3.14 (1.48)
Perception of Nao				
Warmth	3.22 (1.60)	2.84 (1.48)	3.28 (1.76)	3.11 (1.62)
Competence	5.66 (1.64)	5.53 (1.52)	5.66 (1.74)	5.62 (1.63)
Discomfort	2.76 (1.69)	3.25 (2.00)	2.62 (1.41)	2.87 (1.72)
Note: significant effects are marked with *				

of communication style on social exclusion, $H(2) = 71.11$, $p < .001$. Post-hoc test (all Bonferroni corrected) revealed that the robotic language significantly differed from the natural language ($U = 366.5$, $p < .001$, $r = -.68$), and the silent condition ($U = 359$, $p < .001$, $r = -.66$), while there were no significant differences between natural language and silent ($U = 1546$, $p = .313$, $r = -.09$).

Analysis of Answers to Open-Ended Questions

Our open-ended questions included whether people were aware that information had been exchanged between the robots. In all three conditions, most participants were aware that information had been exchanged between robots though we see a clear difference between conditions (natural language: 90%; robotic language: 80%; silent: 54%). In the natural language condition, participants mostly repeated what they overheard in the video, that the two robots were talking about the procedure of the assessment center and that the applicant in the video just completed a specific test. In the silent condition, about half of the people were not sure whether information has been submitted and if such information was submitted, they assumed it would be test results, not details about the procedure of the assessment center. In the robotic language condition 80% of those who thought information was shared stated it would be test results. In the silent condition, this was the case for 70% of participants who previously stated that information has been shared.

Discussion

The presented study investigated how different styles of robot-robot communication are perceived by humans. In contrast to humans, robots have the ability to silently exchange information via wireless networks. Do humans feel left out and trust robots less when they recognize that information about them has been exchanged via unobservable channels of communication? To explore the socio-psychological effects of different styles of robot-to-robot communication, participants in our online study watched videos observing two robots that interact and exchange information (prior and upcoming parts of assessment center and information a test has been completed) about a human who completed tests in an assessment center session. The robots were either communicating covertly via their wireless network directly transmitting information from one robot to the other without making any sounds, or they communicated overtly, either in natural language or using a robotic language (beeps and clicks).

Effect of Robot-Robot Communication Style on Social Perception and Trust

We assumed that when robots communicate in natural language, they send more social cues which potentially leads to a more favorable social perception by the human observers (Duffy, 2003; Hegel, 2012; Schaefer et al., 2012) in contrast to situations in which the content of their information exchange is not understandable for humans as is the case in the silent or robotic language conditions. More precisely, we hypothesized that participants would trust the robots more (H1a) and perceive them as warmer (H1b), more competent (H1c), and less discomforting (H1d) in the natural language condition compared to the robotic language condition and silent condition. Our results only partly supported our hypotheses. While robots communicating in beeps and clicks were trusted less compared to the natural language condition (lower trust and higher distrust), trust was not significantly different for the silently communicating robots. This effect is not due to a wrong assessment of the situation on the participants' side. Most participants stated in open-ended check questions that they were aware that information has been transmitted—also in the silent condition with still 54% stating some information has been transmitted. Rather it seems that if participants cannot hear and/or understand what is being said, they largely assumed that test performance information (i.e., the applicant in the video) was exchanged instead of information on the procedure of the assessment center. Evaluations of the robots regarding warmth and competence were not affected by their communication style; however, we found a descriptive (not significant) tendency that robots communicating in robotic language were perceived as more discomforting. This is interesting since several participants stated in the open-ended interviews that the silence in the silent condition was awkward and discomforting. However, observing communication and not being able to understand it was obviously more unsettling as the results regarding feelings of social exclusion show.

Effect of Robot-Robot Communication Style on Feelings of Social Exclusion

Based on previous studies by Erel et al. (2021) and Nash et al. (2018) we assumed that also in interactions with robots, the human hypersensitivity to ostracism cues (Zadro et al., 2004) will result in experiencing a social exclusion episode in the silent and robotic language condition. While previous studies worked with directly formulated rejection by the robot (Nash et al., 2018) or excluding participants in a Cyberball game (Erel et al., 2021), we created a scenario where participants were left out of the robot-robot communication. In line with our hypothesis, we found a strong significant effect for social exclusion. Participants experienced higher social exclusion when observing the robots on the robotic language condition compared to the natural language condition (H2a) and unexpectedly also in comparison to the silent condition. Again, no difference was found between the natural language condition and the silent condition (H2b). Hence, we can constitute that in our study human observers were indeed affected differently by a covert (silent) and a non-understandable overt (robotic language) communication style. It seems that the usage of beep sounds for communication is a strong trigger for ostracism detection, while obviously transmitting information silently is not. However, this effect might also be context dependent. In the context of our study, three participants in the robotic language condition stated that wireless communication might be quicker and easier in the assessment center scenario and would save the applicant time, so why bother with clicks and beeps. But it is conceivable that in less formal situations like being at a friend's house who coincidentally has two robots at home chatting with you, obvious silent communication between the robots might also trigger ostracism detection. Our interpretation of the found social exclusion effect is that the non-understandable robotic language hurts more, because it is perceived as doing this for the reason of social exclusion rather than for robotic efficiency in processing information. The comments in the open-ended questions (what did you like or dislike about the interaction in the video?) seem to support this. Several participants mentioned in the robotic language condition that they experienced a feeling of social exclusion: "Dislike: feeling of being excluded," "I didn't like that they obviously communicated about me, but I didn't understand what." Others wondered "why they did not use a language I can understand," or explicitly stated they disliked "robots beeping when interacting with each other instead of human speech." One participant directly contrasted the silent and robotic communication style: "Dislike: exchange between the robots, which in my opinion should have happened either silently or in a language in which I, as an applicant, could understand what was being said." Indeed, as mentioned before three participants mentioned that a silent communication would be more efficient. To our surprise the robot-robot communication style did not influence perceptions of warmth which might be expected given that participants felt excluded. But generally, warmth ratings were rather low and had high standard variations. This could also be due to the setting of the situation and the social roles of the robots (Oliveira et al., 2019). Both robots acted as formal unknown interviewers in an assessment center and not as peers, friends, or colleagues. This professional social distance could explain the generally low ratings in warmth and might also explain the similar warmth ratings between communication styles. Unfortunately, we cannot relate these findings to previous social exclusion studies directly because those studies did not measure how the robots were perceived regarding warmth, competence, and discomfort. However, the direct rejection that participants experienced in Nash et al.'s study (2018) lowered self-esteem (i.e., participants showed need threat). But their rejection did not affect their willingness for future interaction.

Limitations and Future Directions

In contrast to previous studies on social exclusion in HRI, our study did not involve direct interaction with a physically present robot, but participants had to self-project themselves into what was displayed in the videos. While this constitutes a limitation of our study, we still found a quite strong effect on feelings of social exclusion. Interestingly, some participants seemed to self-project very strongly answering in the open-ended questions with self-referring statements such as "they talked about my test results" or "they talked about where I go next." Potentially, effects in live interactions will be even stronger. Some participants mentioned that the scenario itself, an assessment center, is not an area for which they regard robots as useful, since applicants might feel strange and disconnected. While this does not necessarily limit the study results, it is relevant for future studies, rendering how important it is to create realistic and meaningful future applications also in our experimental studies. We observed that our manipulation check questions were in part misinterpreted by study participants although they explicitly referred to the second, manipulated, video. Some participants seemed to consider all three videos when answering these questions ("Could you hear that the robots were communicating with each other in the second video?"; " Did you understand what the robots were talking about in the second video?"). This became apparent when checking their answers to the three open-ended questions. For instance, one participant in the silent condition answered both questions with yes but described how awkward it was to observe the two silent robots in the second video. Hence, only the combination of the closed and open questions was reliable checking for successful manipulation. Moreover, as mentioned previously, the trust and social exclusion effects might be context-dependent and thus generalization to situations in different social settings should be addressed in future research.

Social exclusion is very likely to happen in HRI, because robots have components known to be biased (Howard & Borenstein, 2017; Righetti et al., 2019). For instance, face recognition is better for White people than for people of color and natural language recognition is better for male than female language users, not to speak of variations in language such as regional or foreign accents, or colloquial language or jargon. Moreover, Rosenthal-von der Pütten and Abrams (2020) discussed that users "might have more or less time or might be more or less motivated to provide these interactions [with robots] that are needed for [machine] learning" (pp. 400–401). Meaning that if a robot interacts with multiple users, it might perform better in user modelling for some users (which provided much training data) and worse for others (with less training data) resulting in different subsequent interactions which could easily be perceived as biased or excluding. Zou and Schiebinger (2018) emphasized the pressing need to make AI and thus also robots fairer by identifying biases and implementing strategies to diminish bias. In this vein, Rosenthal-von der Pütten and Abrams discussed how robots might analyze participant behavior to detect if a social exclusion episode has happened and enable them to engage in repair mechanisms. In consequence, investigating when, in which scenarios, and how people are experiencing social exclusion in HRI and how they are reacting within and after exclusion episodes is not only interesting regarding generalizability of results, it can inform future developments in explainable robot behavior, positively shaping social dynamics in human-robot group situations.

Conclusion

Our video-based online study explored how different styles of robot-robot communication are perceived by humans comparing humanlike communication via natural language to silent communication via wireless connection and communication in a robotic language based on beeps and clicks. The study results suggest that when robots transmit information in a robotic language this leads to lower trust and more feelings of social exclusion than in the silent or natural language conditions. Like previous laboratory work in which participants were either directly verbally rejected or excluded from a variation of the cyberball game, our participants were very sensitive too to signs of ostracism which seems to be detected in this style of overt but nonhuman robot-robot communication. Completely leaving out humans from a communication loop (silently transmitting information), however, did not negatively impact observers. These quantitative results are reflected in participants' comments showing that participants were overall aware that information had been shared between the robots but had different assumptions of what kind of information had been shared and why this was done covertly (i.e., participants in the robotic language condition disliked to be the topic of a secret conversation between the robots and felt being left out). Given the very specific social setting and the connected social roles, two robots working in an assessment center, we assume that social exclusion effects might also occur for silently communicating robots in less professional contexts. Hence, future research is needed to explore social exclusion across different situational contexts.

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