Research Article

Emotional reactions to robot colleagues in a role-playing experiment

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ARTICLE INFO

ABSTRACT

We investigated how people react emotionally to working with robots in three scenario-based role-playing survey experiments collected in 2019 and 2020 from the United States (Study 1: $N = 1003$; Study 2: $N = 969$, Study 3: $N = 1059$). Participants were randomly assigned to groups and asked to write a short post about a scenario in which we manipulated the number of robot teammates or the size of the social group (work team vs. organization). Emotional content of the corpora was measured using six sentiment analysis tools, and socio-demographic and other factors were assessed through survey questions and LIWC lexicons and further analyzed in Study 4. The results showed that people are less enthusiastic about working with robots than with humans. Our findings suggest these more negative reactions stem from feelings of oddity in an unusual situation and the lack of social interaction.

1. Introduction

People have been using automation and working with robots in industry fields such as manufacturing for many years. Researchers suggest that the exceptional situation caused by COVID-19 and social distancing guidelines will further increase the use of advanced information systems, such as robots, at work (Coombs, 2020; He, Zhang, & Li, 2021). Due to the development of more interactive, collaborative, and social robots, people are more likely to be in situations in which they must work and interact with robots as coworkers or teammates (Dwivedi et al., 2021; Haidegger et al., 2013; Mörtl et al., 2012). As a result, new-generation robots will create new social and psychological challenges that could impact work life profoundly.

There is a sufficient body of evidence confirming that social psychological processes such as attitudes and trust are essential factors in successful collaboration with robots and ultimately accepting them in everyday life (Hancock et al., 2011; Schaefer, Straub, Chen, Putney, & Evans, 2017; Sheridan, 2016; Yusif, Soar, & Hafeez-Baig, 2016). In addition to these extensively researched factors, robotization is likely to arouse both positive and negative emotional reactions in human workers. Introducing advanced technology such as social robots as co-workers in the same organization or work team presents human workers with a new situation. Adapting to this could be more challenging to some

workers than others, causing negative attitudes and emotions that could have an unwanted effect on emotional well-being.

In addition to examining acceptance of robots through attitudes and trust, researchers have investigated emotional attachment to companion robots (Friedman, Kahn, & Hagman, 2003); emotional reactions to ill-treatment of robots (Rosenthal-von der Pütten, Krämer, Hoffmann, Sobieraj, & Eimler, 2013); and the connection between negative emotions, such as anxiety, and negative attitudes (Nomura, Kanda, & Suzuki, 2006). Even though working closely with robots has been argued to arouse negative attitudinal and emotional reactions in human workers (Groom & Nass, 2007), we do not currently know how people would respond emotionally to working with robots on the same work team or in the workplace community with robots.

In addition to explicit methods of measuring attitudes and emotions, such as surveys, emotional and attitudinal reactions toward robot co-workers can be investigated through more implicit means such as examining textual data collected from role-playing scenarios. Computer-aided analysis methods have generated the massive new field of affective computing, which offers fast and quantitative means of analyzing large amounts of text with the help of emotional lexicons (Piryani, Madhavi, & Singh, 2017).

Our study was designed to fill the research gap through analysis of textual data collected from three role-playing experiments that involved

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introduction of robots as work team members or as coworkers within a workplace. We focused on emotional reactions to the hypothetical situations, as identified via sentiment analysis, in three studies and further investigated the associated factors in a fourth study. Computational social scientific analysis methods combined with an experimental design and online role-playing data collection method generated a unique multi-methodological approach that has not previously been utilized to investigate the acceptance of robots.

2. Literature review

The concept of emotion has a long and complex history in philosophy and psychology, and it has traditionally been used as a metaconcept that combines different words describing feelings and attitudes (Dixon, 2012). One empirical study considered emotion as an intense mental state with hedonic content (Cabanac, 2002). There is no consensus on the definition, process, or hierarchical levels of emotion among multiple emotion theories, but most support some form of connection between emotion and cognitive appraisal (Barnard & Teasdale, 1991; Moors, 2009).

Theories of attitudes often include both cognitive and emotional perspectives, and this is specifically manifested in a multicomponent model of attitude (Zanna & Rempel, 2008). In the context of technology, researchers have investigated possible connections between cognitive and emotional constructs in the framework of the technology acceptance model (TAM) and its extensions (Kulviwat, Bruner, Kumar, Nasco, & Clark, 2007; Lee, Xiong, & Hu, 2012; Saadé & Kira, 2006; Venkatesh, 2000). For example, in a model called consumer acceptance of technology, affective and cognitive attitude dimensions explain the behavioral attitude toward adoption, which then predicts adoption intention (Kulviwat et al., 2007). According to a literature review about the history of TAM (Marangunić & Granić, 2015), further integration of emotions into TAM is still needed.

In research focused on the advanced technology of robots specifically, attitudes and emotions have often overlapped, especially in research measuring and focusing on negative emotions, such as anxiety, and negative attitudes (Nomura et al., 2006). TAM and its extensions have also been used in research on human–robot interaction and user studies, but some researchers have stressed caution when applying it to interactive technology such as robots (Young, Hawkins, Sharlin, & Igarashi, 2009). For this reason and because this research area is an emerging field, the tools used to measure different social and psychological constructs have varied. Because emotion is linked to attitudes and behavior (Gursoy, Chi, Lu, & Nunkoo, 2019; Kulviwat et al., 2007), and because the cognitive measures of attitude have their weaknesses (Peters & Slovic, 2007), investigating emotional responses in acceptance of emerging technologies such as robots is an important research avenue.

Evidence that humans can feel empathy and get emotionally attached to artificial beings confirms that artificial entities such as robots can arouse emotional reactions (Krämer, Eimler, von der Pütten, & Payr, 2011; Rosenthal-von der Pütten et al., 2013). Other researchers suggested that even imagined contact with a robot can affect emotions toward robots (Wullenkord, Fraune, Eyssel, & Šabanović, 2016). The examination of emotions toward robots is essential because they affect social processes such as identification and play an important role in human behavior (DeSteno, Dasgupta, Bartlett, & Cajdric, 2004; DeSteno, Petty, Rucker, Wegener, & Braverman, 2004). This has consequences for the intended use and possible benefits gained from larger utilization of robots in work life.

Emotional detection literature offers different ways to examine emotions from facial expressions, speech, and writing (Cowie & Cornelius, 2003; Russell, Bachorowski, & Fernández-Dols, 2003). For example, females and older people are more likely to express positivity in writing (Pennebaker & Stone, 2003; Thelwall, Wilkinson, & Uppal, 2010), neurotic people are likely to use negative language, and

extraverted and agreeable people are more likely to use positive words (Yarkoni, 2010). However, different associations could emerge in the context of robots. The more traditional research literature on robot acceptance gives some information about the expected associations and factors to consider when studying emotional expressions in written reactions toward robots.

Some literature has suggested a difference in attitudes toward robots based on age and gender, with young individuals and males being more willing to accept robots (Flandorfer, 2012). However, some research reports conflicting findings, and some researchers have argued that these sociodemographic findings will be invalidated after controlling for other factors such as prior experience using or interacting with robots (Flandorfer, 2012). The positive effect of prior experience reported in human–robot interaction research (e.g., Bartneck, Suzuki, Kanda, & Nomura, 2007) is also in line with familiarity principle (Reis, Maniaci, Caprariello, Eastwick, & Finkel, 2011) and mere-exposure effect (Zajonc, 1968). It should be noted, however, that not all researchers have found a difference between users and non-users of robots (Rosenthal-von der Pütten et al., 2013) and that negative encounters could also have an opposite effect (Ebbesen, Kjos, & Konečni, 1976).

Besides socio-demographic background and previous encounters with robots, emotional reactions toward robots could be affected by general attitude toward robots and perceived suitability of robots to a specific context. Furthermore, previous user experience and general attitude toward robots have been found to positively correlate with the intention to use robots and technology in general, therefore potentially impacting the implementation and desired benefits (Heerink, Kröse, Wielinga, & Evers, 2008; Ivanov, Webster, & Garenko, 2018; Venkatesh & Davis, 2000). For these reasons, prior experience with technology and robots and general attitudes toward robots should be measured to control for the confounding effect with socio-demographic factors.

Though some critique of the measure exists (Zillig, Hemenover, & Dienstbier, 2002), personality traits have long been measured via the Big Five personality inquiry, which is considered robust for assessing personality in occupational psychology, among other fields (Hurtz & Donovan, 2000). There is a limited number of studies exploring different personality factors behind attitudinal and emotional responses toward robots in general and especially regarding working with robots. However, in one literature review, Robert (2018) searched for personality assessments in human–robot interaction studies and found some evidence for extraverts being more likely and neurotic people being less likely to accept robots. Evidence related to other personality traits appears to be insufficient to support any conclusions (Robert, 2018).

Finally, negative emotions detected in written texts could also be the result of other factors, such as negativity toward the lack or quality of social interaction (Taipale, Luca, Sarrica, & Fortunati, 2015) or anxiety about new technology (Sinha, Singh, Gupta, & Singh, 2020). Investigation of emotional reactions is important in understanding implementation of technology and the new situations created by the use of novel technologies. Emotional reactions people express in everyday life and on social media may have further consequences on wider societal attitudes toward robotics.

3. Theoretical background and hypotheses development

In the current four studies, we utilized an experimental design, role-playing data collection, and computational social scientific analysis methods to examine linguistic positivity toward robot colleagues. The main theoretical framework of our research is based on social psychological theories of prejudice, which define prejudice as a negative attitude or emotion toward a person or a thing (Allport, Clark, & Pettigrew, 1954; Brown, 2011). Theorists argue that prejudice is not based on or develops before personal experiences and decreases with frequent favorable interaction with the target (Allport et al., 1954; Paluck, Green, & Green, 2019). This is in line with a more general notion of fear of the unknown (Carleton, 2016), which could reasonably apply to emerging

technology such as robots. According to the integrated threat theory, negativity can stem from realistic or symbolic threats (Stephan & Stephan, 2000; Stephan, Renfro, & Davis, 2008). Drawing on argumentation that realistic (e.g., robots steal our jobs) and symbolic (e.g., human identity is endangered) threats may provoke prejudice (Vanman & Kappas, 2019), we investigated if robot coworkers had a negative impact on the linguistic positivity of human workers' written reactions.

H1. People write less positively about working with robots than about working with other people.

We further investigated the impact of subgroup status on reactions to robot colleagues by manipulating the number of subgroup members (robots and humans). Thus, we designed the work team compositions so that humans had either a minority or majority status in the group. Drawing on integrated threat theory about intergroup anxiety and the potential negative effect of mere numerical minority status in a group posing an identity threat (Brown, 2011; Carton & Cummings, 2012; Stephan & Stephan, 2000), we expected the positivity of the written language to decrease when more robot teammates and fewer human teammates are presented.

H2. People write less positively about working with robots when humans are a minority than when robots are a minority in a work group.

An identity threat inside a work team could cause distrust toward the other group members, prevent a formation of a collective identity, and reduce the desire to work closely with other subgroup members (Carton & Cummings, 2012). If robot colleagues pose an identity threat to human workers (Vanman & Kappas, 2019), the idea of having robot colleagues in small and intimate teams compared with large groups, such as entire organizations, could arouse less positive reactions. Thus, we investigated the impact of conceptualization of the shared group (a teammate vs. a coworker in the same organization) and expected the written language to be less positive when robots are presented as part of a more intimate in-group, such as a team, compared to perceiving them as members of a larger group of coworkers.

H3. People write less positively about working with robots when the mutual ingroup is small and requires more interaction (a team vs. an organization).

In addition, we analyzed individual factors associated with the emotions expressed toward robots in the experiments. Based on previous research and theories on technology acceptance, we expected individuals' positive general attitude toward robots to be connected to positivity of the written reactions (Venkatesh & Davis, 2000). Other factors from the context of robots and technology included perceived robot suitability to one's own field of work, prior experience in using or interacting with robots, and having education in the field of technology or engineering (Heerink et al., 2008; Ivanov et al., 2018; Venkatesh & Davis, 2000). Personality traits and the sociodemographic factors age and gender were also treated as control variables. According to previous research, females and older people are more likely to express positivity in text (Pennebaker & Stone, 2003; Thelwall, Buckley, Paltoglou, Cai, & Kappas, 2010), but based on some findings (Flandorfer, 2012), they are also more likely to have negative attitudes toward robots. Considering personality differences, negative language is more likely to be used by people with neurotic personalities, and positive vocabulary by extraverted and agreeable people (Yarkoni, 2010). In addition, as humans have a social need to relate to others (Baumeister & Leary, 1995; Ryan & Deci, 2000), we expected writings that use social vocabulary to express less positivity in reactions to robot coworkers.

H4. People with a positive attitude toward robots in general write more positively about working with robots

We investigated these hypotheses in four studies that were designed to investigate the difference in reactions to robot colleagues compared to human colleagues. Study 1 was designed to analyze if being the only human on a team otherwise consisting of robots (no other humans on the team) differs from having only one robot as a teammate (other humans on the team). Study 2 tested further the significance of majority or minority status in the group (3 robots & 1 human teammate). Study 3 was designed to analyze the significance of group conceptualization (teammate vs. coworker in the same organization). In addition to testing the connection between general attitude toward robots and the responses to the presented situation, Study 4 explored other influencing factors behind the reactions.

4. Study 1

The aim of Study 1 was to investigate via a role-playing survey experiment if people use more positive language when writing about their first day at a new job working in a team with people compared to working in a team that includes robots (H1) and if the positivity of the written language differs depending on the number of robots on the team (H2).

4.1. Method

4.1.1. Participants and procedure

We recruited participants ($N = 1003$, 48.16 % male, $M_{age} = 37.36$ years, $SD_{age} = 11.80$, range 19–78 years) in January 2019 from Amazon's Mechanical Turk. They lived in the United States and represented 47 of the 50 states (38.83 % South, 21.89 % West, 21.10 % Midwest, 18.18 % Northeast). This distribution closely resembles that of the 2019 U.S. census data (38.26 % South, 23.87 % West, 20.82 % Midwest, 17.06 % Northeast; U.S. Census Bureau (n.d.), 2021). Respondents ($Mdn_{age} = 35$ years; 27.40 % 15–29-year-olds; 48.16 % male) were younger but fairly representative in terms of gender when compared to the current U.S. census data of citizens 15-years and older ($Mdn_{age} = 38$ years; 24.80 % 15–29-year-olds; 48.55 % male) (U.S. Census Bureau, 2019).

We collected the data through a role-playing method involving short imaginary writings, which has been defined more precisely as a nonactive or passive role-playing method or method of empathy-based stories (Greenberg & Eskew, 1993; Wallin, Koro-Ljungberg, & Eskola, 2019). In this paper, the term *role-playing* is used in reference to the nonactive role-playing data collection method, which relies on the ability of humans to engage in an imaginary situation and presumes a connection between imagined behavior or feelings and actual behavior or feelings in given circumstances (Sage, 2003). In line with guidelines by Greenberg and Eskew (1993), we asked participants to imagine themselves rather than someone else in the situation and offered them non-restrictive open answer fields. When examining judgmental or cognitive processes in contrast to behavior, minimal contextual information should be used to allow a relatively neutral background and uncontaminated results (Greenberg & Eskew, 1993).

To answer the research questions, we designed a role-playing experiment in which participants were randomly assigned to one of three groups (Atzmüller & Steiner, 2010). We asked the participants to first imagine they had just started their first day at a new job under conditions we described to them and then asked them to write about it on their favorite social media site (max. 160 characters). The only manipulation between randomly assigned groups was the number of human and robot members on the associated work team. The first group of participants was told that they would work in a team with robots as the other four teammates; the second group was primed with one robot and three human teammates; and the third group was told they would have four other teammates, with no mention of robots. Hence the last group of participants was the control group of the study.

The purpose of the different experimental conditions was to see if the participants would express higher positivity of sentiments in the written social media posts in experimental groups with a higher number of robot teammates. The randomization was judged to be successful based on the

lack of significant differences among the experimental groups in gender, age, and presence of a degree in technology and engineering. The local Academic Ethics Committee approved our research.

4.1.2. Measures

All Study 1 variables are presented in Table 1. We measured the dependent variable, the sentiments of the written social media posts, using six different sentiment tools: the WKB lexicon, Vader compound score (Hutto & Gilbert, 2014), positive and negative measures of SentiStrength (Thelwall, Buckley et al., 2010), and positive and negative emotion lexicons of LIWC (Tausczik & Pennebaker, 2010). From the WKB lexicon (Warriner, Kuperman, & Brysbaert, 2013), we used the measure for valence (pleasantness). The independent variable was the experimental group, indicating which hypothetical condition the participant was introduced to before writing the social media post. The control group was not primed with robots and was given a value of 0. The group of participants assigned one robot and four human teammates was given a value of 1, and a value of 2 was given to the group assigned four robot teammates.

4.1.3. Analysis

We used Kruskal-Wallis H test, Dunn's pairwise multiple comparison post hoc test with Bonferroni corrections, and eta square effect sizes (η_H^2) in addition to reporting descriptive statistics. Sample sizes were equal between the experimental groups, and variance was equal in measures of WKB valence ($\chi^2[2] = .27$, $p = .874$) and positive lexicon of SentiStrength ($\chi^2[2] = .04$, $p = .982$). However, based on Bartlett's test for equal variances, variance was not equal in measures of negative SentiStrength ($\chi^2[2] = 27.37$, $p < .001$) and Vader compound score ($\chi^2[2] = 29.18$, $p < .001$). Because the normality was violated in some of the dependent variables, we report the results using nonparametric methods. The results did not differ from the results of a statistically more powerful one-way ANOVA. We performed all statistical analyses with Stata 16 software and used a Stata package *dunntest* programmed by Alexis Dinno (2015) to perform Dunn's pairwise multiple comparisons. Eta square sizes for the Kruskal-Wallis H test were calculated using Barry Cohen's formula (Cohen, 2008).

4.2. Results

The results of Study 1 are presented in Table 2. A Kruskal-Wallis H test was performed to explore the sentiment scores of social media posts among role-playing experimental groups. There were statistically significant differences between the sentiments in the three groups in the Vader compound score (χ^2 with ties [2, $N = 1003$] $= 91.33$, $p < .001$, $\eta_H^2 = .09$), WKB valence score (χ^2 with ties [2, $N = 991$] $= 49.66$, $p < .001$, $\eta_H^2 = .05$), SentiStrength positive sentiment score (χ^2 with ties [2, $N = 1003$] $= 48.88$, $p < .001$, $\eta_H^2 = .05$), SentiStrength negative sentiment score (χ^2 with ties [2, $N = 1003$] $= 30.52$, $p < .001$, $\eta_H^2 = .03$), LIWC positive emotion (χ^2 with ties [2, $N = 1003$] $= 53.24$, $p < .001$, $\eta_H^2 = .05$), and LIWC negative emotion (χ^2 with ties [2, $N = 1003$] $= 42.48$, $p < .001$, $\eta_H^2 = .04$). The effect size was small in

Table 1
Descriptive Statistics of Study 1 Variables ($N = 1003$).

Measure	n	%	M	SD	Range
Vader: Compound	1003		.44	.40	−.77 to .98
WKB: Valence	991		6.23	.36	4.20–7.25
SentiStrength: Positive	1003		2.41	.93	1–5
SentiStrength: Negative	1003		−1.23	.61	−4 to −1
LIWC: Positive emotion	1003		7.05	5.86	0–33.33
LIWC: Negative emotion	1003		.86	2.57	0–33.33
Experimental group	1003				
0 = No robots	333	33.20			
1 = One robot	358	35.69			
2 = Four robots	312	31.11			

negative scores of SentiStrength and intermediate in all other measures (Cohen, 1988).

The results of Dunn's multiple nonparametric pairwise post hoc test with Bonferroni correction showed significant differences between all the sentiment scores and experimental groups, except in the SentiStrength negative sentiments between the control group and the group primed with one robot. Overall, the results showed that having more robots on the team resulted in less positive written posts. However, there was only a significant difference in negativity between the group primed with four robot teammates and the other groups. We found no statistically significant difference in negativity between the control group and the group primed with one robot.

5. Study 2

In Study 2, we aimed to replicate the findings from Study 1 (H1–H2). The only difference from the research design in Study 1 was the number of robots in one of the experimental groups (three instead of one). Hence, in Study 2, we introduced the other experimental group to the idea of working in a team with one human and three robots, which could elicit different results now that the participant is not the only human on the team.

5.1. Method

5.1.1. Participants and procedure

We recruited participants for the second sample ($N = 969$, 48.09 % male, $M_{age} = 37.15$ years, $SD_{age} = 11.35$ years, range 15–94 years) from Amazon's Mechanical Turk in April 2019. The second sample did not include the same participants as in Study 1 to guarantee the validity of the data and avoid problems caused by nonnaive respondents (Chandler, Mueller, & Paolacci, 2014; Chandler, Paolacci, Peer, Mueller, & Ratliff, 2015). They lived in 48 states in the United States (40.34 % South, 16.88 % West, 20.81 % Midwest, 21.97 % Northeast), while the distribution based on the 2019 U.S. census data is: 38.26 % South, 23.87 % West, 20.82 % Midwest, 17.06 % Northeast (U.S. Census Bureau (n.d.), 2021). The study participants ($Mdn_{age} = 34$ years; 28.07 % 15–29-year-olds, 48.09 % male) were younger but similarly distributed by gender compared to U.S. citizens based on the U.S. census data of 15-year-olds and older ($Mdn_{age} = 38$ years; 24.80 % 15–29-year-olds; 48.55 % male) (U.S. Census Bureau, 2019).

The procedure was similar to Study 1. The control group involved only human teammates and one of the experimental groups was introduced to a hypothetical work team with four robot teammates. In contrast to Study 1, we told the other experimental group that their work team consisted of three robots and one human. We found no significant differences between the three randomly assigned groups in terms of gender, age, and or presence of technology degree; thus, randomization was also successful in Study 2.

5.1.2. Measures

Study 2 variables are shown in Table 3. Dependent variables were measured using the same sentiment analysis tools as in Study 1. The experimental group again functioned as the independent variable. Unlike in Study 1, in the second study, we assigned the value of 1 to the group primed with three robots and one human.

5.1.3. Analysis

Study 2 utilized similar analyses methods as Study 1. Sample sizes of the experimental groups were equal, and variance was equal in the positive lexicon of SentiStrength but not in negative SentiStrength ($\chi^2[2] = 81.96$, $p < .001$) and the Vader compound ($\chi^2[2] = 19.54$, $p < .001$), based on Bartlett's test for equal variances. To take into account the violations of normality, we report the nonparametric Kruskal-Wallis test results. The results did not differ from the statistically more powerful one-way ANOVA results. As in Study 1, statistical analyses

Table 2
Study 1 Analysis of Variance Results: Mean Rank Differences ($N = 1003$).

Dependent variable	Experimental group	n	M	SD	Rank Sum	0.	1.
Vader: Compound	0. No robots	333	.59	.33	205273.00		
	1. One robot	358	.43	.37	172897.00	−6.07***	
	2. Four robots	312	.29	.45	125336.00	−9.43***	−3.63***
WKB: Valence	0. No robots	328	6.33	.35	189174.50		
	1. One robot	355	6.23	.36	173883.50	−3.97***	
	2. Four robots	308	6.13	.35	128478.00	−7.03***	−3.26**
SentiStrength: Positive	0. No robots	333	2.65	.92	191962.00		
	1. One robot	358	2.40	.92	179020.00	−3.64***	
	2. Four robots	312	2.16	.90	132524.00	−6.99***	−3.53***
SentiStrength: Negative	0. No robots	333	−1.15	.52	177587.00		
	1. One robot	358	−1.20	.57	183334.00	−1.54	
	2. Four robots	312	−1.35	.71	142585.00	−5.36***	−3.94***
LIWC: Positive emotion	0. No robots	333	8.69	5.79	196851.00		
	1. Three robots	358	6.75	6.01	172414.50	−4.92***	
	2. Four robots	312	5.62	5.32	134240.50	−7.07***	−2.36*
LIWC: Negative emotion	0. No robots	333	.45	2.02	155032.50		
	1. Three robots	358	.66	1.95	175620.00	1.85	
	2. Four robots	312	1.53	3.44	172853.50	6.34***	4.63***

Note: Reported statistics: Frequencies (*n*), Means (*M*), Standard Deviations (*SD*), Rank Sums, and results for the Dunn's multiple Comparison Test with Bonferroni Corrections.
*p < .05; **p < .01; ***p < .001.

Table 3
Descriptive Statistics of the Study 2 Variables ($N = 969$).

Measure	n	%	M	SD	Range
Vader: Compound	969		.40	.42	−.74 to .97
WKB: Valence	952		6.20	.43	3.72–7.89
SentiStrength: Positive	969		2.30	.95	1–5
SentiStrength: Negative	969		−1.27	.68	−5 to −1
LIWC: Positive emotion	969		7.46	9.14	0–100
LIWC: Negative emotion	969		1.04	2.73	0–20
Experimental group	969				
0 = No robots	351	36.22			
1 = Three robots	292	30.13			
2 = Four robots	326	33.64			

were performed with Stata 16 software and the Stata package *dunntest* programmed by Alexis Dinno (2015), and eta square sizes for the Kruskal-Wallis H test results with Barry Cohen's formula (Cohen, 2008).

5.2. Results

The main results are presented in Table 4. We performed a Kruskal-Wallis H test to explore the sentiment scores of social media posts among role-playing experimental groups. There was a statistically significant difference between the three groups in sentiments according to the Vader compound score (χ^2 with ties [2, $N = 969$] = 140.29, $p < .001$, $\eta_H^2 = .14$), WKB valence score (χ^2 with ties [2, $N = 952$] = 94.58, $p < .001$, $\eta_H^2 = .10$), SentiStrength positive sentiment score (χ^2 with ties [2, $N = 969$] = 88.27, $p < .001$, $\eta_H^2 = .09$), SentiStrength negative sentiment score (χ^2 with ties [2, $N = 969$] = 30.17, $p < .001$, $\eta_H^2 = .03$), LIWC positive emotion (χ^2 with ties [2, $N = 969$] = 110.18, $p < .001$, $\eta_H^2 = .11$), and LIWC negative emotion (χ^2 with ties [2, $N = 969$] = 41.21, $p < .001$, $\eta_H^2 = .04$).

The results of the Dunn's multiple nonparametric pairwise post hoc test with Bonferroni correction showed no differences between experimental groups primed with three or four robot teammates based on multiple sentiment analysis scores. Only SentiStrength negative scores demonstrated that a higher number of robots on the team slightly increased the negativity of the written posts. The difference between

either experimental group and the control group was significant in all dependent sentiment measures.

6. Study 3

In Study 3 we aimed to confirm that the main finding in Studies 1 and 2 (H1) can also be found when robots are introduced as coworkers of the same workplace instead of members of the same small work team. Thus, in Study 3 we were manipulating the size of the social group rather than the number of teammates. In addition, we tested the difference in responses to different framing of the group members within social group, as coworkers or as teammates (H3).

6.1. Method

6.1.1. Participants and procedure

We recruited participants in the third sample ($N = 1059$, 48.29 % male, $M_{age} = 37.97$ years, $SD_{age} = 11.75$ years, range 18–79 years) from Amazon's Mechanical Turk in April 2020. Participants in the third sample lived in the United States and represented 48 states (36.24 % South, 29.05 % West, 17.93 % Midwest, 16.78 % Northeast). This distribution was similar to the 2019 U.S. census data: 38.26 % South, 23.87 % West, 20.82 % Midwest, 17.06 % Northeast (U.S. Census Bureau (n.d.)). Age and gender distribution of the respondents ($Mdn_{age} = 35$ years; 25.19 % 15–29-year-olds; 48.29 % male) was fairly close to U.S. citizens based on the U.S. census data of 15-year-olds and older ($Mdn_{age} = 38$ years; 24.80 % 15–29-year-olds; 48.55 % male; U.S. Census Bureau, 2019).

In Study 3, we randomly assigned the participants into four groups. Different to Studies 1 and 2, this time we manipulated the framing of the social group as either team members (as in Studies 1 and 2) or just co-workers starting their jobs at the same time. Thus, one group was primed with four teammates, and another group with four coworkers. Both groups had equivalent control group priming, without mention of robots.

6.1.2. Measures

Table 5 shows the variables used in Study 3. We measured the dependent variable with the same six sentiment analysis tool measures

Table 4
Study 2 Analysis of Variance Results: Mean Rank Differences ($N = 969$).

Dependent variable	Experimental group	*n*	*M*	*SD*	Rank Sum	0.	1.
Vader: Compound	0. No robots	351	.60	.34	219683.00		
	1. Three robots	292	.29	.41	118972.50	−9.88***	
	2. Four robots	326	.28	.42	131309.50	−10.39***	−.21
WKB: Valence	0. No robots	348	6.37	.39	205308.50		
	1. Three robots	289	6.13	.40	122466.50	−7.60***	
	2. Four robots	315	6.09	.45	125853.00	−8.91***	−1.08
SentiStrength: Positive	0. No robots	351	2.66	.89	207798.00		
	1. Three robots	292	2.10	.92	124355.00	−7.85***	
	2. Four robots	326	2.08	.91	137812.00	−8.23***	−.15
SentiStrength: Negative	0. No robots	351	−1.14	.48	183504.50		
	1. Three robots	292	−1.27	.67	141416.00	−2.64*	
	2. Four robots	326	−1.41	.82	145044.50	−5.49***	−2.65*
LIWC: Positive emotion	0. No robots	351	9.81	6.88	213638.00		
	1. Three robots	292	6.24	10.08	122766.00	−8.60***	
	2. Four robots	326	6.02	9.87	133561.00	−9.35***	−.48
LIWC: Negative emotion	0. No robots	351	.31	1.18	153412.50		
	1. Three robots	292	1.35	3.18	145799.50	4.33***	
	2. Four robots	326	1.56	3.27	170753.00	6.21***	1.67

Note: Reported statistics: Frequencies (*n*), Means (*M*), Standard Deviations (*SD*), Rank Sums, and results for the Dunn's multiple Comparison Test with Bonferroni Corrections.
*$p <$ .05; **$p <$ .01; ***$p <$ .001.

Table 5
Descriptive Statistics of Study 3 Variables ($N = 1059$).

Measure	*n*	%	*M*	*SD*	Range
Vader: Compound	1059		.47	.40	−.86 to .98
WKB: Valence	1044		6.13	.42	4.82–8.48
SentiStrength: Positive	1059		2.50	.98	1–5
SentiStrength: Negative	1059		−1.26	.64	−5 to −1
LIWC: Positive emotion	1059		9.21	12.21	0–100
LIWC: Negative emotion	1059		.84	2.34	0–33.33
Experimental group	1059				
0 = No robot coworkers	268	25.31			
1 = No robot teammates	242	22.85			
2 = Four robot coworkers	290	27.38			
3 = Four robot teammates	259	24.46			

as in Studies 1 and 2. The experimental group functioned as the independent variable, which refers to the first and second control groups with values of 0 and 1, and to the group primed with four robot coworkers and four robot teammates with values of 2 and 3, respectively.

6.1.3. Analysis

As in Studies 1 and 2, in Study 3 we utilized the same methods and performed the calculations with Stata 16 software, the Stata package *dunntest* (Dinno, 2015), and Barry Cohen's formula (Cohen, 2008). The results were similar to the results of a statistically more powerful one-way ANOVA.

6.2. Results

Sentiment analysis results for all Study 3 experimental groups are presented in Table 6. Compared to four human teammates, four robot teammates received more negative emotional reactions, as in Studies 1 and 2. In Study 3, similar results were found for the two other experimental groups for which the role-play scenario had no mention of team membership, thus measuring emotional reactions toward coworkers in general. Besides negative measures, four robot coworkers received less positive reactions than four human coworkers, the difference being statistically significant but slightly weaker than when comparing robot

and human teammates: the Vader compound score (χ^2 with ties [1, $N = 558$] = 16.65, $p <$ .001, $\eta_H^2 = .03$), WKB valence score (χ^2 with ties [1, $N = 551$] = 16.39, $p <$ .001, $\eta_H^2 = .03$), SentiStrength positive sentiment score (χ^2 with ties [1, $N = 558$] = 9.54, $p =$ .002, $\eta_H^2 = .02$), and LIWC positive emotion (χ^2 with ties [1, $N = 558$] = 16.17, $p <$ .001, $\eta_H^2 = .03$).

In the pairwise comparison of all groups, the differences between coworkers in general and teammates were small and nonsignificant, both when primed with robots and when primed with humans. However, when comparing only two groups, the small difference of robot teammates receiving less positive reactions than robot coworkers became statistically significant in the Vader compound score (χ^2 with ties [1, $N = 549$] = 4.77, $p =$ .029, $\eta_H^2 = .01$), the WKB valence score (χ^2 with ties [1, $N = 539$] = 4.37, $p =$ .037, $\eta_H^2 = .01$), and SentiStrength positive score (χ^2 with ties [1, $N = 549$] = 4.31, $p =$ .038, $\eta_H^2 = .01$). This was not found in the case of the two control groups.

7. Study 4

In Study 4, we further investigated the factors behind the positivity of texts written in the three role-play experiments reported in Studies 1–3 (H4). Specifically, we were interested in the reasons for the lower positivity toward working with robots found in the experimental groups, and thus did not consider the control groups in Study 4. In addition, we analyzed the debatable observations done in previous studies more closely: the difference between a work team of four robots or three robots and one human (Study 2) and the difference between robots as coworkers of the same workplace or as members of the same work team (Study 3).

7.1. Method

7.1.1. Participants

For Study 4, we utilized the three samples from the previous studies, excluding the control groups ($N = 1837$, 48.01 % male, $M_{age} = 37.46$ years, $SD_{age} = 11.60$ years, range 15–78 years). The participants in the final sample lived in the United States, representing 49 of the 50 states (38.71 % South, 21.84 % West, 20.34 % Midwest, 19.12 % Northeast).

Table 6
Study 3 Analysis of Variance Results: Mean Rank Differences ($N = 1059$).

Dependent variable	Experimental group	n	M	SD	Rank Sum	0.	1.	2.
Vader: Compound	0. No robot coworkers	268	.56	.38	161352.50			
	1. No robot teammates	242	.54	.38	142483.50	−.49		
	2. Four robot coworkers	290	.43	.41	143813.00	−4.10***	−3.49**	
	3. Four robot teammates	259	.35	.41	113621.00	−6.14***	−5.50***	−2.19
WKB: Valence	0. No robot coworkers	265	6.21	.43	157938.50			
	1. No robot teammates	240	6.18	.37	137095.50	−.92		
	2. Four robot coworkers	286	6.10	.43	140141.00	−4.12***	−3.08**	
	3. Four robot teammates	253	6.03	.43	110315.00	−6.04***	−4.98***	−2.07
SentiStrength: Positive	0. No robot coworkers	268	2.67	.92	156073.00			
	1. No robot teammates	242	2.67	1.02	140119.50	−.13		
	2. Four robot coworkers	290	2.42	.96	147086.00	−3.04**	−2.83*	
	3. Four robot teammates	259	2.27	.97	117991.50	−4.99***	−4.73***	−2.07
SentiStrength: Negative	0. No robot coworkers	268	−1.25	.64	143851.00			
	1. No robot teammates	242	−1.21	.62	132845.50	.69		
	2. Four robot coworkers	290	−1.25	.60	152217.00	−.70	−1.39	
	3. Four robot teammates	259	−1.31	.68	132356.50	−1.48	−2.13	−.81
LIWC: Positive emotion	0. No robot coworkers	268	1.75	1.33	153970.00			
	1. No robot teammates	242	1.76	1.34	138869.50	−1.22		
	2. Four robot coworkers	290	1.46	1.26	146590.00	−4.06***	−2.71*	
	3. Four robot teammates	259	1.31	1.19	121840.50	−5.46***	−4.11***	−1.54
LIWC: Negative emotion	0. No robot coworkers	268	.15	.41	139218.00			
	1. No robot teammates	242	.13	.45	120681.50	−1.34		
	2. Four robot coworkers	290	.19	.44	156455.50	1.46	2.78*	
	3. Four robot teammates	259	.24	.50	144915.00	2.37	3.64***	.97

Note: Reported statistics: Frequencies (n), Means (M), Standard Deviations (SD), Rank Sums, and results for the Dunn's multiple Comparison Test with Bonferroni Corrections. *$p < .05$. **$p < .01$. ***$p < .001$.

7.1.2. Measures

Study 4 variables are presented in Appendix A. The dependent variable used in this study was Vader compound score, which can have values from –1 to 1 based on the direction and intensity of emotional content on the analyzed text.

The first independent variable was the experimental group. In this study, we excluded the control groups because those participants were not primed with robots. The experimental group variable included all other conditions: four robot coworkers (Study 3), four robot teammates (Studies 1 and 2), three robot teammates (Study 3), and one robot teammate (Study 1). Experimental group was treated as a categorical variable in the regression analyses with four robot teammates as the reference group.

Control variables included age, gender, presence of a degree in technology or engineering, and personality traits, which we measured with the short 15-item Big Five Inventory (BFI-S). The BFI-S includes statements on neuroticism, extraversion, openness, agreeableness, and conscientiousness on a 7-point Likert scale (Lang, John, Lüdtke, Schupp, & Wagner, 2011). We used a three-item mean sum variable for each trait: neuroticism ($\alpha = .84–.81$), extraversion ($\alpha = .86–.78$), openness ($\alpha = .80–.82$), agreeableness ($\alpha = .61–.58$), and conscientiousness ($\alpha = .70–.68$).

In the first survey, perceived attitude toward robots was measured with one item on a 7-point Likert scale (1 = *very negative* to 7 = *very positive*). In the following surveys, perceived attitude toward robots was also measured with affective, cognitive, and behavioral attitude questions, two items each. The items were self-generated based on theoretical assumptions of multicomponent theory of attitude (Zanna & Rempel, 2008) and applied to the context of acceptance of robots. All items were measured on a scale from 1 to 7 (1 = *very negative* to 7 = *very positive*; 1 = *strongly disagree* to 7 = *strongly agree*; see Appendix B). To consider the influence of occupational differences, we also measured perceived suitability of robots to one's own field of work with one item on a 7-point Likert scale. Last, we measured prior interactional

experience with robots by asking participants whether they had used or interacted with a robot. We used a binary dummy variable (1 = yes, 0 = no/don't know) in the analysis.

In addition to survey measures, we utilized six different LIWC lexicon categories for the OLS regression analyses: social, negate, negative emotion, anxiety, anger, and sad. Social and negate categories were used together as a proxy to measure whether participants were writing about the absence of social contact. This measured the occurrences of social relations and interaction vocabulary, provided the negation was present in the same text. The four negative-affect LIWC categories were used to test which type of negativity best explained the lower positivity of Vader compound sentiment scores. Even though the other three lexicons are included in the LIWC negative emotions category, it also includes negative words not included in the other categories. We ran the LIWC score results using LIWC 2015 software (Tausczik & Pennebaker, 2010).

7.1.3. Analysis

In Study 4, we utilized word clouds for descriptive analyses, followed by ordinary least squares (OLS) regression analysis. We report unstandardized regression coefficients (B) and their standard errors ($B\ SE$), standardized beta coefficients (β), and p values for the different measures, in addition to model goodness of fit measure (R^2), model test (F), and the p value of the model. We did not detect problematic multicollinearity or heteroscedasticity of residuals in the regression models. Multicollinearity criteria were violated only in the case of an interaction term, which is a cross-product term and thus acceptable. OLS regression analyses were performed with Stata 16 software.

For word clouds, we utilized Python WordCloud Generator and the Python module for Stata 16. The first word cloud (Fig. 1) was generated from the role-play text corpus after excluding texts categorized as positive or neutral with Vader compound scores greater than −.05, resulting in a word count of 5353. The second word cloud (Fig. 2) was formed by further excluding all other words except adjectives using the LIWC adj category, resulting in 362 adjectives. Minimum font size was
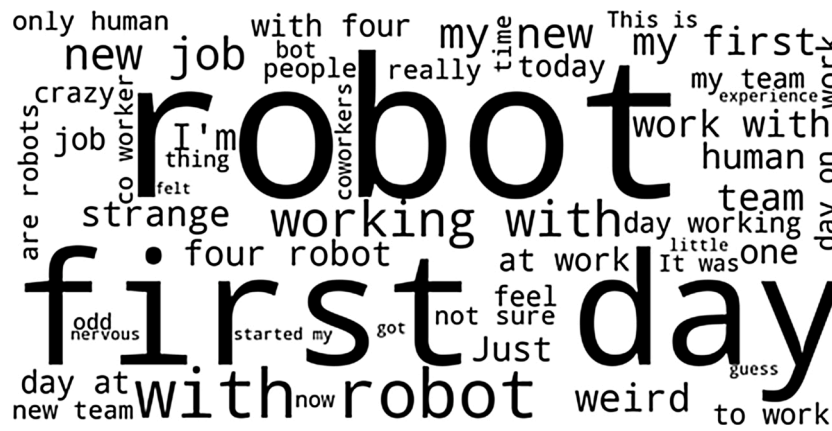
Fig. 1. Word cloud generated from experimental condition participants' negative texts.
Note: Texts: $n = 253$, word count: 5353.

Fig. 2. Word cloud generated from all the adjectives used in experimental condition participants' negative texts.
Note: Texts: $n = 253$, word count: 362.

set to 10, maximum words to 50, and the relative scaling to 0.5. In Fig. 2, the smallest font size was assigned to words occurring only once, such as *upset*; in Fig. 1, the lowest frequency was observed for the word *felt* ($n = 9$).

7.2. Results

7.2.1. Word cloud analysis

Experimental group participants' written posts categorized as negative addressed the issue of working with robots with feelings of skepticism in the face of an unfamiliar situation. For example, one participant wrote, "My first day at work was very strange, I only worked with robots and this made communication very weird." There were also texts suggesting some degree of nervousness or uneasiness: "Worked with a bunch of robots today. Literally didn't talk to a human all day. Send help." Some participants also wrote about the lack of familiar human interaction, as evident in the previous example and in an example addressing the issue of humor: "I'm not sure how I feel about telling jokes to robots at work all day. No one ever groans. But they never laugh either…"

Similar observations can be drawn from the results of the word cloud analyses (see Figs. 1 and 2). First, Fig. 1 demonstrates that the more frequently used words and collocations in negative texts written by the experimental condition groups mainly addressed the key concepts of the designated role-play scenarios: *working* (83/5353), *with* (158/5353), and *robot* (215/5353). In addition, dealing with nonhumans such as robots elicits an emphasis on the category of *human*. Because the most

frequently used words and collocations also repeated the vocabulary used in the scenario introductions, the word cloud in Fig. 2, which includes only the adjectives from the same texts, gives a more informative overview on the participants' own descriptions of the situation.

Besides from *new* (89/362), which was the only adjective used in the scenario introductions, *weird* (40/362) and *strange* (35/362) were the adjectives most frequently used by the participants. Being faced with an unusual hypothetical situation can also be seen from other words expressing novelty (*different, unique, unexpected, surprised*: 7/362). To some extent, participants seemed to use adjectives indicating anxiety (*nervous, anxious, scary*: 16/362) and insecurity (*hard, difficult*: 7/362). In addition, the use of the words *alone, personal,* and *talkative* (11/362) could indicate that social factors are involved in the negative reactions. Considering the negations combined with lexicons, such as *social,* could give a better picture of the associated factors.

7.2.2. Regression analysis

Results of the regression analyses for Vader compound scores are presented in Table 7. Based on OLS regression in Model 1, participants primed with four robot coworkers starting the job at the same time expressed higher positivity than those primed with being assigned to a team with four robot teammates ($\beta = .09$, $p < .001$). This gives more support to the weak finding in Study 3 pointing to participants reacting slightly less positively when they were supposed to work more closely with robots. OLS regression analysis also confirmed the finding from Study 2 that no differences could be found between experimental groups primed with four robot teammates or a team with three robots and one

Table 7
Regression Analyses of Study 4 Variables (*N* = 1837).

Measure	Model 1 (*n* = 1814)			Model 2 (*n* = 1814)			Model 3 (*n* = 1155)		
	B	SE B	β	B	SE B	β	B	SE B	β
Experimental group									
4 robot coworkers	.10	.03	.09***	.10	.03	.09***	.10	.03	.10**
4 robot teammates	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.
3 robot teammates	−.00	.03	−.00	−.02	.03	−.02	−.01	.03	−.01
1 robot teammate	.13	.03	.13***	.12	.03	.12***			
Attitude to robots	.05	.01	.16***	.05	.01	.16***	.07	.01	.22***
Suitability of robots to one's own field	.02	.01	.09**	.02	.01	.09**	.01	.01	.06
Prior robot experience	−.05	.02	−.05*	−.05	.02	−.05*	−.04	.03	−.05
Degree in technology	.07	.02	.07**	.30	.07	.32***	.38	.08	.43***
Age	−.00	.00	−.07**	−.00	.00	−.01	−.00	.00	−.05
Female gender	.07	.02	.08**	.07	.02	.08**	.10	.03	.11***
Neuroticism	.00	.01	.02	.00	.01	.02	−.00	.01	−.00
Extraversion	.00	.01	.02	.00	.01	.01	.00	.01	.01
Openness	−.00	.01	−.01	−.01	.01	−.02	−.01	.01	−.03
Agreeableness	.02	.01	.05	.02	.01	.05	.01	.01	.04
Conscientiousness	.01	.01	.02	.01	.01	.02	.01	.01	.02
LIWC social	−.00	.00	−.01	.00	.00	.02	−.00	.00	−.02
LIWC negate x LIWC social				−.00	.00	−.16***	−.00	.01	−.13***
Age x Degree in technology				−.01	.00	−.26***	−.01	.00	−.31**
Model R^2		.08			.11			.14	
Model F		10.82			13.16			11.68	
Model p		***			***			***	

Note: Dependent variable: Vader compound score. Model 2: Two interaction terms added (age x technology degree, LIWC negate x LIWC social). Model 3: General attitude toward robots measured with 7-item measure instead of 1-item measure. *$p < .05$; **$p < .01$; ***$p < .001$.

human (β = − .00, *p* = .861). As in Study 1, people reacted more positively when primed with one robot teammate than four robot teammates (β = .13, *p* < .001). These results did not change across the models.

General positive attitude toward robots was a strong predictor of positive sentiment when measured with one item in Models 1 and 2 (β = .16, *p* < .001) and as a 7-item measure in Model 3 (β = .22, *p* < .001). The models were also controlled with perceived robot suitability to one's own field of work and prior interactional experience with robots. Suitability of robots to one's own field predicted higher positivity in Models 1 and 2 (β = .09, *p* = .001) but became nonsignificant in Model 3 (β = .06, *p* = .092). Previous encounters with robots had a weak but statistically significant connection to less positive sentiment in Models 1–2 (β = − .05, *p* = .027–.020), which became nonsignificant in Model 3 (β = −.05, *p* = .109). This indicates that general attitude toward robots is a stronger factor behind reactions to working with robots than occupational suitability or prior experience with robots.

Having a technology degree was a small predictor in Model 1 (β = .07, *p* = .004), but became a strong predictor in Models 2 and 3 (β = .32–.43, *p* < .001). We discovered a strong interaction between age and technology education that canceled out the negative effect of age found in the first model. The interaction term added to Models 2 and 3 was negative (β = −.26 to −.31, *p* = .001), indicating that older participants with technology education reacted more negatively to working with robots. This means that technologically educated younger participants were much more likely to write positive texts. Female gender was associated with higher positivity in the role-play texts across models (β = .08–.11, *p* = .001 – *p* < .001). We found no interaction effect for gender.

Aside from the case of agreeableness, we found no evidence that personality traits were connected to the positivity of written texts in a role-play across different regression models. A weak association between agreeable personalities and positive reactions was statistically significant only in Model 2 (β = .05, *p* = .047), but not in Model 1 (β = .05, *p* = .061) or Model 3 (β = .04, *p* = .245). The personality traits were left in the models as control variables, but they did not change the results for other factors in the models.

Finally, LIWC social lexicon was not associated with the outcome on its own, but it had a moderate connection to negative reactions to working with robots when combined with LIWC negate lexicon as an interaction term in Models 2 and 3 (β = −.16 to −.13, *p* < .001). Thus, those experimental groups' participants, who used more vocabulary dealing with social relations and interaction (provided that negations were also present), were also the ones whose texts scored more negatively. Besides age and technology education, and LIWC social and LIWC negate, no other interaction effects were found. Model 3 explained 14 % of the variance of the Vader compound score.

Even though LIWC anxiety score assumably overlaps with the Vader compound score because they measure similar phenomena, we added four different LIWC negative lexicons to the last model to determine whether anxiety explained the sentiment results of Vader compound scores better than other types of negativity scores (see Model 4, Appendix C). LIWC categories anger and sad had no connection to the outcome, LIWC anxiety had a small but nonsignificant negative association with the outcome (β = −.05, *p* = .094), and LIWC negative emotion explained the negative sentiments best compared to the other three negative sentiment scores (β = −.32, *p* < .001). This finding implies that negativity toward working with robots is not based on anxiety, as suggested by the word cloud analysis, or anger or sadness, but on other negative affects included in the LIWC negative emotions lexicon, such as *weird, strange*, and *crazy*. Combined with the word cloud analysis, the results suggest the negativity toward working with robots stems from the negativity toward unexpected and unfamiliar situations.

8. Discussion

Our series of role-playing experiments investigated emotional reactions to robot colleagues. The main finding of our studies was that people reacted more positively to working with humans than working with robots. In addition to finding positive expressions influenced by minority status, group size, and individual differences, we discovered that the negative reactions to robot colleagues could be explained by feelings of oddity and lack of social interaction.

Our results confirmed that introducing robots as colleagues decreased the positivity of the writings about the first day at the imagined new job (H1). Respondents wrote less positively about robot teammates (Studies 1–3) and robot colleagues in the same organization (Study 3) compared to human teammates and colleagues. Reservations about working with robots were also seen in the content of the writings

(Study 4). The results confirmed Groom and Nass's (2007) suspicion that working with robots could arouse negative reactions in human workers. In line with Vanman and Kappas (2019), our findings suggest that robots pose a threat to and elicit prejudice in human workers. Our results complement the literature regarding attitudinal and emotional reactions toward robots (Friedman et al., 2003; Nomura et al., 2006) and verify that even imagined work-context interaction with a robot can affect emotions toward robots (Wullenkord et al., 2016).

The results also confirmed our second hypothesis regarding a minority status (H2). The writings were less positive when the team had four robot members compared to a team with one robot and three human teammates (Study 1). Thus, the emotional language differed significantly between a robot-majority team and having just one robot on an otherwise human team. Compared to a team consisting of three robots and one human, adding another robot to a work team that already had a robot majority did not affect the emotional reactions as much as introducing participants to a team with only human coworkers (Study 2). The finding is in line with the integrated threat theory about intergroup anxiety and with the notion that a mere numerical minority status in a group might pose an identity threat and have negative effects (Brown, 2011; Carton & Cummings, 2012; Stephan & Stephan, 2000).

We also found support for the third hypothesis regarding the size and closeness of the shared group (H3). The emotional reactions to human coworkers and human teammates did not differ, but we found that people reacted slightly more positively to robot coworkers in general than to sharing a small work team with robots (Studies 3–4). This was in line with the argument that robot colleagues could pose an identity threat to human workers (Vanman & Kappas, 2019), and workers whose identity is being threatened by another subgroup are reluctant to work closely with those subgroup members (Carton & Cummings, 2012). Our results show that people might react more negatively to robot coworkers if they have to share small teams with them, as opposed to merely being in the same organization where working as closely as teammates would is not required.

By further examining the factors behind the positivity in the texts about working with robots (Study 4), we found that people with positive attitude toward robots in general reacted more positively toward working with robots, providing support for H4. In line with previous research and theories on technology acceptance (Ivanov et al., 2018; Venkatesh & Davis, 2000), general attitude toward a technology is connected to attitudinal and behavioral reactions to a more specific situation regarding that technology. Accordingly, a generally positive attitude toward robots was strongly associated with positive reactions to working with robots, and it explained the sentiment outcome better than the perceived suitability of robots to one's own occupational field.

From other factors examined in Study 4, the results regarding prior interaction experience with robots were not significant in some models. In contrast to previous literature, those who had used or interacted with robots before did not express more positivity toward working with robot teammates; weak evidence from our findings even suggests a reverse connection. This contradicts the familiarity principle (Reis et al., 2011) and mere-exposure effect (Zajonc, 1968) and previous research on robots (Flandorfer, 2012). A possible explanation for this could be that people who are familiar with certain existing robots express less positivity because they are not convinced about working with these robots

and considering them teammates or coworkers. Previous interaction encounters might also have been negative for some participants, which would lead to greater dislike of the target stimulus (Ebbesen et al., 1976). On the other hand, the results could also be promising for those working on new robot innovations, because people who have no experience interacting with robots would be more positive and open to the possibility of working and collaborating with robots.

Education in technology predicted positive sentiments, which is in line with previous evidence on technology use in general (Flandorfer, 2012). It was also a strong predictor of positive sentiments among youth, but the effect was opposite for older participants. Older age on its own was not associated with sentiments; thus, older people were not more positive in their sentiments as suggested by research on emotional language (Pennebaker & Stone, 2003; Thelwall, Buckley et al., 2010). This could be due to the robot-specific context and the conflicting effect of older age on attitudes toward robots (Flandorfer, 2012). We found that females reacted more positively toward working with robots. This was in line with research on emotional language in general, as sentiments in texts written by females tend to be more positive (Pennebaker & Stone, 2003; Thelwall, Buckley et al., 2010).

We found no differences among personality traits, other than weak evidence of slightly higher positivity in writing about robot teammates by agreeable persons who tend to seek social harmony. This suggests that highly agreeable people express more positivity toward working with robots, which would be in line with the literature on personality differences in emotional language in a more general context (Yarkoni, 2010). Surprisingly, we did not find consistent results regarding the positive relationship between positive sentiments and extraversion or emotional stability, even though the existence of this relationship has been suggested by previous research on personality in general (Yarkoni, 2010) and by research on human–robot interaction (Robert, 2018).

Finally, Study 4 provided further insight into the reasons behind the negativity toward robot coworkers found in the experiments. Our findings suggest that people's reaction to working with robots may be less positive because of feelings of oddity in an unfamiliar situation and the lack of social interaction. Based on descriptive word cloud analysis and regression analysis on different types of negative lexicons, people react less positively to working with robots because of feelings of strangeness in a situation that is unusual and differs vastly from the situations they are familiar with. This finding is somewhat in line with the more general notion of fear of the unknown (Carleton, 2016), although we did not find evidence on anxiety specifically, which would have been more closely related to fear. It could be argued that our findings would be better described as discomfort or even disgust in the face of the unknown, a feeling which Plutchik (2001) places opposite trust and acceptance. The results from our multimethod analyses in Study 4 suggest that negativity also stems from the lack of social relations and interaction, which is in line with previous research on robots in social life domains (Taipale et al., 2015). Table 8 shows a summary of the findings of all four studies.

8.1. Theoretical contributions and implications

Our findings expand on the existing theoretical frameworks used to research negativity, such as fear and anxiety toward robots. In line with the integrated threat theory, robots positioned as social actors may bring

Table 8
Summary of All Four Studies' Results.

Hypotheses	Study 1	Study 2	Study 3	Study 4
H1: Prejudice: Negative sentiments about working with robots Prejudice increases if…	supported	supported	supported	supported
H2: Minority status (more robots than humans in a group)	supported	supported		
H3: Close group (team vs. organization)			supported	supported
H4: Negative attitude toward robots in general				supported

forth realistic and symbolic threats (Stephan & Stephan, 2000; Stephan et al., 2008). Our studies did not directly pose a realistic threat to respondent' economic capital, such as being replaced by robot workers or losing income, but it did pose a threat to individuals' work life social capital, as it introduced a threat of losing human coworkers and therefore the possibility for familiar human interaction. The realistic threat of loss or deteriorated social interaction shows that it cannot be taken for granted that people will accept social robots as social actors designed to fill their social need to relate to others (Baumeister & Leary, 1995; Ryan & Deci, 2000).

Our studies also support the notion that antipathy toward robots arises from a symbolic threat, wherein the identity of being a human is threatened by replacing humans with technology and giving them equal positions in the social hierarchy (Vanman & Kappas, 2019). We found that specific group processes such as minority anxiety can take place with nonhuman social actors such as robots. The positivity of the written reactions decreased due to a mere numerical minority status in a group, suggesting that robot coworkers pose an identity threat for human workers (Brown, 2011; Carton & Cummings, 2012; Stephan & Stephan, 2000). The small evidence found regarding the closeness of the in-group also implies that an intimate work team requiring closer interaction poses a greater threat to people than a loose mutual in-group membership on an organizational level. In addition to threat caused by prejudice, it could be argued that the negative reactions toward robots are due to fear of the unknown (Carleton, 2016), or speciesism which has been noted to be an obstacle to robot adoption (Schmitt, 2020).

The results also support the link between a general attitude and a situation-specific reaction in technology acceptance (Venkatesh & Davis, 2000). The strong connection of the multicomponent survey measure of attitude with our sentiment analysis results also suggests that sentiment analysis tools capture information closely related to cognitively oriented opinions, as well as the emotional spectrum and even interactional attitudes and intentions. Measuring the emotional characteristics of written texts avoids the risk pertaining to cognitively oriented survey measures potentially having a stronger relationship with each other, as has been noted regarding some personality measures (e.g., openness and agreeableness; Zillig et al., 2002).

The methodological contribution of our research was to use sentiment analysis on texts collected via a role-playing experiment, extending the means through which we can investigate issues such as emerging technology acceptance. Our findings also highlight the significance of language and the representations associated with different concepts. Our results point in the direction that robot coworkers and robot teammates are associated with negative representations or schemas (de Groot, 1989; Wagner et al., 1999), which should be taken into account both in research and practice.

8.2. Implications for practice

Our findings provide information on whether and with what conditions people would be willing to interact or collaborate with robots at work. This has critical consequences for the gains envisioned in introducing robots to workplaces as teammates or coworkers. The results imply that when introducing new and advanced technology in a workplace context, it is preferable to familiarize people with one robot instead of surrounding them with multiple unfamiliar entities at once. We recommend ensuring that the majority of the workforce around a human worker consists of other humans, rather than humans being the minority in an otherwise machine-dominated workplace.

Our results also imply that people hold reserved expectations of robots as coworkers, particularly when they are introduced as members of a work team. Smaller teams suggest coherent social groups that work more intimately with each other than mere coworkers of the same organization do. Therefore, if robots are introduced as coworkers, it is not advisable to instruct the human workers that they will be working closely with the robots and sharing the same small work group.

These results highlight the significance of social representations and the language used in the workplace context. The same robot product could be received differently depending on the social status and group membership it is assigned when introduced to the human workers. Management should be aware not only of the potential resistance caused by unfamiliar technology and situations, but also about the mental images and expectations they convey when choosing to call robots as coworkers or teammates instead of calling them as tools or assistance. Using the concepts of coworkers and team members gives technology equal status and level of power with human workers. Calling technology assistants on the other hand leaves higher power status to humans and implies enhancing human capabilities rather than replacing them (Coombs et al., 2021).

The concepts of coworker and teammate also hold social interaction expectations on the part of human workers who work closely with each other, such as discussing the workday or office rumors. Unfamiliar technology combined with the expectancies of communication in the workplace that people are used to might raise concerns about whether technology can substitute for the need for social interaction. Management should make sure that new-generation social robots are not intended as substitutes for human coworkers especially in cases where people are not used to working alone. In addition to productivity, workers have social functions in the work community that are sensitive to individual preferences and group dynamics. The potential disadvantages of framing robots as social actors should be carefully considered, because even autonomous and human-like artificial intelligences could be introduced as assistants (Hu, Lu, Pan, Gong, & Yang, 2021).

8.3. Limitations and future research direction

Even though our samples closely correspond to the population of the United States in terms of sociodemographic factors such as gender, and there is some evidence in favor of the generalizability of survey experiment results using Mechanical Turk convenience samples (Coppock, 2019), our research does not attempt to make statements about the representativeness of the data or generalizability of the results to all humans from different cultural backgrounds. Rather, we aim to demonstrate a sociopsychological and linguistic mechanism between priming of a hypothetical robot teammate or coworker and emotional response in written language during a role-play experiment. Our experimental design and convenience samples were chosen because they were appropriate methods to fulfill this aim, but they are limited in their potential to produce hard evidence for other populations and cross-cultural contexts.

Our samples included participants from 49 states of the United States and people from different types of communities ranging from rural areas to cities. We also estimated our samples based on level of education, occupational field, income level, employment status, marital status, and race, and concluded that the samples' diversity was good and matched closely with the adult population of the United States. In addition to the diversity of the samples, we considered the sample size. To maximize the power of our analyses, we altered the stimuli of the experimental design with the number of robots and the size of the framed social group to validate the results from Study 1. Considering sufficient sample sizes, with a margin of error of 5% and confidence level of 99 %, a sample size of at least 664 was considered appropriate. Thus, we collected samples of 1003, 969, and 1059 participants to account for possible data loss and subgroups. We also reported effect sizes to validate and maximize the power of our findings. Our findings were statistically significant often at the level of $p < .001$, and the effect sizes ranged from small to intermediate (Cohen, 1988).

Our results provide insights about the emotional and attitudinal processes taking place when robots are introduced as coworkers, but the hypothetical study design has limitations compared to real-life situations. Role-play tasks in survey experiments rely on humans' ability to imagine a hypothetical situation (Armstrong, 2001; Rungtusanatham,

Wallin, & Eckerd, 2011). The linguistic data that they result in is not comparable to literal descriptions of reality, but it offers insights on potential scenarios (Wallin et al., 2019). It is argued to be suitable for research on sociocultural representations, mental images, values, perceptions, and expectations of emerging phenomena (Wallin et al., 2019). Although the value of role-playing in predicting behavior has gained some support (Armstrong, 2001; Rungtusanatham et al., 2011), the interest in comparing reactions between randomly assigned roles makes the use of role-playing more valid than just trying to produce the precise behavior of the individual under circumstances similar to the simulation (Sage, 2003).

Our study design choices regarding group compositions were guided by theory and empirical findings of majority or minority status effects on group processes (Brown, 2011; Carton & Cummings, 2012; Stephan & Stephan, 2000). However, future studies could consider including one balanced team of two robots and two human coworkers as another experimental group. Although lacking a specific robot type, the strength of this research is in the establishment of general emotional tendencies toward robots as coworkers that is not dependent on constantly evolving technological products. Because general attitude toward robots has been found to predict behavior and attitudes toward specific robot types and in specific contexts (Heerink et al., 2008; Ivanov et al., 2018), general attitudinal and emotional tendencies are important subjects of basic research.

Our findings should be further investigated in longitudinal research examining the effect of the contact hypothesis (Paluck et al., 2019). Future studies should further examine the extent and quality of bias toward social robots in a workplace context. If similar findings are made in longitudinal studies including exposure to robots, research on the ethical perspective should aim to establish guidelines for technology operating as social actors.

9. Conclusions

Our studies showed that people are less enthusiastic about working with robots than with humans, suggesting that robot coworkers pose a threat to human workers and might generate prejudice against robots.

This prejudice is further enhanced by minority status of the humans in a group, small in-group requiring more interaction, and negative general attitudes toward robots. Our findings suggest that the reason for the negative reactions lies in the threat stemming from feelings of unease in an anomalous situation and uncertainties surrounding social interaction with robots. Our results imply that the same robot product could be received differently depending on the social status and group membership it is given. To minimize prejudice, it is advisable to avoid introducing robots as social actors of a social status equal to or higher than that of the human workers. Our results extend the existing research evidence on the impact of language on expectations, attitudes, and emotions relating to the new phenomenon of robotization. Our study is also the first to use sentiment analysis tools in a role-playing experiment, thus providing a new methodological opening to the field.

CRediT authorship contribution statement

Nina Savela: Conceptualization, Methodology, Investigation, Data curation, Formal analysis, Visualization, Writing - original draft, Writing - review & editing. **Atte Oksanen:** Project administration, Funding acquisition, Supervision, Conceptualization, Methodology, Investigation, Resources, Data curation, Formal analysis, Writing - review & editing. **Max Pellert:** Software, Validation, Formal analysis, Writing - review & editing. **David Garcia:** Methodology, Software, Formal analysis, Resources, Writing - review & editing, Supervision.

Declaration of Competing Interest

None of the authors has a conflict of interest to declare.

Appendix A. Descriptive Statistics of Study 4 Variables ($N = 1837$)

Categorical variables	n	%
Experimental group		
Four robot coworkers	897	48.83
Four robot teammates	290	15.79
Three robot teammates	292	15.90
One robot teammate	358	19.49
Prior robot experience	1837	
1 = Yes	555	30.21
0 = No/Maybe	1282	69.79
Degree in technology	1837	
1 = Yes	510	27.76
0 = No	1327	72.24
Age	1834	
Gender	1817	
1 = Female	935	51.46
0 = Male	882	48.54

Continuous variables	n	M	SD	Range	n of items	α
Age	1834	37.46	11.60	15–78		
General attitude toward robots	1837	4.89	1.40	1–7		
Perceived robot suitability to one's own field of work	1837	3.81	1.86	1–7		
Neuroticism	1837	3.66	1.69	1–7	3	.84
Extraversion	1837	3.81	1.54	1–7	3	.86
Openness	1837	5.19	1.27	1–7	3	.80
Agreeableness	1837	5.14	1.19	1–7	3	.61

(*continued*)

Continuous variables	n	M	SD	Range	n of items	α
Conscientiousness	1837	5.44	1.12	1.33–7	3	.70
LIWC social	1837	8.54	8.40	0–100		
LIWC negate	1837	1.65	6.70	0–100		
LIWC negative emotion	1837	1.19	2.91	0–33.33		
LIWC anxiety	1837	.25	1.38	0–33.33		
LIWC anger	1837	.10	.81	0–16.67		
LIWC sad	1837	.10	.86	0–16.67		

Appendix B. Study 4 items used to measure attitude toward robots: General, affective, cognitive, and behavioral attitude questions

How positive or negative is

1 … your view on robots in general?
2 … your view on robots if you think about your gut feeling?
3 … your view on robots if you think about the facts you know about robots?
4 … your view on robots if you think about using or interacting with a robot?
5 I would interact with a robot, if given the opportunity.
6 I feel excited when I think about robots of the future.
7 Based on my knowledge about robots, I think they are a necessary part of the future.

Appendix C. Regression Analysis for Study 4 Variables (*N* = 1837*)*

Measure	Model 4 (*n* = 1155)		
	B	SE B	β
Experimental group			
4 robot coworkers	.07	.03	.08**
4 robot teammates	ref.	ref.	ref.
3 robot teammates	−.01	.03	−.01
Attitude toward robots	.05	.01	.22***
Suitability of robots to one's own field	.01	.01	.06*
Prior robot experience	−.04	.02	−.05
Degree in technology	.33	.08	.37***
Age	−.00	.00	−.05
Female gender	.07	.02	.09**
Neuroticism	.00	.01	.01
Extraversion	−.00	.01	−.01
Openness	−.01	.01	−.02
Agreeableness	.01	.01	.04
Conscientiousness	.01	.01	.03
LIWC social	−.00	.00	−.02
LIWC negate x social	−.00	.00	−.09**
Age x Technology degree	−.01	.00	−.30**
LIWC negative emotion	−.05	.00	−.32***
LIWC anxiety	−.02	.00	−.05
LIWC anger	−.02	.00	−.03
LIWC sadness	−.01	.00	−.02
Model R^2		.26	
Model F		20.04	
Model p		***	

Note: Dependent variable: Vader compound score. New independent variables added to Model 3: four LIWC negative lexicons (negative emotion, anxiety, anger, and sadness). *p < .05; **p < .01; ***p < .001.

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