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Sharing a work team with robots: the negative effect of robot co-workers on in-group identification with the work team

[1]Nina Savela, [2]Markus Kaakinen, [1]Noora Ellonen, and [1]Atte Oksanen

[1]Faculty of Social Sciences, Tampere University

[2]Institute of Criminology and Legal Policy, University of Helsinki

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Abstract

This study investigated whether the introduction of robots as teammates has an impact on in-group identification. We used two samples from the United States (N = 1003, N = 969). Participants were asked to imagine a hypothetical situation in which they were assigned to a work team at a new job. The number of robot teammates was manipulated, and the control group included only humans. Two studies examined perceived in-group identification with variance analysis and individual differences with regression analysis. Having a robot on the work team had a negative impact on in-group identification. The results suggest that when humans are members of minority subgroup within a work team, their subgroup identity is threatened. Identification with a work team including robot members is associated with individual factors such as attitude towards robots, technological expertise, and personality. Our findings indicate that introducing a robot as a teammate may affect in-group identification process negatively with some individual differences.

Keywords: robot, teammate, identification, in-group, work team

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Robots, especially industrial robots, have traditionally been separated from human workers for safety reasons. Recent advancements in the field of interacting social robots and the efforts to develop more collaborative robots, if successfully integrated, will force humans to work more closely with robots than before (Haidegger et al., 2013; Reed & Peshkin, 2008). Thus, a vast number of field experiments has investigated human-robot collaboration in the perspective of high task performance and adequate levels of robot autonomy (Gombolay, Gutierrez, Clarke, Sturla, & Shah, 2015; Hoffman & Breazeal, 2004; Musić & Hirche, 2017; Nikolaidis, Lasota, Ramakrishnan, & Shah, 2015; Scheggi, Aggravi, & Prattichizzo, 2017). There is even some evidence suggesting that humans prefer autonomous and collaborative versus more controlled and supervised human-robot teamwork (Azhar & Sklar, 2017). However, social-psychological processes such as the fear of being replaced by robots could affect the reactions to robots at work (Dekker, Salomons, & Waal, 2017). Thus, working closely with robots poses new social and psychological challenges to workers (e.g. Hancock et al., 2011; Schaefer, Straub, Chen, Putney, & Evans III, 2017; Sheridan, 2016).

Group processes such as in-group bias and favoritism apply to human-robot groups, and there is some evidence even suggesting that robots are preferred over humans if humans are part of the out-group (Eyssel & Hegel, 2012; Eyssel & Kuchenbrandt, 2012; Fraune, Šabanović, & Smith, 2017; Kuchenbrandt, Eyssel, Bobinger, & Neufeld, 2011; Kuchenbrandt, Eyssel, Bobinger, & Neufeld, 2013). Therefore, having a robot as a team member could influence the development and maintenance of group identity among the workers in the organization. This may eventually have impact on the work done by the team. Victoria Groom and Clifford Nass (2007) argue that “lacking humanlike mental models and a sense of self, robots may prove untrustworthy and will be rejected from human teams” (Groom & Nass, 2007, pp. 483). In contrast to this, Joanna Bryson and Philip Kime (2011) have expressed a concern that humans are ready to perceive artificial intelligence and robots as moral agents and treat them as humans based on some superficial similarities, such as language and reason.

Finally, a substantial amount of research has revealed that identifying with the collective organization or team has a positive impact on performance and work motivation (Bell, 2007; Chen, Kirkman, Kanfer, Allen, & Rosen, 2007; Van Knippenberg, 2000). There is evidence that suggests this is also true when collaborating with robots (You & Robert, 2018). Team composition and the perceived cognitive abilities of the members of the team have been found to affect performance (LePine, 2005). However, we currently do not know how adding robots into the teams impacts team identification.

Our work will contribute to the shortcoming in the previous research literature by analyzing whether introducing robots as teammates has an impact on identifying with a work team. Our article reports findings from studies examining if having one or more robots on a work team impacts the in-group identification and its dimensions compared to having only humans on the team. We also analyzed if individual differences in identifying with teams including robots exist. The knowledge gained will advance our understanding of how intragroup processes are affected by robot teammates and what are the facilitating or hindering factors on individual level. This social psychological approach to robotics is novel and will offer new information on identity processes and working with robots to the multidisciplinary research field investigating the new generation of social robots.

Social Identity and In-Group Identification

The social identity approach is a well-used theoretical framework for the analysis of group membership and group processes (Ashforth, Harrison, & Corley, 2008; Ellemers, De Gilder, & Haslam, 2004; Heere & James, 2007). The social identity perspective to identifying with groups has traditionally focused on identification with abstract social categories, but it has also been used in studying more interactive and task-oriented groups such as organizations and work teams (Hogg, Abrams, Otten, & Hinkle, 2004). The concept of work team identification is rooted in social identity tradition in social psychology that argues that people form groups on a minimal basis (Tajfel, Billig, Bundy, & Flament, 1971; Ashforth & Mael, 1989; Hogg et al., 2004). Social identity theory states that social identity comprises cognitive and emotional factors, which indicate an individual's different kind of relatedness to the group membership (Tajfel, 1982; Tajfel & Turner, 1979). Being part of the social identity approach, self-categorization theory aims to explain the underlying processes in which people perceive themselves as members of a common group (Turner, 1999; Turner & Oakes, 1986).

Treating collective identity as a general construct has been critiqued (Ashmore, Deaux, & McLaughlin-Volpe, 2004), which has led to the use of more specific factors of in-group identification. With respect to this, Colin Wayne Leach and his colleagues (2008) tested the multicomponent model of in-group identification and found two distinctive though intercorrelated dimensions that include multiple specific components: (group-level) self-investment and self-definition. Self-investment refers to perceived centrality, solidarity, and satisfaction regarding the group membership. Self-investment is manifested in a sense of bond to in-group and increased salience and emotional value of group membership (Leach et al., 2008). For work teams this would mean that individual feels a bond with a team and the team membership is a significant and valued part of his or her identity.

Self-definition, in turn, refers to perceived similarities between in-group members and perceiving oneself similar to group prototypes (Leach et al., 2008). In the case of work teams, an individual would see her or his team as a cohesive group that shares certain essential features and perceives oneself as a typical member of this group. People tend to conceive social groups in terms of group prototypes, that is, a collection of characteristics related to a certain group and its members (Hogg et al., 2004). These prototypes indicate what the average group members should be like. Those group members who resemble salient group prototypes are perceived as being more socially attractive (Hogg et al., 2004). In addition, the perceived similarities have been found to mediate the positive effects of actual group homogeneity on identification (Garcia, 2017).

The tendency to identify with an in-group consisting of members with similar characteristics is related to homophily. The homophily principle states that social ties and relationships of different contexts, such as work, are affected by the need to connect with similar others (McPherson, Smith-Lovin, & Cook, 2001). Similarly, higher identification is said to be associated with demographic homogeneity (Milliken & Martins, 1996; Tsui, Egan, & O'Reilly, 1992). However, shared similarities as the only foundation of identification has been critiqued by Jans, Postmes, and Van der Zee (2012). They argue that diverse groups can form strong social identities through inductive process where they can express their individual differences, while homogenous groups form strong social identities by deducing the similarities. They propose that identifying with a heterogenous group depends on which identification process is more dominant (Jans, Postmes, & Van der Zee, 2012).

Identification Approach to Working with Robots

Introducing robots as group members is challenging from a social identity approach framework. On one hand, we know that people form groups on a minimal basis (Tajfel et al., 1971; Ashforth & Mael, 1989; Hogg et al., 2004), but on the other, we have evidence suggesting that they tend to feel a higher level of closeness to similar others (McPherson et al., 2001; Milliken & Martins, 1996; Tsui et al., 1992). The ability to identify and the level of identification with a group including robot members address precisely the question of whether arguably superficial similarities between humans and advanced technology such as robots are sufficient for identification, or if differences are too vast for similarities to be perceived, thus challenging the group identification. Specifically, perceiving oneself fundamentally different to the average member of the group would lead to decreased self-definition.

Changes in organization social structure, such as multiple team identities and organizational mergers, pose challenges to how workers identify themselves within the organization and work teams (Rapp & Mathieu, 2019; Terry, Carey, & Callan, 2001). Similarly, introducing advanced technology such as robots as co-workers, rather than technological equipment, may result in a profound transformation to the feeling of shared identity between the workers in an organization. Although a sense of bond, solidarity, satisfaction, and centrality can also develop in heterogenous groups, for example, through expressions of individuality (Jans, Postmes, & Van der Zee, 2012), positive correlation between self-investment and self-definition (Leach et al., 2008) suggests that introducing robots as team members would be challenging for the emotional investment as well as the self-definition.

In addition to the remarkably different co-workers, the number of robots as team members would affect the group composition significantly. Group composition, in turn, can influence social identification within work team subgroups. Being a member of a minority subgroup within a work team tends to induce perceived identity threats (Carton & Cummings, 2012). A high proportion of robot group members on the team could decrease the extent of team identification by reducing the number of potentially more relatable and similar human co-workers. Thus, being a minority as a human in an otherwise robot majority work team could decrease the level of identification with the team, as it does in the context of political parties (Kelly, 1990).

Individual differences in personality have been found to affect team processes such as identification (Barrick, Stewart, Neubert, & Mount, 1998). Peeters, Rutte, van Tuijl, and

Reymen (2006) found high team satisfaction to be connected to agreeableness and emotional stability, and a link between dissimilarity and conscientiousness. In work and other contexts, personality has largely been assessed through the big five personality traits and it has been widely accepted but criticism also exists (Hurtz & Donovan, 2000; Zillig, Hemenover, & Dienstbier, 2002). Personality factors have not been studied in identifying with teams including robots, but according to Lionel Robert's (2018) literature review of personality in human-robot interaction studies, extroverts are more receptive to robots. There is some evidence that low neuroticism is connected to high acceptance, but research on other personality traits are still mixed and unclear (Robert, 2018).

Literature on individual differences on social identification based on age and gender is scarce, which suggests a more situational relationship rather than a universal one. Results on socio-demographic factors and acceptance of robots have also been mixed in previous studies (Flandorfer, 2012). Some studies have found males and young people to be more positive toward robots. However, Flandorfer (2012) argues that the effects of gender and age are small and disappear after adjusting for prior experience with robots. Education in the field of technology is also considered as an influencing background factor that should be considered (Nomura & Takagi, 2011).

In addition to individuals having different demographic characteristics such as age, gender, and personality traits, robot-related contexts could be affected by previous interactional experience with robots and attitudes towards them, which are positively associated with the successful implementation of robots and the intention to interact with them (Heerink, Kröse, Wielinga, & Evers, 2008; Venkatesh & Davis, 2000). Based on mere exposure effect (Zajonc, 1968), previous exposure to and familiarity with a target is linked to positive attitudes. This is in line with research on intergroup contact theory (Pettigrew, Tropp, Wagner, & Christ, 2011). Unknown on the other hand can generate fear and inhibit attachment (Carleton, 2016).

Individual values and characteristics such as attitudes and openness have been found to influence tolerance and in-group identification with a heterogeneous group (Roccas & Amit, 2011).

Research overview and development of hypotheses

We investigated whether the introduction of robots as teammates has an impact on identifying with a work team in two studies. Our hypothesis development was based on previous research and theories on the mechanisms of in-group identification (Carton & Cummings, 2012; Jans, Postmes, & Van der Zee, 2012; Kelly, 1990; Leach et al., 2008; McPherson et al., 2001; Milliken & Martins, 1996; Tsui et al., 1992). Because working on a team with robots could potentially hinder the formation of a social identity among the workers (Groom & Nass, 2007), we expected that having a robot as an in-group member decreases in-group identification (H1).

Previous research demonstrates that although people form groups on a minimal basis (Tajfel et al., 1971; Ashforth & Mael, 1989; Hogg et al., 2004), they have a tendency to prioritize similar others (McPherson et al., 2001; Milliken & Martins, 1996; Tsui et al., 1992). Self-definition refers to the cognitive process of identifying with other group members. When the other group members are nonhumans such as robots and therefore vastly different to oneself, this cognitive identification may become more difficult. Thus, we expected lower self-definition with work teams that include one or more robot members (H2). In heterogenous groups, strong emotional investment seems to require induced identity formation through expressions of individuality (Jans, Postmes, & Van der Zee, 2012). As robots potentially are not considered as individual and do not validate the individuality of other group members as humans do, the emotional bond may remain weaker. Because of this and the positive correlation between self-investment and self-definition (Leach et al., 2008), we expected similar results for self-investment (H3).

In addition to in-group identification being challenged by a lack of homophily, being a member of a minority subgroup as a human within a robot majority work team could induce perceived identity threats and decrease the level of identification with the team (Carton & Cummings, 2012; Kelly, 1990). Because a group composition potentially influences social identification, we expected that in-group identification and both self-investment and self-definition decrease when the number of robot members in a group increases (H4).

In additional exploratory analyses we examined individual differences in identifying with work teams including robot co-workers. Previous research suggests that demographic factors such as gender and age could influence in-group identification (Milliken & Martins, 1996; Tsui et al., 1992). Based on previous findings regarding team satisfaction, neuroticism and conscientiousness could be negatively and agreeableness positively associated with identifying with a work team (Peeters, Rutte, van Tuijl, and Reymen, 2006). However, human-robot interaction research notes evidence only for extroverts being more accepting to robots (Robert, 2018). In addition to socio-demographic variables and personality traits, the robot-specific context was considered with indicators of prior experience with and attitude towards robots found to be influencing factors in human-robot interaction literature (Heerink et al., 2008; Pettigrew et al., 2011; Venkatesh & Davis, 2000). Thus, as additional exploratory analyses, we investigated individual factors behind identifying with work teams that includes robots: education in technology, prior interactional experience with robots, positive attitude towards robots, and personality traits neuroticism, extroversion, openness, agreeableness, and conscientiousness. Age and gender were treated as control variables.

Our hypotheses were pre-registered at the Open Science Framework before collecting the data (Oksanen, Savela, Kaakinen, & Ellonen, 2019). In our studies, the target of interest is a work team. A work team can be defined as a formally recognized organizational unit set to accomplish some objective. A team can be considered as a group consisting of team members. However, teams can also involve subgroups that consist of subset of team members with separate identity. (Carton & Cummings, 2012.) Thus, from the different approaches described by Fisher & Hunter (1997), our study treats the concept of team as a group with something extra. According to their study, the concepts are sometimes considered as synonyms, but they also found differences pointing toward *team* stressing the harmonious internal relations more than *group*.

Study 1

Method

Procedure. To test the hypotheses, a vignette survey experiment was designed (see, e.g., Atzmüller & Steiner, 2010). Vignette survey experiment design was chosen as an appropriate method, considering the minimal conditions people form and identify with arbitrary and artificial groups (Tajfel et al., 1971) and the robustness of such methods for predicting actual behavior and intentions with appropriate design and number of participants (Aguinis & Bradley, 2014; Evans et al., 2015; Hainmueller, Hangartner, & Yamamoto, 2015).

Participants were randomly assigned into one of three groups. They were then asked to imagine a following hypothetical situation: *Imagine that you have just been assigned to a new team in your new job. Based on merit,* ***you and four robots / you and three other people and a robot / you and four other people*** *have been chosen to this new work team*. One experiment group was told that the four other members of the team were robots, and the other experiment group was described a team of one robot and three other people. The third group was the control group and the respondents were told that their team consisted of four other people and no robots were mentioned.

Merit was used to give some context for how the group composition was formed and why the participant was matched with these team members in particular. In addition to heightening the association with harmonious intragroup relations with the concept of *team* (Fisher & Hunter, 1997), using the wording of *work team* in the introduction aimed at providing the participants with a more precise framing of the social group with a shared goal (Sherif, 1958). The overall size of five members in each team was chosen in order to enable an idea of a compact social group and cohesion (Menon & Phillips, 2011).

The number of robot members on the work team was the only variable manipulated for the randomly assigned groups. After the vignette assignment, the participants were asked to respond to questions about in-group identification, which were based on a measure proposed by Leach and colleagues (2008). The objective of the experimental conditions was to see how strongly the participants identified themselves with the hypothetical work team depending on the number of robot members included on the team. In addition, participants answered survey questions about socio-demographic information, personality, and attitude towards and prior interactional experience with robots.

Based on power analysis, 664 would be an appropriate sample size with 5% margin of error and 99% confidence level. To ensure sufficient number of participants in the subgroups such as experimental groups after possible data loss, we decided to collect a sample of more than 900 respondents. In addition, we will calculate effect sizes to confirm the reliability of the results. For eta square effect sizes (η^2) .01 and for Cohen's d effect sizes .2 will be considered as a small effect, .06 and .5 as a medium effect, and .14 and .8 as a large effect, respectively.

The local Academic Ethics Committee stated that our research does not include any ethical problems.

Participants. A survey experiment was conducted, and a data sample was collected in January 2019 (N = 1003, 51.11% female, M_{age} = 37.36 years, SD_{age} = 11.80 years). Participants were recruited from Amazon's Mechanical Turk, which has been recognized as a quality source of attentive research participants in the social sciences and psychology (Buhrmester, Kwang, & Gosling, 2011; Hauser & Schwarz, 2016; Paolacci & Chandler, 2014). We were aware of potential issues of non-U.S. residents using virtual private servers or managing to access the survey although they are not living in the United States. We followed the procedure suggested by Kennedy et al. (2020) and excluded the potentially fraudulent participants coming out of the United States.

Study 1 participants were aged from 19 to 78 years, located in the United States. The participants were from 47 states and District of Columbia, with the highest response rates coming from California (8.91%), Texas (7.59%), Florida (6.49%), and New York (6.38%). To ensure the data quality was not compromised, participants and their answers were screened for duplicate participation and abnormal response behavior, for example, via page timers (Cheung, Burns, Sinclair, & Sliter, 2017). When examining the differences between the experimental groups, no significant differences were found in gender, age, and technology degree, which means the randomization was successful in that regard.

Measures. The measures used in the study are presented in Table 1. The dependent variable, the in-group identification with the work team, was measured by a 14-item instrument (Leach et al., 2008) that includes questions about self-investment (e.g. "I am glad to be a member of this team") and self-definition (e.g. "Members of this team have a lot in common with each other") (see Appendix A). Participants responded to each statement on a scale from 1 to 7 (1 = *Strongly disagree* and 7 = *Strongly Agree*). As Leach and colleagues (2008) proposed, the whole measure is divided into a 10-item measure of (group-level) self-investment and a 4-item measure of (group-level) self-definition. Despite referring to group-level constructs, the measures reflect individual identification with the group — overall, individuals' self-investment with the group, and individuals' self-definition. For the analyses, three mean sum variables were created – for the whole measure (α = .95) and the two sub-scales: self-investment (α = .94) and self-definition (α = .89).

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

Measure	*n*	%	*M*	*SD*	Range	*n* of items	α
In-Group Identification	1003		4.48	1.27	1–7	14	.95
Self-Investment	1003		4.59	1.31	1–7	10	.94
Self-Definition	1003		4.22	1.45	1–7	4	.89
Experimental group	1003						
0. No robots	333	33.20					
1. One robot	358	35.69					
2. Four robots	312	31.11					
Age	1000		37.36	11.80	19–78		
Gender	988						
1 = Female	505	51.11					
0 = Male	483	48.89					
A degree from technology	1003						
1 = Yes	203	20.24					
0 = No	800	79.76					
Neuroticism [BF]	1003		3.68	1.74	1–7	3	.88
Extraversion [BF]	1003		3.75	1.60	1–7	3	.86
Openness [BF]	1003		5.21	1.27	1–7	3	.79
Agreeableness [BF]	1003		5.18	1.20	1–7	3	.68
Conscientiousness [BF]	1003		5.52	1.13	1–7	3	.74
Prior experience with robots	1003		.30	.46	0–1		
1 = Yes	301	30.01					
0 = No/Maybe	702	69.99					
Attitude towards robots (pos)	1003		4.96	1.37	1–7		

When examining the normality of the in-group identification and its sub-scales, the dependent variable was found to be slightly negatively skewed. Based on skewness statistics however, the whole measure is still close to symmetrical (skewness = – .34, *SE* = .08). Also, the self-investment (skewness = – .42, *SE* = .08) and self-definition (skewness = – .34, *SE* = .08) are approximately symmetrical. Based on the kurtosis statistics, the dependent variable was found to be platykurtic which has lighter tails than those of a normal distribution. The value of kurtosis (0 indicating normal distribution) was found to be moderate for self-definition (kurtosis = – .26, SE = .15), but better for self-investment (kurtosis = – .06, SE = .15) and the whole measure (kurtosis = – .12, SE = .15).

The main independent variable of this study was the experimental group, which indicated whether the hypothetical work team consisted of one or more robots or only of humans. In the variable, the control group that was not asked to picture robot teammates was given a value 0, a group asked to imagine a work team with one robot and three other humans was given a value 1, and finally a group imagining working on a team with four robot team members was given a value 2.

Individual influencing factors examined in the additional analyses and used as control variables were age, gender, a technology degree, and personality traits. Neuroticism, extraversion, openness, agreeableness, and consciousness were measured with a short 15-item Big Five Inventory (BFI-S), in which participants scored the statements on a scale from 1 to 7 (Lang, John, Lüdtke, Schupp, & Wagner, 2011). From each trait, a three-item mean sum variable was created: neuroticism (α = .88), extroversion (α = .86), openness (α = .79), agreeableness (α = .68), conscientiousness (α = .74).

Because of previous research on acceptance of robots, we also examined the influence of participant's prior interactional experience with robots and perceived attitude towards robots. Participants were asked whether they had used a robot or had been in an interaction with one, with answer options "Yes", "No", or "Don't know", which were recoded into a dummy variable that indicates prior interaction experience with robots (1 = Yes, 0 = No / Don't know). The general view on robots was scored on a scale from 1 to 7 (1 = *Very negative* and 7 = *Very positive*) and inquired by asking how positive or negative participant's view on robots is in general.

Analysis. In addition to descriptive statistics, the one-way ANOVA variance analysis method, eta square effect sizes, independent two-sample T-test, and Cohen's d effect sizes were used. Sample sizes of the experiment were equal, but their variances were not based on Bartlett's test for equal variances (self-investment: $\chi^2[2] = 10.26$, $p = .006$; self-definition: $\chi^2[2] = 33.56$, $p < .001$). Hence, Welch's test for unequal variance and one-tailed test results were used to test the hypotheses about two dimensions of the in-group identification measure: self-investment and group level self-definition (see Appendices 4 and 5). Given the moderate skewness and kurtosis of our dependent variable and the large sample size (see George & Mallery, 2010; Gravetter & Wallnau, 2017; Tabachnick & Fidell, 2013; Waternaux, 1976), the violations of normality in the dependent variable and its sub-scales were found to be minor for using a parametric T-test for the two dimensions of in-group identification.

Analysis for the whole in-group identification measure is reported in Table 2. Variances were not equal in the whole in-group identification measure based on Bartlett's test for equal variances ($\chi^2[2] = 12.23$, $p = .002$). However, one-way ANOVA is stated to be robust against moderate heterogeneous variance, when the ratio of maximum and minimum variance is less than three (Dean & Voss, 1999). The ratio does not exceed the suggested threshold in the case of the whole in-group identification measure (1.45) or the two dimensions: self-investment (1.42) and self-definition (1.77). But to consider the unequal variance between groups, the Games & Howell multiple comparison test was used as a post hoc analysis (see Appendix B). To justify the use of ANOVA further, we conducted an additional nonparametric Kruskal-Wallis test. Since the results did not change, the results from a statistically more powerful one-way ANOVA were reported.

For additional analyses and for testing interaction effects we used the ordinary least squares (OLS) regression and single-level mediation analysis methods. Standardized beta coefficients (β) and p-values were reported. All the regression models were controlled by age and gender. Problematic multicollinearity was not detected and Huber-White standard errors (i.e. robust standard errors) were used if heteroscedasticity of residuals was detected. Analyses were mostly conducted with Stata 16, but we used IBM SPSS Statistics 25 for skewness and kurtosis statistics and Games and Howell test.

Results

The one-way ANOVA results for in-group identification between the three groups in the experiment are presented in Table 2. The experimental group that describes a work team consisting of four robots had the lowest mean score for in-group identification ($M = 3.85$, $SD = 1.33$) compared to the one robot team ($M = 4.67$, $SD = 1.16$) and the all human team ($M = 4.88$, $SD = 1.11$) (see Fig. 1 and Appendix B). Based on the analysis, there is a statistically significant difference between groups ($F(2,1002) = 65.35$, $p < .001$).

Table 2. *One-way Analysis of Variance of In-Group Identification (whole measure) by Experimental group in Study 1 (N = 1003).*

	Sum of Squares	*df*	Mean Square	*F*	*p*
Between groups	187.92	2	93.96	65.35	< .001
Within groups	1437.85	1000	1.44		
Total	1625.77	1002	1.62		

A Games & Howell multiple-comparison post-hoc test (see Appendix B) revealed that in-group identification was significantly lower in the team consisting of four robots compared to the team consisting one robot ($-.81 \pm .10$, $p < .001$) and the all human team ($-1.03 \pm .10$, $p < .001$). In addition, in-group identification was statistically significantly lower for the team including one robot than for the all human team ($-.21 \pm .09$, $p = .038$). The eta square effect size for ANOVA was large when comparing a group imagining a team with four robots to control group ($\eta_p^2 = .15$) and medium to imagining a team with one robot ($\eta_p^2 = .10$).

Small effect was found between a control group and group asked to imagine a team with one robot (η_p^2 = .01). Previous analyses support the first hypothesis (H1).

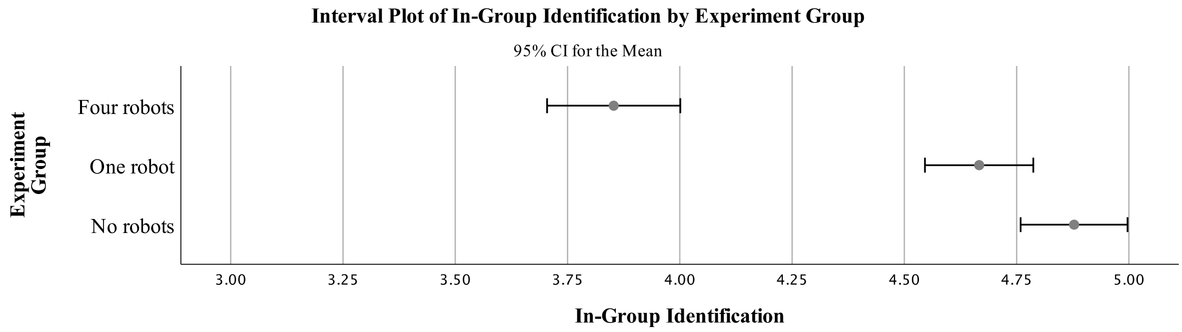

Fig. 1. *In-Group Identification means (95% CI) in a scale of 1–7 by Experimental group in Study 1 (N = 1003).*

Welch's T-test showed similar results for self-definition (see Appendix C). The all human team has a higher score in self-definition (M = 4.76, SD = 1.17) than the team with one robot and three humans (M = 4.53, SD = 1.20) according to a one-tailed Welch's t-test, t(689.65) = 2.59, p = .005, with a small effect (Cohen's d = .2). The all human team has a higher score in self-definition than the team with four robots (M = 3.30, SD = 1.55) according to a one-tailed Welch's t-test, t(577.76) = 13.47, p < .001, the effect size being significant (Cohen's d = 1.1). The team with one robot and three humans has a higher score in self-definition than the team with four robots, according to a one-tailed Welch's t-test, t(583.43) = 11.36, p < .001, with a large effect (Cohen's d = .9). Results support Hypothesis 2.

Welch's T-test confirmed similar results for self-investment (see Appendix C). The all human team had a higher score in self-investment (M = 4.92, SD = 1.16) than the team with one robot and three humans (M = 4.72, SD = 1.23) according to a one-tailed Welch's t-test, t(690.90) = 2.23, p = .013, with a small effect (Cohen's d = .2). The all human team has a higher score in self-investment than the team with four robots (M = 4.07, SD = 1.38) according to a one-tailed Welch's t-test, $t(610.58) = 8.43$, $p < .001$, the effect size being relatively large (Cohen's d = .7). The team with one robot and three humans has a higher score in self-investment than the team with four robots according to a one-tailed Welch's t-test, $t(630.30) = 6.36$, $p < .001$, with a medium effect size (Cohen's d = .5). Results support Hypothesis 3.

In the additional analyses we found several potential factors influencing in-group identification with work teams that include robots. High neuroticism was associated with low in-group identification in the experiment groups ($\beta = -.12$, $p = .006$) and the control group ($\beta = -.18$, $p = .003$). A positive relationship to higher identification was found in the experiment groups and the control group for extroversion ($\beta = .15$, $p = .001$; $\beta = .21$, $p = .001$), openness ($\beta = .15$, $p = .001$; $\beta = .26$, $p < .001$), agreeableness ($\beta = .21$, $p < .001$; $\beta = .31$, $p < .001$), and conscientiousness ($\beta = .11$, $p = .007$; $\beta = .24$, $p < .001$). In addition, having a degree in technology ($\beta = .15$, $p < .001$) and positive attitude towards robots ($\beta = .46$, $p < .001$) were associated with high in-group identification in the experiment groups. No connection was found between in-group identification and age, gender, or prior interactional experience with robots.

The main result that one or four robot teammates reduce the in-group identification compared to the control group was confirmed in a model for all experiment groups and attitude towards robots as a control variable (one robot: $\beta = -.07$, $p = .017$; four robots: $\beta = -.38$, $p < .001$). The interaction between the experiment group and positive attitude towards robots was statistically significant when comparing the control group to four robot teammates ($\beta = .40$, $p = .004$) but not when comparing to one-robot experiment group ($\beta = .27$, $p = .075$). No statistically significant interactions were found between experiment group and age, gender, technology education, prior experience with robots, or personality traits.

Discussion

Study 1 shows that identification with a work team is challenged when robots are introduced as co-workers of the same team. The results imply that having a robot as a team member discourages social identification with a work team, and the identification further decreases when the number of robot team members increases, providing preliminary support for all four hypotheses. However, in this study, the increase in the robot team members indicated a dramatic difference in composition of the team from one condition to another, in other words a change from a robot minority (only one robot and three other humans) to a robot majority team (all other team members were robots). Thus, it is possible that this substantial compositional difference between conditions is what is accounting for the results and the increase merely reflected the effect of moving from a team with a robot minority to a team with a robot majority (see, e.g., Carton & Cummings, 2012). Based on Study 1 findings it is unclear whether the increase in robot members would still have an effect when the minority/majority composition remains the same, which would confirm our fourth hypothesis (H4).

In addition, in-group identification is affected by individual differences in personality, technological expertise, and attitude towards robots. People with negative attitude towards robots tend to have more difficulties in identifying with work teams that include robot teammates.

Study 2

In the previous study (Study 1), there was a large difference in group composition between two experimental groups, one having four robots on the work team and the other having just one robot and three other people. Considering that belonging to a minority subgroup within a team could lead to identity threats and decreased team identification (Carton & Cummings, 2012; Kelly, 1990), the impact of minority/majority composition should be investigated further. The aim of Study 2 was to explore whether the results for first three hypotheses (H1–H3) from Study 1 could be replicated. Its central aim was also to confirm H4 by investigating a situation where there is a smaller increase in the number of robot team members and the minority/majority composition within the team remains unaffected. In order to confirm whether the in-group identification and both self-investment and self-definition decrease when the number of robot members in a group increases, we utilized also a merged data from both Study 1 and 2.

Method

Procedure. Study 2 used a similar research design to that used in Study 1: The participants were randomly assigned into three groups and they were asked to imagine a hypothetical situation in which they were assigned to a work team at a new job, based on merit. The number of robot members on the work team was the only variable manipulated for the randomly assigned groups. The experiment used similar priming to that used for Study 1 concerning the second experiment group (all teammates robots) and control group (all teammates humans and no robots were mentioned). However, the middle group was described a situation with three robot teammates instead of one: *Imagine that you have just been assigned to a new team in your new job. Based on merit, you, another person, and three robots have been chosen to this new work team*. After this, the participants were asked to respond to questions about in-group identification, socio-demographic information, personality, and attitude towards and prior experience with robots (see Study 1).

Participants. A second data sample was collected in April 2019 (N = 969, 51.15% female, M_{age} = 37.15 years, SD_{age} = 11.35 years). Participants were again recruited from Amazon’s Mechanical Turk. The sample included only unique participants who did not take part 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). Study 2 participants were aged from 15 to 94 years and located in the United States. The participants were from 49 states and District of Columbia with the highest response rates coming from California (8.36%), Florida (7.84%), New York (7.84%), and Texas (7.22%).

Participants and their answers were screened for duplicates and abnormal response behavior eliminating one responder finishing the survey in less than one minute. The procedure suggested by Kennedy et al. (2020) was utilized also in Study 2 dataset. When examining the differences between the experimental groups, no significant differences were found in gender, age, and technology degree, which means that the randomization was successful in that regard.

Measures. The measures used in the study are presented in Table 3. The dependent variable, the in-group identification with the work team, was measured by the same 14-item instrument as in Study 1 which included questions about (group-level) self-investment and self-definition. Participants responded to each statement on a scale from 1 to 7. As Leach and colleagues (2008) proposed, the whole measure is divided into a 10-item measure of self-investment and a 4-item measure of self-definition. For the analyses, three mean sum variables were created – for the whole measure (α = .97) and the two sub-scales: self-investment (α = .95) and self-definition (α = .94).

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

Measure	*n*	%	*M*	*SD*	Range	*n* of items	α
In-Group Identification	969		4.15	1.45	1–7	14	.97
Self-Investment	969		4.25	1.45	1–7	10	.95
Self-Definition	969		3.90	1.69	1–7	4	.94
Experimental group	969						
No robots	351	36.22					
Three robots	292	30.13					
Four robots	326	33.64					
Age	969		37.15	11.35	15–94		
Gender	954						

1 = Female	488	51.15					
0 = Male	466	48.85					
A degree from technology	969						
1 = Yes	260	26.83					
0 = No	709	73.17					
Neuroticism [BF]	969		3.66	1.68	1–7	3	.84
Extraversion [BF]	969		3.76	1.58	1–7	3	.82
Openness [BF]	969		5.10	1.27	1–7	3	.79
Agreeableness [BF]	969		5.09	1.19	1–7	3	.63
Conscientiousness [BF]	969		5.39	1.11	1.33–7	3	.69
Prior experience with robots	969						
1 = Yes	322	33.23					
0 = No/Maybe	647	66.77					
Attitude towards robots (pos)	969		4.89	1.34	1–7		

When examining the normality of the in-group identification and its sub-scales, the dependent variable was found to be slightly negatively skewed, as in Study 1. Based on skewness statistics however, the whole measure is still close to symmetrical (skewness = – .28, *SE* = .08). Also, the self-investment (skewness = – .36, *SE* = .08) and self-definition (skewness = – .21, *SE* = .08) were approximately symmetrical. Similar to Study 1, the dependent variable was again found to be platykurtic. The value of kurtosis (0 indicating normal distribution) was found to be high for self-definition (kurtosis = – .94, SE = .16), but moderate for self-investment (kurtosis = – .53, SE = .16) and the whole measure (kurtosis = – .62, SE = .16).

The independent variable of this study was the same as in Study 1: the experimental group. As in Study 1, the control group was given a value 0 and a group that was asked to imagine a team with four robot team members was given a value 2. In this second study, a value 1 was assigned to a group that was described a team with three robots and one other human.

In the additional analyses and as control variables we used variables of age, gender, technology degree, personality traits, prior interactional experience with, and perceived attitude towards robots (see Table 3). These were measured the same way as in Study 1, with similar personality trait measures' internal consistency: neuroticism (α = .84), extroversion (α = .82), openness (α = .79), agreeableness (α = .63), conscientiousness (α = .69).

Analysis. In addition to descriptive statistics, one-way ANOVA variance analysis, eta square effect sizes, an independent two-sample T-test, and Cohen's d effect sizes were used. Sample sizes of the experiment were equal, but their variances were not based on Bartlett's test for equal variances (self-investment: $\chi^2[2] = 18.90$, $p < .001$; self-definition: $\chi^2[2] = 33.45$, $p < .001$). Hence, Welch's test for unequal variance and one-tailed test results were used to test the hypotheses about two dimensions of the in-group identification measure: self-investment and self-definition (Appendices 7 and 8). Due to the large sample size, the violations of normality in the dependent variable and its sub-scales were found to be minor so the use of a one-tailed Welch's T-test for the two dimensions of the in-group identification was justified.

Analysis for the whole in-group identification measure is reported in Table 4. Variances were not equal in the whole in-group identification measure based on Bartlett's test for equal variances ($\chi^2[2] = 19.53$, $p < .001$). As in Study 1, the ratio was at acceptable levels in the case of the whole in-group identification measure (1.60) and the two dimensions: self-investment (1.61) and self-definition (1.79). However, to take into account the unequal variance, the Games & Howell multiple comparison test was used as a post hoc analysis (Appendix D). To further justify the use of ANOVA, we conducted an additional nonparametric Kruskal-Wallis test. Since the results did not change, the results from a statistically more powerful one-way ANOVA were reported.

For additional analyses and for testing controlling effects we used the ordinary least squares (OLS) regression and single-level mediation analysis methods. Standardized beta coefficients (β) and p-values were reported. Problematic multicollinearity was not detected and Huber-White standard errors (i.e. robust standard errors) were used if heteroscedasticity of residuals was detected. All the analyses are conducted with Stata 16. Analyses were mostly conducted with Stata 16, but we used IBM SPSS Statistics 25 for skewness and kurtosis statistics and Games and Howell test.

Results

The one-way ANOVA results for in-group identification between the three groups in the experiment are presented in Table 4. Based on the analysis, there was a statistically significant difference between the groups ($F(2,966) = 26.95$, $p < .001$). Games & Howell's multiple-comparison post-hoc test revealed that in-group identification was statistically significantly lower in the team consisting of four robots ($-.76 \pm .11$, $p < .001$) and in the team consisting of three robots ($-.60 \pm .11$, $p < .001$) compared to the all human team (see Appendix D). However, the team with three robots did not differ significantly from the team with four robots, based on the Games & Howell test ($-.16 \pm .12$, $p = .390$) and eta square effect ($\eta_p^2 = .00$). There was a small eta square effect when comparing the control group to a group imagining a team with three robots ($\eta_p^2 = .05$) and a medium size effect compared to a group of four robots ($\eta_p^2 = .07$).

Table 4. *One-way Analysis of Variance of In-Group Identification (whole measure) by Experimental group in Study 2 (N = 969).*

	Sum of Squares	*df*	Mean Square	*F*	*p*
Between groups	108.00	2	54.00	26.95	< .001
Within groups	1935.73	966	2.00		
Total	2043.73	968	2.11		

The analysis produced similar results to Study 1 and confirmed H1. The group that was asked to imagine a work team consisting only of humans had the highest mean score of in-group identification ($M = 4.58$, $SD = 1.23$) (see Fig. 2 and Appendix D). The mean scores of in-group identification in the group with three robots ($M = 3.99$, $SD = 1.46$) and the group with four robots (*M* = 3.83, *SD* = 1.55) were closer to each other than in Study 1, which is in line with the more similar group composition in the present study design. For the identification with the hypothetical work team, based on some statistical tests there was no statistically significant difference whether the team consisted of four robots or three robots and one other human. That would suggest that adding one more robot to the team might not further decrease the identification.

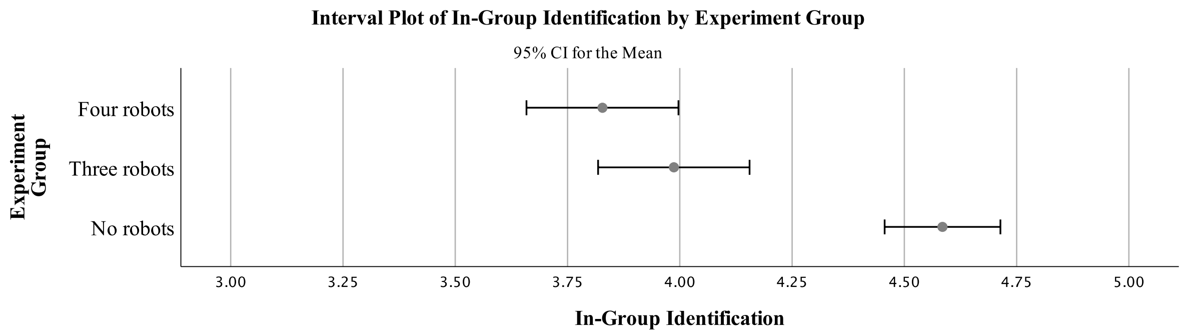

Fig. 2. *In-Group Identification means (95% CI) in a scale of 1–7 by Experimental group in Study 2 (N = 969).*

The T-test results for self-definition (see Appendix E) revealed that defining oneself in relation to the work team does not differ statistically significantly between groups imagining a team with four robots (*M* = 3.47, *SD* = 1.73) and three robots and one other human (*M* = 3.52, *SD* = 1.76), according to Cohen's d (.0) and a one-tailed Welch's *t*-test, *t*(608.06) = .36, *p* = .361. According to a one-tailed Welch's *t*-test and relatively large effect sizes, the all human team had a higher score in self-definition (*M* = 4.62, *SD* = 1.31) than the team with three robots and one other human (*t*[530.70] = 8.81, *p* < .001, Cohen's d = .7) or the team with four robots (*t*[607.32] = 9.67, *p* < .001, Cohen's d = .8), providing support for H2.

Welch's T-test results for self-investment confirmed H3 and the result of Study 1 (see Appendix E). The all human team had a higher score in self-investment (*M* = 4.57, *SD* = 1.25) than the team with three robots and one other human (M = 4.17, SD = 1.43) according to a one-tailed Welch's t-test, $t(584.38) = 3.71$, $p = .000$, Cohen's d = .3. The all human team had a higher score in self-investment than the team with four robots (M = 3.97, SD = 1.59) according to a one-tailed Welch's t-test, $t(619.36) = 5.44$, $p < .001$, with a medium effect size of Cohen's d = .4. The team with three robots and one other human had a higher score in self-investment than the team with four robots, according to a one-tailed Welch's t-test, $t(617.96) = 1.67$, $p = .048$, Cohen's d = .1.

The T-test results validate the results of Study 1 in confirming H2 and H3. However, H4 is confirmed only for self-investment dimension of in-group identification. In addition, the mean scores of in-group identification and its two dimensions in the middle group of Study 1 were lower and differed statistically significantly from corresponding scores in the middle group of Study 2 (see Appendix F).

In the additional analyses for Study 2 we found several potential factors influencing in-group identification with work teams that include robots. A positive relationship to higher identification was found in the experiment groups and the control group for extroversion (experimental groups: $\beta = .29$, $p < .001$; control group: $\beta = .19$, $p = .001$), openness ($\beta = .17$, $p < .001$; $\beta = .28$, $p < .001$), agreeableness ($\beta = .11$, $p = .013$; $\beta = .20$, $p = .001$), and among the control group for conscientiousness ($\beta = .17$, $p = .004$), but not in the experimental groups ($\beta = -.07$, $p = .074$). In addition, having a degree in technology ($\beta = .34$, $p < .001$), prior interactional experience with robots ($\beta = .11$, $p = .006$), and positive attitude towards robots ($\beta = .45$, $p < .001$) were associated with high in-group identification for those in the experiment groups. No connection was found between in-group identification and age, gender, or neuroticism.

The interaction analyses revealed similar results found in Study 1. A model including all experiment groups and attitude towards robots as a control verifies the main result that three (β = – .14, $p < .001$) or four (β = – .21, $p < .001$) robot teammates reduce the in-group identification compared to the control group. The interaction between experiment group and attitude was statistically significant for both experiment groups (β = .33, $p = .019$; β = .41, $p = .003$, respectively). A statistically significant interaction was also found for at least two experiment groups and technology education (β = .13, $p = .003$; β = .06, $p = .184$), female gender (β = – .13, $p = .018$; β = – .10, $p = .070$), extraversion (β = .14, $p = .135$; β = .25, $p = .010$), and conscientiousness (β = – .49, $p = .006$; β = – .57, $p = .002$), but controlling the model with these variables did not affect the main results. No interactions were found for prior experience with robots, age, or personality traits of neuroticism, openness, and agreeableness.

Examination of merged data from Study 1 and 2 also indicate that fewer robot teammates predict higher identification. Compared to a team with four robots, a team with only one robot was strongly connected to higher scores in in-group identification (β = .24, $p < .001$) and both of its dimensions: self-investment (β = .20, $p < .001$) and self-definition (β = .28, $p < .001$). When controlled also for attitude towards robots, a similar but weak connection was found comparing four robots to three robots and one other human in the whole in-group identification measure (β = .05, $p = .025$) and self-investment (β = .06, $p = .018$), but for self-definition it remained statistically nonsignificant (β = .04, $p = .100$). The identification decreased as the number of robot co-workers on a team increased, highlighting the impact of proportional change in robot teammates on identification.

Discussion

The analyses partly confirmed the hypotheses and results from Study 1. From Study 2 it was discovered that adding one robot to a work team in which there was already robot majority has a slight effect only on self-investment dimension of team identification, the effect being weaker than adding one robot to a human only team in Study 1. The findings indicate that defining oneself in respect of the work team and its members seems to be less dependent on having at least one human member on the team than is the case with self-investment. In other words, adding one human co-worker on the otherwise all robot team slightly increases investing oneself in the work team but not defining oneself in respect to the group and its prototypes. In-group identification is affected by individual differences in personality, technological expertise, and prior experience of and attitude towards robots. As in Study 1, people with negative attitude towards robots tend to have more difficulties in identifying with work teams that include robot teammates.

Summary and Concluding Discussion

We investigated whether people identify themselves with a hypothetical work team including robot members. We expected the team identification to decrease when the number of robot members increased. Our hypotheses H1–H4 were confirmed in Study 1. Having a robot on the work team was associated with lower in-group identification than being part of a work team consisting only of humans. Furthermore, being the only human on the team resulted in even lower in-group identification than having just one robot on the team. The results suggest that introducing a robot as a teammate will result in difficulties for the human workers in terms of identifying with the same in-group, which may challenge the collaboration and desired benefits from utilization of robots in the workplace.

The hypotheses were mostly confirmed also in Study 2 to further validate the results from Study 1. However, one human team member made a significant difference to the team identification of the participant only in terms of self-investment but not self-definition or team identification as a whole when compared to an all robot team. This finding could be explained by the differences between the two in-group identification dimensions: while self-investment items deal with the affections toward being a member of a group, self-definition items capture more cognitive judgements and direct the attention towards evaluating the differences between the respondent and her or his perception of the average member of the group (Leach et al., 2008). As the average team member does not change substantially between the two conditions with robot majority (four robot teammates vs. three robots and one human teammates), it is understandable that no differences were found in cognitive evaluations of identification in these two conditions. Even though we found some evidence that one human teammate in an otherwise robot majority team seems to increase the commitment and positive affections towards being a part of the team, this was not enough to change the overall identification with a robot majority work team.

The results show that simply adding one more robot does not affect the work team identification significantly if the robot members are the majority in the team composition in both situations. In addition, having three robots and one other human in the same work team (the middle group in Study 2) had more negative connection to work team identification than having only one robot and three humans (the middle group in Study 1), which strengthens the idea that significant difference in identification will be found when comparing robot minority teams to robot majority teams.

This is in line with the theory of subgroups in work teams (Carton & Cummings, 2012). According to the theory, members of minority subgroups within a work team tend to feel their subgroup identity threatened. On the other hand, introducing minority and majority subgroups can increase identification with the work team if the minority group members can adopt the majority group identity (assimilate themselves to the majority group) (Carton & Cummings, 2012). This is not likely to happen in the case of robots as a majority subgroup. Thus, when assimilation to the majority group is not possible, perceived minority status leads to decreased identification with the work team. Furthermore, it is possible that introducing a robot subgroup within a work team (especially when it is a majority group) can strengthen cohesion within the human subgroup.

Based on additional analyses, it was discovered that identifying with a team including robots depends significantly on attitude towards robots and, to some degree, on technological expertise, which is in line with previous research regarding the acceptance of robots or technology in general (Heerink et al., 2008; Venkatesh & Davis 2000). The results of the influence of attitudes coincides with previous findings that individual values and characteristics such as openness can affect tolerance and in-group identification with a heterogeneous group (Roccas & Amit, 2011). We also found a positive connection to identifying with work teams in the cases of openness, extraversion, and agreeableness, and some evidence for negative relationship with neuroticism and conscientiousness.

The findings about agreeableness and neuroticism are in line with previous research on team satisfaction in general (Peeters, Rutte, van Tuijl, and Reymen, 2006) and the results regarding neuroticism and extroversion are is in line with the few studies investigating personality and human-robot interaction (Roberts, 2018). The relationship between different personality traits and identifying with teams was similar whether the team included robots or only humans, in contrast to attitude towards robots, which was a significant factor specifically when identifying with robot teammates. In addition, to consider some criticism related to the widely used personality measures (Zillig et al., 2002), openness and agreeableness including cognitive items may correlate more strongly with a dependent variable that also includes cognitive elements. These findings however provide new information and supplement the mixed results in the research literature about personality factors in human-robot interaction (Roberts, 2018).

Our research indicates that the idea of having a robot as a team member influences the anticipated social identity of the workers. In contrast to the concern expressed by Bryson and Kime (2011), humans did not misidentify with robots over humans. In line with Groom and Nass (2007) and our hypotheses, robot team members were not seen as qualified prototypes for identification with the work team. Despite the criticism on the prevalence of homophily in identification (Jans et al., 2012), it seems that more similar characteristics and closeness to the prototype of the in-group is needed especially for investing oneself in the group than what robot members can offer. Thus, our research contributes to this conversation in strengthening the argument about the relevance of homophily in in-group identification (Hogg et al., 2004; Milliken & Martins, 1996; Tsui et al., 1992). The results are also in line with research concluding that in-group identification decreases when the person is in a minority subgroup inside the team (e.g., Kelly, 1990).

The number of similar teammates and therefore the issue of homophily could suggest that the level of in-group identification is different in 5-member teams than in 2-member teams, for example. However, since the decrease in self-investment was also quite substantive, it could be argued that the comparison to the average team member is not the only reason for our findings. Rather, we propose that the core psychological mechanism is that when humans are a minority subgroup within a work team their subgroup identity seems to be threatened. Same mechanism could apply to other non-human teammates as well. However, here our analyses concerned robots, perhaps the most timely and relevant example of non-human teammates and social identification.

Strengths and limitations

Our results present a unique overview on people’s anticipated identification with robot teammates. Taking into account individual factors and previous knowledge of robots and technology provides robust evidence on how group composition contributes to identifying with a work team with robot teammates. The results of the individual differences provide much needed new evidence for the young field of human-robot interaction. Even though self-investment refers to an emotional value of group membership rather than similarity and is argued to be another route to identification among different group members (Jans, Postmes, & Van der Zee, 2012), our results suggest that both self-definition and self-investment dimensions of in-group identification measurement are influenced by homophily in the general level of being human beings. If technology or other fundamentally different actors are introduced as co-workers, this should be considered in the measures we use to examine the level of identification with the in-group. Future research should test if our results hold true for other fundamentally different actors, but as robots with artificial intelligence capable of processing information similarly and faster than humans are being designed to take part in social processes as well, advanced robots are an urgent research avenue for this type of research.

Participants presumably have their own idea of how similar robots are to humans, thus they could differ based on their mind perception. For example, robots could be perceived as moral agents, as argued by Bryson and Kime (2011). This aspect was not considered in our studies, but similarity and mind perception measures (e.g. Kozak, Marsh, & Wegner, 2006) could be a relevant direction for future work. Also, we used the concept of *team* in the questionnaire instead of *group*. Based on research on the different conceptual approaches described by Fisher & Hunter (1997), this should have a positive rather than a negative effect on identification, while for some participants the meaning is the same. Therefore, our choice of wording should not weaken the reliability of the finding of negative effect.

Because of the fast advancements of robotics and the increasing number of new products coming out, our research did not focus on a particular robot type or product. We wanted to investigate identifying with robot teammates through a general idea people have about what working with robots would be like. We chose not to provide a narrower definition of a robot to emphasize the significance of language regarding word association and mental representations people have about robots and robot teammates. However, considering the hypothetical nature of the experiment, future research should aim to examine whether similar results can be found in real context-specific situations, with participants interacting or sharing the same space with actual robots of specific type or product.

We chose to use a vignette survey experiment method for its utility for testing identification with artificial beings taking technical difficulties and other situational factors out of the equation. Even though vignette experiments measure evaluations instead of behaviour (see, e.g., Atzmüller & Steiner 2010), appropriately designed vignette experiments are robust predictors of actual behaviour and intentions (Aguinis & Bradley, 2014; Evans et al., 2015; Hainmueller, Hangartner, & Yamamoto, 2015). They are well suitable for testing our hypotheses considering the minimal conditions people form and identify with arbitrary and artificial groups (Tajfel et al., 1971), but they have also limitations. The vignette experiments in our studies were designed so that they would not direct the respondent's attention to a specific robot type or the capabilities of the robot in question, but rather arouse the more general mental representations people associate the concept of *robot teammate* with. The number of robot teammates was the only manipulation between the experiment groups in order to pinpoint the significance of group composition of human and robot teammates. However, our studies were limited in not investigating other nonhuman actors besides robots, which should be the focus of future studies. It would also be important to study what other consequences the introduction of robots as co-workers in the context of work team has for the individual workers and the social environment in the organization.

Conclusion

Our research provides new evidence on how people anticipate identifying with work teams of different combinations of robot and human teammates. This social psychological novel approach to robotics has not been done before and offers new information on identity processes regarding working with robots to the multidisciplinary field of new generation social robotics. Our findings suggest that introducing a robot as a teammate could have unfavorable consequences for intragroup processes of work teams with robot members. In turn, the difficulties of human workers to identify with the same in-group may challenge the collaboration, communication, and desired benefits from utilization of robots in the workplace. The effects of in-group identification to team performance and individual well-being has been addressed thoroughly in previous research (Bell, 2007; Chen et al., 2007; Van Knippenberg, 2000; LePine, 2005) and presumably concerns the issue of robot teams as well.

Acknowledgements

None of the authors have a conflict of interest to declare. The datasets will be made publicly available in the end of the project in 2021 and it is available from the authors with a reasonable request.

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Appendix A.

In-group identification -measure including group-level self-investment (items 1.–10.) and self-definition (items 11.–14.) (Leach et al. 2008).

Please answer to what degree you agree with the following statements (Strongly disagree 1 – 7 Strongly agree):

1. I feel a bond with our team.
2. I feel solidarity with our team.
3. I feel committed to our team.
4. I am glad to be a member of this team.
5. I think that this team has a lot to be proud of.
6. It is pleasant to be a member of this team.
7. Being a member of this team gives me a good feeling.
8. I often think about the fact that I am a member of this team.
9. The fact that I am a member of this team is an important part of my identity.
10. Being a member of this team is an important part of how I see myself.
11. I have a lot in common with the average member of this team.
12. I am similar to the average member of this team.
13. Members of this team have a lot in common with each other.
14. Members of this team are very similar to each other.

Appendix B.

Means, standard deviations, frequencies (n), and the results for the Games & Howell multiple comparison test of Study 1: mean difference (standard error) (N = 1003).

Group	*M*	*SD*	*n*	0.	1.
0. No robots	4.88	1.11	333		
1. One robot	4.67	1.16	358	– .21* (.09)	
2. Four robots	3.85	1.33	312	– 1.03*** (.10)	– .81*** (.10)

Note. $*p < .05$. $**p < .01$. $***p < .001$.

Appendix C.

Self-Investment and Self-Definition Welch's t-test results of Study 1 (N = 1003).

Self-Investment		*N*	*M*	*SD*	*df*	*t*	Sig. *t*
Experiment group	0. Only humans	333	4.92	1.16			
					690.90	2.23	.013

	1. One robot	358	4.72	1.23			
Experiment group	0. Only humans	333	4.92	1.16	610.58	8.43	< .001
	2. Four robots	312	4.07	1.38			
Experiment group	1. One robot	358	4.72	1.23	630.30	6.36	< .001
	2. Four robots	312	4.07	1.38			
Self-Definition		*N*	*M*	*SD*	*df*	*t*	Sig. *t*
Experiment group	0. Only humans	333	4.76	1.17	689.65	2.59	.005
	1. One robot	358	4.53	1.20			
Experiment group	0. Only humans	333	4.76	1.17	577.76	13.47	< .001
	2. Four robots	312	3.30	1.55			
Experiment group	1. One robot	358	4.53	1.20	583.43	11.36	< .001
	2. Four robots	312	3.30	1.55			

Appendix D.

Means, standard deviations, frequencies (n), and the results for the Games & Howell multiple comparison test of Study 2: mean difference (standard error) (N = 969).

Group	*M*	*SD*	*n*	0.	1.
0. No robots	4.58	1.23	351		
1. Three robots	3.99	1.46	292	– .60*** (.11)	
2. Four robots	3.83	1.55	326	– .76*** (.11)	– .16 (.12)

**p* < .05. ***p* < .01. ****p* < .001.

Appendix E.

Self-Investment and Self-Definition Welch's t-test results of Study 2 (N = 969).

Self-Investment		*N*	*M*	*SD*	*df*	*t*	Sig. *t*
Experiment group	0. Only humans	351	4.57	1.25	584.38	3.71	.000
	1. Three robots	292	4.17	1.43			
Experiment group	0. Only humans	351	4.57	1.25	619.36	5.44	< .001
	2. Four robots	326	3.97	1.59			

Experiment group	1. Three robots	292	4.17	1.43	617.96	1.67	.048
	2. Four robots	326	3.97	1.59			
Self-Definition		*N*	*M*	*SD*	*df*	*t*	Sig. *t*
Experiment group	0. Only humans	351	4.62	1.31	530.70	8.81	< .001
	1. Three robots	292	3.52	1.76			
Experiment group	0. Only humans	351	4.62	1.31	607.32	9.67	< .001
	2. Four robots	326	3.47	1.73			
Experiment group	1. Three robots	292	3.52	1.76	608.06	.36	.361
	2. Four robots	326	3.47	1.73			

Appendix F.

In-Group Identification (whole measure), Self-Investment, and Self-Definition Welch's t-test result: Samples from Study 1 (N = 1003) and Study 2 (N = 969).

In-Group Identification		*N*	*M*	*SD*	*df*	*t*	Sig. *t*
Experiment group	One robot	358	4.67	1.16	550.11	6.45	< .001
	Three robots	292	3.99	1.46			
Self-Investment		*N*	*M*	*SD*	*df*	*t*	Sig. *t*
Experiment group	One robot	358	4.72	1.23	578.45	5.17	< .001
	Three robots	292	4.17	1.43			
Self-Definition		*N*	*M*	*SD*	*df*	*t*	Sig. *t*
Experiment group	One robot	358	4.53	1.20	497.06	8.33	< .001
	Three robots	292	3.52	1.76			