Tampere University

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Ready for Robot Colleagues?

Affective Attitudes and Prejudice Toward Sharing the Work Domain with Robots

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ACADEMIC DISSERTATION
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When I embarked on the journey to study social sciences at Tampere University almost eight years ago, I did not know where the studies would lead me. Social psychology offered a tremendously interesting perspective not only to psychological phenomena within persons but also to various social situations and environments. My fascination with the basic mechanisms people operate with led me to study them in my bachelor and master theses. Examining novel technologies in social contexts made me realize that I was drawn to the idea of becoming a researcher and continuing this investigation. Doctoral studies have given me valuable experience in academic research while working on my PhD and various research projects. The most memorable part, however, were the wonderful and talented people I got the privilege to work with, who encouraged and still encourage me forward.

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> "You step onto the road, and if you don't keep your feet, there's no knowing where you might be swept off to." – J.R.R. Tolkien

Vantaa, May 2022

ABSTRACT

Robots and artificial intelligence are increasingly utilized for labor in various occupational fields. The interest in designing advanced technological solutions suitable for environments outside of manufacturing has not only shifted to home and leisure activities but also to more interactive robots used at work. Consequently, robots with advanced social and collaboration features are being deployed for work tasks that human workers have previously done. Robots operating closely with the human workforce introduces not only technical challenges but also social and psychological demands for the human workers and people involved. More research is needed to understand people's expectations and the potential social psychological consequences of introducing new-generation robots at work. Considering these novel challenges, this doctoral dissertation utilizes intergroup threat theory as a theoretical framework and investigates the affective attitudes toward robots at work.

The research articles included in this doctoral dissertation in social psychology utilized experimental, computational, and longitudinal research designs to investigate the affective attitudes toward robots. Article I focused on group identification and was based on two vignette-design experiments examining how people react when organizations introduce robots as members of a work team. Article II used three role-playing experiments to capture reactions toward introducing robot colleagues using sentiment analysis tools for analyzing written text. Article III aimed at understanding the public opinion and discussions on robots in general over time, and thus, comments on robotic technologies were collected from social media and analyzed with sentiment analysis and other lexicon-based computational tools. Article IV was a longitudinal survey study on the Finnish working population and within-person analyses enabled investigating how attitudes toward robots as colleagues or tools at work have developed over time before and during the COVID-19 pandemic.

The results show that people hold some prejudice toward deploying robots at work. This is especially true when robots are introduced as social agents such as colleagues. However, although social media discussions on robotic technologies suggested that people perceive robots less positively for work than for leisure activities, conversations around robots were overall positive in the work context compared to the more negative comments within the home setting. Longitudinal analyses also reveal a slight positive trend on affective attitudes toward robots during the pandemic. The findings show how the attitudes toward deploying robots at work have shifted to a more positive direction during the need for social distancing. Attention should be given to how robots are introduced to human workers and the people involved. Human workers could perceive giving robots social roles, such as one of a team member, as a threat, which can lead to prejudice and negativity toward utilizing robots in the work context.

TIIVISTELMÄ

Robotteja ja tekoälyä hyödynnetään useilla eri ammattialoilla yhä enemmän. Kiinnostus edistyneiden teknologisten ratkaisujen kehittämiseen teollisuuden ulkopuolelle on keskittynyt kodin ja vapaa-ajan lisäksi vuorovaikutteisempien robottien hyödyntämiseen työelämässä. Tämän seurauksena roboteille, joilla on edistyneitä sosiaalisia ja yhteistyöhön soveltuvia ominaisuuksia, delegoidaan työtehtäviä, jotka ovat aiemmin kuuluneet ihmistyöntekijöille. Ihmistyöntekijöiden läheisyydessä toimivat robotit tuovat mukanaan teknisten haasteiden lisäksi henkilöstöön ja muihin ihmisiin kohdistuvia sosiaalisia ja psykologisia vaatimuksia. Enemmän tutkimusta tarvitaan sen ymmärtämiseksi, minkälaisia odotuksia ja mahdollisia sosiaalipsykologisia seurauksia uuden sukupolven robottien käyttöönottoon työelämässä liittyy. Huomioiden nämä uudenlaiset haasteet, tämä väitöskirja hyödyntää ryhmienvälistä uhkateoriaa teoreettisena viitekehyksenä ja tutkii affektiivisia asenteita robotteja kohtaan työelämässä.

Väitöskirjan tutkimusartikkeleissa hyödynnettiin koeasetelmia, suurta sosiaalisen median aineistoa ja pitkittäiskyselyaineistoa robotteihin kohdistuvien affektiivisten asenteiden tarkastelemiseen. Ensimmäinen artikkeli keskittyi ryhmäidentifikaatioon ja pohjautui kahteen kehystarinaa hyödyntävään kokeeseen, joissa tarkasteltiin ihmisten reaktioita robottien esittelemiseen työryhmän jäseninä. Toinen tutkimusartikkeli sisältää kolme eläytymiskoetta, joissa mitattiin reaktioita robottikollegojen esittelyyn analysoimalla kokeessa tuotettuja tekstejä sentimenttianalyysillä. Kolmannessa artikkelissa tarkasteltiin robotteihin kohdistuvaa yhteiskunnallista keskustelua keräämällä robottiteknologioita käsitteleviä sosiaalisen median kommentteja ja analysoimalla niitä sentimenttianalyysillä ja muilla sanastoihin pohjautuvilla laskennallisen yhteiskuntatieteen työkaluilla. Neljännessä tutkimusartikkelissa hyödynnettiin suomalaiselta työväestöltä kerättyä pitkittäiskyselyaineistoa ja ihmisten asenteiden muutoksien analysointia tarkastelemaan sitä, miten asenteet robotteihin kollegoina tai työkaluina ovat kehittyneet ajallisesti koronapandemiaa ennen ja sen aikana.

Tulokset osoittavat, että robottien käyttöönotto työelämässä herättää ihmisissä joitain ennakkoluuloja, erityisesti silloin kun robotit esitellään sosiaalisina toimijoina kuten kollegoina. Sosiaalisen median robottiteknologioita käsittelevien keskustelujen

perusteella suhtautuminen robotteihin on kielteisempää työn kuin vapaa-ajan toiminnoissa, mutta työaiheiset robottien ympärillä käytävät keskustelut olivat kokonaisuudessaan myönteisiä verrattuna kotiaiheisiin keskusteluihin. Myös pitkittäisanalyysit paljastivat myönteisen nousujohteisen trendin affektiivisissa asenteissa robotteja kohtaan koronapandemian ajalta. Robottien käyttöönottoon työelämässä kohdistuvat asenteet ovat muuttuneet myönteisemmiksi aikana, jolloin sosiaalisten kontaktien välttäminen on ollut tarpeellista. Robottien esittelyyn tuli kiinnittää erityistä huomiota niitä käyttöönotettaessa. Työntekijät saattavat kokea uhkaavaksi, jos roboteille annetaan sosiaalisia rooleja kutsumalla niitä esimerkiksi kollegoiksi. Seurauksena voi olla ennakkoluuloja ja kielteisyyttä robotteja kohtaan työpaikoilla.

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ABBREVIATIONS

AI	Artificial Intelligence
AME	Average Marginal Effect
ANOVA	Analysis of Variance
HRI	Human–Robot Interaction
LIWC	Linguistic Inquiry and Word Count
M	Mean
OLS	Ordinary Least Square
OR	Odds Ratio
SD	Standard Deviation
VADER	Valence Aware Dictionary and Sentiment Reasoner
WKB	Wholesale Klezmer Band

ORIGINAL PUBLICATIONS

Publication I	Savela, N., Kaakinen, M., Ellonen, N., & Oksanen, A. (2021). Sharing a work team with robots: The negative effect of robot co-workers on in-group identification with the work team. *Computers in Human Behavior, 115*, Article 106585. https://doi.org/10.1016/j.chb.2020.106585
Publication II	Savela, N., Oksanen, A., Pellert, M., & Garcia, D. (2021). Emotional reactions to robot colleagues in a role-playing experiment. *International Journal of Information Management, 60*, Article 102361. https://doi.org/10.1016/j.ijinfomgt.2021.102361
Publication III	Savela, N., Garcia, D., Pellert, M., & Oksanen, A. (2021). Emotional talk about robotic technologies on Reddit: Sentiment analysis of life domains, motives, and temporal themes. *New Media & Society*, Advance Online Publication. https://doi.org/10.1177/14614448211067259
Publication IV	Savela, N., Latikka, R., Oksa, R., Kortelainen, S., & Oksanen, A. (2022). Affective attitudes toward robots at work: A population-wide four-wave survey study. *International Journal of Social Robotics*, Advance Online Publication. https://doi.org/10.1007/s12369-022-00877-y

1 INTRODUCTION

Advances in social robotics have recently increased the interest to deploy robots more for social tasks and in social contexts (Odekerken-Schröder et al., 2020; Wang & Wang, 2021). This is especially true in the work domain where various occupational fields adopt new technology to attract customers, increase profit, and ensure their success in the competitive market environment (Sarkis et al., 2020; Zibafar et al., 2021). The general population participates in public discussions on their desires, fears, and other expectations of robotic technologies being used in various life domains (Javaheri et al., 2020). At the same time, an increasing number of workers encounter and interact with robots at their workplaces (Carradore, 2021; Turja & Oksanen, 2019). Interactive and collaborative robots have gained more ground in work environments, and they are expected to become more commonplace (Wang & Wang, 2021). Sharing a social environment such as a workplace or even the work community or team with novel robots will present new social and psychological demands that require more future-oriented research early on to prevent a transition that disregards the perceptions and wellbeing of the people whose everyday life it effects.

In addition to the potential realistic threats that robots present to the human workforce, such as loss of livelihood or competitive advantage in the labor market (Acemoglu & Restrepo, 2020; Bessen, 2019), introducing robots as coworkers or teammates could pose a symbolic threat to human workers (Mende et al., 2019; Stein et al., 2019; Vanman & Kappas, 2019; Yogeeswaran et al., 2016). The concept of a robot colleague holds expectations of a social and autonomous actor (Banks, 2019; Nyholm & Smids, 2020), which might threaten human workers' identity and social processes, depending on how they react to and feel about the idea of working with a robot colleague. Considering this, it is critical to examine not only people's cognitive appraisals of the topic but also their emotional reactions to the novel work scenarios. Diverse accounts can reveal underlying doubts, fears, or even prejudice people hold that could hinder a successful implementation and cause more harm than benefit (Liu, 2012; Reinders et al., 2008). On the other hand, understanding these perceptions can help to detect the situations and ways to utilize robotic technologies at work sustainably enabling gains while preventing damage to workers' wellbeing (Delgosha & Hajiheydari, 2021; Peters et al., 2018).

Researchers have called on more research on social and psychological processes in the robotization of work life, such as changes to traditional roles, career satisfaction, and employees' cynicism, and the changing expectations and concerns over time (Lu et al., 2020). Researchers have noted that instead of focusing solely on user acceptance, there is a need to widen the scope of acceptability to other people and society (Salvini et al., 2010). Considering other technology acceptance factors besides usefulness and ease-of-use, such as perceived potential, has also been proposed (Pickering et al., 2019). Thus, more research from diverse perspectives is needed to enhance the understanding of the effects of advancements in robotics on human lives.

The analyses in this dissertation involve the concept of a robot used in public social media discussions, robots at work as tools or colleagues, and robot ingroup members of a shared team. Thus, I note the relevance of language used to describe the attitude target through considering multiple conceptualizations of robots at work domain. By discovering implicit attitudes and emotions rooted in the ways robots are discussed in socially regulated public social media conversations, I acknowledge the effect of word associations and representations interconnected with the robot concepts. The hypothetical scenarios highlight the perspective of preconceptions and expectations associated with it, and the longitudinal perspective considers the attitudinal changes over time. The relevant responses to and perceptions of robots at work under investigation in this dissertation include emotional investment, affective attitudes, and emotional qualities in written text. I examine these affective constructs with an ingroup identification survey measure in survey experiments, positivity detection of written responses in survey experiments, positivity detection in naturally occurring social media discussions, and an attitude survey measure in a longitudinal survey. This dissertation focuses on the affective dimensions of these perceptions by referring to them as affective attitudes toward robots at work.

This dissertation aims to investigate affective attitudes toward and potential prejudice against robots from a social psychological perspective while focusing on the social context of work. I use intergroup threat theory (Stephan & Stephan, 2000) as the general theoretical framework which has been proposed to be useful for examining the potential prejudice toward a robot workforce (Vanman & Kappas, 2019). The theory demonstrates how perceived realistic and symbolic threats can cause prejudice toward an outgroup (Stephan & Stephan, 2000). Based on the intergroup threat theory, prejudice can manifest as cognitive judgements, such as negative stereotypes, and affective states, including anxiety toward interacting with outgroup members (Stephan & Stephan, 2000). This dissertation covers affective orientation from a broader perspective as it focuses on the affective dimensions of group identity, attitudes, and positivity detection from text.

For examining various affective reactions and expressions toward robots, I use different data collection methods, data types, and analysis techniques to complement each other. This dissertation comprises of studies reported in four published research articles. Article I comprises of two experimental vignette studies utilizing a validated survey measure of ingroup identification and data from U.S. respondents. Article II utilizes a similar experimental survey design to analyze emotional orientation of written responses collected via a role-play method from U.S. respondents. Article III extends the use of computerized text analysis tools and analysis level through analyzing emotional and thematic content of social media discussions on robots and related concepts. Article IV investigates temporal changes in affective attitudes toward robots at work using longitudinal survey data based on a nationwide sample of Finnish workers. In addition to descriptive statistics, I chose appropriate regression and variance analysis methods based on the study design and data type for each research article included in my dissertation.

This dissertation makes a methodological contribution to the field of social psychology through combining traditional survey methods together with advanced experimental and longitudinal designs and computational social science methods. It also provides theoretical insights to the multidisciplinary field of human–robot interaction (HRI) from the social psychological point of view. In addition, the findings provide the policymakers and practitioners with crucial aspects to consider when designing, planning, and ultimately implementing robots to social situations that have previously operated without robots.

In the next two chapters, I will review the research literature and theoretical and methodological discussions relevant to this dissertation. I will then present the dissertation's research aims. After that, I will present the data collection, measurement, and analysis methods utilized in the research articles, followed by an overview of the results. In the discussion section, I will address the findings from the perspective of the general aims and research questions of this dissertation, theoretical and practical implications, and strengths and limitations. The last part of the dissertation includes the original research articles published in international peer-reviewed journals.

2 ROBOTS IN THE SOCIAL CONTEXT OF WORK

In this chapter, I will provide the context for the attitude target concepts under investigation in this dissertation. I will first provide an overview of the development of deploying robotic technologies in different life domains while focusing on the context of work. I will then discuss the potential social implications that treating robots as colleagues or teammates and giving them social roles causes compared to treating them as mere technical tools, and this way, address the topic of robots as social and autonomous actors. Thus, from the macro level of robot technologies and the work domain, I will move closer to the micro level and address how sharing an organization-level environment or a work team with robots might affect human workers' sense of autonomy and their social relations. Lastly, I will consider the influence of the terminology, and hence, the potentially different attitudes and emotions associated with the symbolic representations of the concepts of *robot*, *robotic tool*, *robot colleague*, and *robot teammate*.

2.1 Robotic technologies at work and other life domains

While intangible solutions such as virtual robots are sometimes included in the definitions, the term robot commonly refers to technologies with some degree of autonomy and actuated mechanism, which are what robotic devices lack (ISO, 2012; Lin et al., 2011). Tangible or embodied service robots for professional use such as transportation or cleaning are becoming a more common sight at workplaces demonstrating an increasing trend in robotization (IFR, 2021a; Smids et al., 2020). However, robots are not new to the work domain. Industrial robots were the first generation of robots implemented widely and their use in the manufacturing field has only grown after the early days. Fortunati, Esposito, and Lugano (2015) evaluated from the 2013 figures that robots were still a small proportion in the information technology market. Since then, the global robot density in manufacturing industries (from 62 to 126 robots per 10,000 employees), the sales of industrial robots (from 178,132 to 384,000 units), and the operational stock of industrial robots (from 1,332,000 to 3,015,000 units) have all more than doubled, based on the 2020 figures of the newest report the International Federation of Robotics released (IFR, 2021b). Industrial robots are becoming more common each year and the trend has only accelerated in recent years.

Organizations are introducing robots, for example, to compensate a lack of employees due to demographic changes in society, to increase efficiency, or to demonstrate innovativeness (Smids et al., 2020). Traditional industrial robots are still the most common ones in the manufacturing field, but collaborative robots are slowly finding ground. Collaborative robots are designed for direct interaction with humans and refer to robots with advanced cooperation and responsive collaboration features, albeit current collaborative industrial robots mainly coexist and do sequential collaboration with human workers (IFR, n.d.; ISO, 2012). Although they have increased from 11,000 units to 22,000 units in 3 years (2017–2020), collaborative robots in practice are still in their initial stages (IFR, 2021a). However, employee–robot teams have been suspected to transform the service sector through services delivered via a joint effort with AI and human workers (Lu et al., 2020). In addition to collaborative robots, another trend in the work domain occurs in fields aside from manufacturing as the professional use of service robots becomes more popular. With 131,800 units, the professional service robot sales have increased 41% in 2019–2020 (IFR, 2021c).

Various routine services are suspected to become robot-delivered in the future and to enhance the availability and quality of services necessary for a functional society (Wirtz et al., 2018). The increasing trend of implementing delivery, cleaning, medical, restaurant, and social robots during the pandemic (IFR, 2021a) shows that the potential of service robots will be utilized when there is an acute demand for transforming the existing paradigms. People also seem to accept robots relatively well in the work domain for tasks too challenging or too monotonous for humans, but robots in social and leisure contexts have received a more mixed reception (Naneva et al., 2020; Savela et al., 2018; Taipale et al., 2015; Takayama et al., 2008). Robots are increasingly entering domains other than work where robots are newer, which can be seen from the robot product sales for domestic and leisure use (Fortunati, Esposito, & Lugano, 2015). Because of this, researchers have also called for further investigations on people's attitudes and expectations toward utilizing robots in the domestic sphere (Fortunati, Esposito, & Lugano, 2015).

In addition to the increasing trend of sharing home and leisure spaces with robots, embodied service robots and collaborative robots present a shift in the work domain toward humans working closer with robots and sharing with them spaces that are built for human inhabitation (El Zaatari et al., 2019; Salvini et al., 2010).

Teaming up with intangible robots in extended reality will also mean closer HRI and cooperation in augmented, mixed, or virtual spaces (Ajoudani et al., 2018; Arntz et al., 2021; Lu et al., 2020). Some researchers have highlighted the negative effect of automation on employment and wages on the industry level (Acemoglu & Restrepo, 2020; Frey & Osborne, 2017), and some have argued in favor for job- and task-level estimations that instead stress changes to needed skillsets and allocation of work (Arntz et al., 2017; Bessen, 2019) or even show a positive effect on employment (Klenert et al., 2022). While the concerns over robotization have predominantly focused on replacing human workers completely with a robot workforce, increasing the use of robot applications in workplaces for united human–robot workflow introduces different challenges for workers who robots do not replace. Consequently, understanding the potential social factors and implications in HRI is becoming more relevant at work as well (Bankins & Formosa, 2020; Henschel et al., 2020).

It remains to be seen how convincing the social features of new-generation robots will become compared to human–human interaction. However, from the social interaction perspective, often the only thing needed is that people perceive the robot as a social entity having some sort of social presence (van Doorn et al., 2017). If this does not happen, people consider robots as technical tools like any other technology. Some findings suggest that people prefer to use robots as tools and are less willing to accept them as autonomous agents due to the fear of losing control and autonomy (Barrett et al., 2012; Latikka et al., 2021a; Savela et al., 2018). Mende and colleagues (2019) also reported negative effects of humanoid service robots from the perspective of customers experiencing discomfort. Advances in human–robot collaboration presents an interesting social psychological perspective on work life research because humans are still needed in the work process, which could maintain a sense of purpose for human workers involved (Ajoudani et al., 2018). Research is needed to examine further the consequences of introducing robots at work as tools, colleagues, or members of a shared team.

2.2 Robots as colleagues or team members

Robotization is a part of a long history of automation along with other technical devices (Stone, 2004). However, due to automation potentially replacing human workers (Acemoglu & Restrepo, 2020) and the association of the concept of a robot with humanoid appearance and behavior that science fiction fuels (Fortunati, Esposito, Sarrica, et al., 2015), robots also raise the question of to what extent such technical devices could be treated as human substitutes. The advancements in the robotics field have caused not only psychological investigations on robot's appearance (e.g., for anthropomorphism or human-likeness and uncanny valley, see Kätsyri et al., 2015) and other factors influencing people's perceptions of robots (e.g., trust; Hancock et al., 2011; Hancock et al., 2021) but also extensive ethical considerations that are critical for policies and legislations (Lin et al., 2011). Nonhuman entities that can be treated as humans are also a highly relevant research topic from the social psychological point of view. Rather than striving to establish ethical rules to follow or make a stand on whether robots should be treated as humans, social psychological perspective enables the researchers to focus on whether and how treating robots as humans versus technical tools changes people's perceptions of and behavior toward robots.

As Bankins and Formosa (2020) noted, work life is undergoing a paradigm shift from workers using technology as tools to interacting and forming partnerships with intelligent agents designed for teamwork and social interaction. Researchers have argued in favor for the fundamentally social nature of human–machine interaction and utilized the perspectives of relationships and teamwork to design better interfaces (Degani et al., 2017). People tend to anthropomorphize or attribute mental states such as intentionality to nonhuman entities (Urquiza-Haas & Kotrschal, 2015) and some people already treat technologies (Reeves & Nass, 1996) and robots (Nyholm & Smids, 2020) in a similar manner as they treat human beings. Previous research proposes that social robots could be perceived as moral agents regardless of their actual moral status (Banks, 2019). Nyholm and Smids (2020) argued that although current robots lack the qualifications of being considered friends or romantic partners, robots can more easily pass many of the criteria of a good colleague.

Talking about and presenting AI systems as social agents instead of functional tools has been reported to increase the perceived anthropomorphicity of an AI system (Epstein et al., 2020) and negative attitudes toward AI (Kim et al., 2021). Smith et al. (2021) found that robots were considered more human-like if they behaved socially rather than functionally and that group mechanisms followed human–human interaction more closely with anthropomorphic robots. These examples demonstrate the interplay between social cues and their impact on people's perceptions and behavior. When considering workplace robots as colleagues rather than technical tools, questions arise about both autonomy and sociability. If robots are referred to as colleagues or teammates, they are not only given some degree of supposed autonomy but also assumptions on social agency, as previous studies suggest (Epstein et al., 2020; Smith et al., 2021). These assumptions arrive from the social roles and capabilities associated with the concepts in question such as, for example, a colleague or a team member. Treating robots as social actors could have similar social and psychological consequences as interacting with humans, as a finding of decreased self-esteem due to a robot's rejection demonstrates (Nash et al., 2018).

Aside from the perceived social agency, treating robots as team members can have consequences for group dynamics and performance, as a study on human–robot teamwork demonstrates by reporting a connection between emotional attachment to robot teammates and higher team performance (You & Robert, 2018). Identification with nonhuman targets has previously been studied from perspectives other than technology, such as environment and place identities. Prior research has shown that humans have a need to relate to each other and to belong to their social environment (Baumeister & Leary, 1995; Deci & Ryan, 2008; Hauge, 2007; Twigger-Ross & Uzzell, 1996). Belonging to an environment connects to social factors. Relational ecologies of belonging states that people form identities through relationships with humans and nonhuman entities (Poe et al., 2014). People can form such identities subconsciously without consciously reflecting upon them (Jørgensen, 2010). Thus, even a physical setting with inherent social roles such as a workplace could affect the workers' identity formation as the research on place identity suggests (Proshansky et al., 1983).

People can also form bonds with and feel attachment to objects (Wheeler & Bechler, 2021) or pets (Tovares, 2010). Forming identities with places, objects, and animals points toward a conclusion that people can become attached to and form identities also with robots, as seems to be the case with technology in general (Reeves & Nass, 1996). People are prone to humanize such objects and treat them as social entities (Reeves & Nass, 1996). Against this background, it becomes more conceivable that this could also be the case with robots. Interacting with new-generation robots with advanced social features could leave less to the imagination, and as a result, it could be easier to treat them as social agents.

Some researchers have argued that humans could accept robots as social or moral actors to some degree or in some specific situations (Banks, 2019; Latikka, Rubio-Hernández, et al., 2021; Lee et al., 2006; Nyholm & Smids, 2020). Social categorization processes such as ingroup bias seem to apply to robots as well, as shown in studies reporting favoritisms toward and higher anthropomorphism of ingroup versus outgroup robots (Eyssel & Kuchenbrandt, 2012; Smith et al., 2021).

A study on AI voice provides some evidence that shared similarities and a perceived common identity with advanced technology positively affects perceptions such as perceived credibility and social presence of the technology (Edwards, Edwards, Stoll, et al., 2019).

Sharing a common ingroup with robots and humans could, however, show favoritism toward humans because robots do not share the fundamental similarity of being human (Fraune, 2020). Thus, when sharing a work community or team with robots, robot workers could highlight a common identity between human workers and decrease prejudice toward human outgroup members, which recent studies have demonstrated (Jackson et al., 2020; Smith et al., 2021). It is also in line with a HRI study on customer perspectives reporting customers' discomfort toward humanoid service robots that are perceived as eerie and threatening to human identity (Mende et al., 2019). These findings provide support for the notion that robots could be untrusted and rejected as group members (Groom & Nass, 2007), at least when compared to humans. Thus, prior HRI research on social identification suggests that people still prefer to share their ingroups with human members, but they might accept social robots as group members when no suitable human members are available (Fraune, 2020; Eyssel & Kuchenbrandt, 2012). This is also in accordance with prior research that shows that at least when no human contact is available, humans' social needs could be satisfied with robots (Latikka, Rubio-Hernández, et al., 2021; Lee et al., 2006).

2.3 Robot concepts and symbolic representations

Concepts of representations have been used to describe schemes or ideas of targets that hold certain values or beliefs. Mental representations are intrapersonal symbols of outside reality that people form, hold, and retrieve from memory (Smith, 1998). On the other hand, social representations refer to socially shared knowledge to perceive and conceptualize socially relevant objects (Moscovici, 1961; Moscovici, 1988). Social representations have been proposed to consist of dimensions of information, visual representation fields, and attitudes, and even to substitute concepts of image or opinion (Moscovici, 1963). Breckler (1984) used the concept of symbolic representation to describe measuring attitudes toward a concept of an attitude target, which is a useful broader way to capture these different conceptualizations for the purpose of the present dissertation.

The robot has become a cultural archetype associated with various representations (Fortunati, Esposito, & Lugano, 2015). These representations can affect people's thinking, as shown in a study reporting that the high number of visual examples children could retrieve from their memory associated with more human-like appraisals of robots (Fortunati, Esposito, Sarrica, et al., 2015). Knowledge and imaginary information can co-exist in a representation, which leads to an interesting result and tension between robots that exist and fictional robots that could alter and inflate the beliefs about the capabilities and appearance of robots today (Fortunati, Esposito, Sarrica, et al., 2015). Findings of lowered perceived eeriness of robots in one study showed that fiction could sometimes be an even stronger influence on people's thinking compared to fact-based information (Mara & Appel, 2015). A recent study reported that fact-based media exposure of robots affects trust formation positively and found both fiction and fact-based media effects on a general attitude toward robots (Savela et al., 2021).

Social robots are commonly defined as having little to a full level of autonomy and capabilities that enable them to perform work tasks and interact with humans (Sarrica et al., 2019). Sarrica and colleagues (2019) argued that instead of functionalities, future definitions will likely focus on autonomy and social aspects. The expectations of autonomy and sociability are relevant on people's reactions toward robots. One study showed how people based their expectations of interacting with and social presence of a humanoid social robot on their knowledge of human–human interaction (Edwards, Edwards, Westerman, et al., 2019). Thus, in addition to representations people have about robots, people will apply other familiar representations of beliefs and practices to judge and navigate novel situations such as introducing robots as colleagues or teammates at work.

Measuring attitudes and emotions toward a symbolic representation of the attitude target will likely yield slightly different results compared to, for example, measuring physiological responses to the attitude object's presence (Breckler, 1984). Survey measures and analyzing written text both rely heavily on language and its associated representations (Albarracín et al., 2008). Survey measures concern the symbolic representations of both the researchers whose predefined survey items are utilized and the research subjects that utilize their own representations for evaluating their answers. Analyzing text that research subjects have generated more freely also relies on the symbolic representations of the research subjects and their capabilities and habits of using language for self-expression. These should be acknowledged and discussed for the sake of understanding and openly reporting not only what affective constructs were measured, but also what was the precise attitude target. However, covering only one aspect, such as affective attitudes toward a representation of a robot colleague, does not mean the results could not have any tentative implications concerning the larger phenomenon of accepting robots or enlighten the field of HRI.

3 ATTITUDES AND EMOTIONS TOWARD ROBOTS

In this chapter, I will present the theoretical and methodological background of this dissertation's investigation on affective attitudes and prejudice, giving particular attention to the different ways to measure positivity toward an attitude target. I first present the general framework of social psychological theories of intergroup threat and prejudice because it is used in this dissertation as a theoretical basis for interpreting the potential negativity found in the included research articles. I then review the different concepts used to measure positivity and negativity. Broader perspectives of attitudes and emotions provide a background for the more specific concepts that constitute the measures in the research articles: ingroup identification, attitude, and positive orientation of text. In this dissertation, I focus on these concepts and measures' affective dimensions, namely emotional investment, the affective component of attitude, and the positivity of text based on emotional qualities. Thus, while acknowledging these concepts' different aspects on the positivity perceptions toward the attitude target and considering how appropriate it is to call them either attitudes or emotions, this chapter provides justification for using affective attitudes as the hypernym of the concepts investigated in this dissertation.

3.1 Intergroup threat and prejudice

People seem to accept robots relatively well for tasks too challenging or too monotonous for humans in the work domain, while receptions of robots in social and leisure contexts have been more mixed (Naneva et al., 2020; Savela et al., 2018; Taipale et al., 2015; Takayama et al., 2008). Some cultural differences influence accepting robots at work, such as technology orientation of the given country (Turja & Oksanen, 2019), and individual differences, such as socio-demographics and personality (Reich-Stiebert & Eyssel, 2015; Robert et al., 2020) and prior experience with robots (Bartneck et al., 2007), also play a major role in attitudes toward robots. In addition to individual and context-specific variations, attitudes toward robots could be examined from the perspective of the presence or absence of threats robots pose for people as a group-level explanation (Spears & Tausch, 2015). By integrating the perspectives of realistic group conflict and social identity theories, intergroup threat theory provides one theoretical framework for such investigations (Böhm et al., 2020).

Integrated threat theory was originally developed to explain prejudice between humans considering their relative group memberships (Stephan & Stephan, 2000). Prejudice refers to an orientation, an attitude or affective feeling, toward a group and its members and research has searched for both individual- and group-level explanations for it (Spears & Tausch, 2015). The word's origin also highlights the target's preconceived judgements (Colman, 2015). Investigation on prejudice toward outgroup members has produced multiple theories on the underlying causes that in 1950s and 1960s have been presented under names such as intergroup contact theory (Allport, 1954), realistic conflict theory (Campbell, 1967), and group position theory (Blumer, 1958). During the 1980s and 1990s, the focus turned to research on realistic and symbolic threats, negative stereotypes, and intergroup anxiety, which Stephan and Stephan (2000) integrated into the intergroup threat theory. The integrated threat theory, as it is also named, was later revised to comprise of two components, namely realistic and symbolic threats (Stephan et al., 2008). Instead of actual threat, the theory attempts to explain the origin of prejudice in perceived threats and fears people hold toward outgroup members. Findings of higher intergroup anxiety, negative stereotypes, and realistic threat toward low status outgroups demonstrate that factors such as the outgroup's social status are likely to influence the perceived threat (Riek et al., 2006; Rios et al., 2018).

Integrated threat theory has recently been proposed to explain negative attitudes and emotions also toward robots (Vanman & Kappas, 2019; Yogeeswaran et al., 2016). As Vanman and Kappas (2019) mention, differences may apply because, for instance, robots most likely will not react and express similar emotions and attitudes toward humans. However, robots that are perceived as part of a threating outgroup could in theory have other similar consequences that human outgroup members also have. A robot workforce could pose a threat to human workers and become a target of prejudice, especially if they are accepted as social actors, as some prior research suggests (Banks, 2019; Latikka, Rubio-Hernández, et al., 2021; Lee et al., 2006; Nyholm & Smids, 2020), but not as part of the same ingroup (Groom & Nass, 2007; Jackson et al., 2020). Even in a shared ingroup, robot members could end up highlighting a common identity between humans and decrease prejudice toward human outgroup members (Jackson et al., 2020).

3.2 Group identity and emotional investment

Group identification has been studied as a cause for ingroup bias and prejudice toward outgroup members even in situations where there is no realistic intergroup conflict or threat present (Böhm et al., 2020). Thus, group identity has been treated as an independent variable explaining outgroup prejudice. In other words, prejudice has been examined as an outcome of identifying strongly with an ingroup. However, identification is not necessarily constant and can vary as it becomes stronger in some situations where the social context highlights certain divisions of group memberships, such as a match between national sport teams (Spears & Tausch, 2015). Therefore, a group identity can also be examined and treated as an outcome that other independent variables affect, such as a workplace or teamwork situation where a robot is introduced as an ingroup member while, as technology, it is simultaneously representing an outgroup to human workers.

Group processes have traditionally been studied under the broader framework of the social identity approach (Ashforth et al., 2008; Ellemers et al., 2004; Heere & James, 2007). The social identity research tradition has been interested in and leaned toward basic research on group processes in the presence of abstract social categories, but it has also been applied to specific situations with less distant group categories, such as a work community or team, that are closer to people's everyday life and activities (Hogg et al., 2004). Social psychological literature on social identity states that people form groups on a minimal basis (Ashforth & Mael, 1989; Hogg et al., 2004; Tajfel et al., 1971). Considering this minimal group paradigm, theoretically, robots could be perceived as ingroup members of a given community or small group if they meet the minimal criteria for it.

Research under the self-categorization theory, which is a part of the social identity perspective, has focused on discovering the processes that enable and lead to perceiving membership in a shared group (Turner, 1999; Turner & Oakes, 1986). Investigation on the structure of group identity has resulted in researchers considering multiple dimensions of ingroup identity (Ashmore et al., 2004). Representing different types to relate to one's group, the social identity theory tradition has originally argued in favor of emotional and cognitive dimensions of social identity (Tajfel, 1982; Tajfel & Turner, 1979).

Leach and colleagues (2008) proposed a multicomponent model of ingroup identification with two larger dimensions that correlate with each other: self-investment and self-definition. Self-definition involves cognitive-oriented valuations of the group's cohesion and comparisons of oneself in relation to other group members' qualities or an appraisal of the average group member archetype. In contrast, self-investment refers to feelings of solidarity toward, satisfaction with, and centrality of being a member of a certain group. People who are highly invested in a group sense a bond with the group in which they put emotional value and consider essential for them (Leach et al., 2008). Thus, while self-definition stresses cognitive processes in ingroup identity evaluation, self-investment represents the more emotional dimension of group identification.

The emotional and cognitive emphasis of the two broader dimensions can also be demonstrated through scrutinizing the more specific factors and items of the ingroup identification measure. In the self-investment dimension of Leach and colleagues' (2008) ingroup identity model, centrality demonstrates how important a group membership is to people and how often it occupies their mind. This could be defined as the emotional value a person gives to being part of the group. Solidarity explicitly addresses emotional responses and describes feelings of a bond and commitment (Leach et al., 2008). Thirdly, satisfaction covers emotional states of feeling good or pleasant to be a group member and being glad or proud of it (Leach et al., 2008). In contrast, the self-definition dimension addresses perceived similarities between the person and the average group member, categorized as individual self-stereotyping, and between group members, namely the ingroup homogeneity factor (Leach et al., 2008).

Leach and colleagues (2008) did not describe the two general dimensions of self-definition and self-investment as a cognitive and an emotional dimension of group identification. However, I argue in favor of this interpretation based on the wording used in the measuring items. While self-definition statements beginning with "I am similar" and "people have a lot in common" take the orientation of how the person views the facts on the matter, self-investment items merely claim how the person feels toward or values the group membership. This is visible in statements starting with "I feel," "I am glad," "It is pleasant," and "Being [ingroup] is an important part of how I see myself." In line with Tajfel's (1978) description of higher emotional investment increasing the importance of the group membership, Leach and colleagues (2008) claimed to demonstrate how the five smaller components predict "individuals' orientation to, and emotions about, real intergroup relations (p. 144)."

3.3 Attitude and its affective component

Perceived threat and prejudice ultimately manifest in implicit or explicit expressions of attitude judgements toward the attitude object. Theoretical assumptions, such as intergroup threat theory, make possible hypotheses of the attitude's certain direction. However, without specific situational conditions, it should be assumed that people could react to attitude targets such as robots in various ways and hold different types of perceptions about them.

Attitude refers to an overall evaluation of an object, the attitude target (Haddock & Maio, 2015). Explicit and implicit attitudes have been proposed as either separate systems, structurally the same but reflecting different levels of processing, or separate but interacting based on the activation level (Albarracín et al., 2008). When investigating and measuring explicit attitudes, a common and simple way is to divide attitudes to positive and negative and leave a neutral option for situations where there is no clear positive or negative orientation (Haddock & Maio, 2015). Instead of mere valence or orientation, attitudes can also be positioned in a polar scale from positive to negative or in different scales for both positivity and negativity to measure their strength (Haddock & Maio, 2015). The former is favored due to findings that suggest the structure of attitudes in memory are bipolar, and therefore, bipolar questions are more easily answered and more accurately processed (Albarracín et al., 2008). These are examples of ways to understand an attitude's possible orientations and strength and a means to measure attitudes depending on the aims of the research in question.

Attitude is a broad hypernym for various more specific perceptions, such as "usefulness" or "pleasantness." Traditional attitude theories have also described distinguished attitude components that construct an overall attitude (Ostrom, 1969). Components, such as an affective component, could then be understood as hypernyms for various specific attitudes, such as "pleasantness," in addition to being hyponyms for overall attitude. With respect to the component view, some have argued the formation of attitudes is based on affect or emotion, rational thinking or beliefs, and past behavior (Olson & Kendrick, 2008). Thus, in the classic tripartite model, attitude has three components: affective, behavioral, and cognitive (Eagly & Chaiken, 1998). This attitude component theory is often presented in social psychological textbooks using Rosenberg and Hovland's (1960) outline, but a similar trichotomy can be traced back to the beginning of the field of social psychology and even Greek philosophers (Breckler, 1984).

Although Breckler (1984) and other researchers (Farley & Stasson, 2003; Klop & Severiens, 2007) reported findings that supported the existence of these three distinguish components, other researchers found that treating them as unique dimensions provided little added value and concluded that a single component was as sufficient to measure attitude (Bagozzi & Burnkrant, 1980; Ostrom, 1969). Important validating conditions Breckler (1984) noted, for example, are that both verbal and nonverbal measures of affect and behavior are needed to find distinct components. Another researcher argued that the correlations between the components are stronger when using only verbal self-report measuring techniques that rely more heavily on cognitive processing compared to behavior or emotions (Greenwald, 1982). In his own experiments on attitudes toward snakes, Breckler (1984) highlighted the value of having the attitude target present when measuring different attitude components. He suggested that without this, only cognitive processing would activate, and thus, would measure predominantly the cognitive component and increase the intercomponent correlations.

Breckler (1984) also noted that the target's absence would mean that the responses were toward the attitude object's symbolic or mental representations. In line with Breckler's (1984) reasoning, measuring attitude toward a symbolic representation of the attitude target could yield results that would result in supporting the one component model of attitude. The reason Breckler's (1984) own experiments supported the multicomponent model might be because it measured attitude so widely: not only toward the concept of the attitude target, but also toward the presence, approach, and touching of the attitude target. However, I argue that such a wide scope of attitude-measuring techniques extends the definition of attitude so broadly that it might overlap too much with concepts outside of attitude, such as emotions or reflex. For instance, other researchers have defined some such affective attitudes as emotions or affects instead of attitudes (Beaudry & Pinsonneault, 2010).

In the light of Breckler's (1984) argumentations, I find it relevant that researchers either pursue measuring all aspects of attitudes or define which type of attitude specifically is under investigation instead of measuring ambiguously just attitudes. In addition, depending on the situation and nature of the attitude target under investigation, different types of attitudes might be relevant. If people have no prior interaction experience with the attitude target, they base their attitude on affective and cognitive instead of behavioral information (van Giesen et al., 2015). Furthermore, in the case of an unfamiliar attitude target, such as novel technology, affective attitude items predict people's overall attitude more reliably (van Giesen et al., 2015). Thus, studies on novel concepts such as a robot colleague should include affective attitude measures in their research designs. In addition, some researchers have argued that cognitive evaluation is a secondary process further away from people's readily available associations or representations on which they could base their judgment (Smith & Nosek, 2011). Focusing on affective processing also decreases the need for the distinction between explicit and implicit attitudes that are found more distinguishable when focusing on beliefs and the rational judgement process (Smith & Nosek, 2011).

Based on the literature discussion the theoretical frameworks for attitude, the relationship between attitudes and emotions and their conceptualizations seems ambivalent. In multicomponent perspectives on attitudes, emotions are reduced to one processing type under the overall attitude to serve the role of subjective feelings, facial expressions, physiological arousal, or involuntary reactions (Olson & Kendrick, 2008). Related to this, researchers in favor of attitudinal theory of emotion claim that emotions could be viewed as types of attitudes (Deonna & Teroni, 2012). Sometimes, attitudes and emotions appear as unconnected, independent concepts, for example, in models predicting behavioral constructs. Such is the case with the extended theory of reasoned action where affect and attitude toward an act predict behavioral intention (Triandis, 1979). Other times, cognitive responses connect to and appear alongside affective responses in predicting attitude or behavioral change, as in one suggested extended theory of an elaboration likelihood model (Li, 2013). Against these theoretical discussions, emotional or affective constructs correlate with cognitive constructs, and potentially overlap or are parts of the same construct.

The literature on the emotion theories provides equally complex accounts on the relationship between attitudes and emotions. While theoretical frameworks do not agree on the conceptualization or processes for emotion, some link cognitive appraisal to emotion (Barnard & Teasdale, 1991; Moors, 2009). Based on the traditional accounts of emotion in philosophy and psychology, emotion is a broad concept that includes both feelings and attitudes (Dixon, 2012) that can be defined as a mental state involving hedonic content (Cabanac, 2002). Emotions manifest, for example, in verbally expressed feelings or nonverbal signals, while affect refers to the underlying experience that may or may not manifest itself as emotions (Russell, 2003). Although emotions could be studied via other means, such as physiological responses, survey measures have been widely used for investigating emotions (Marcus et al., 2006). Survey measures of emotion utilize concepts from affect dictionaries to measure feelings and other subjective experiences via self-ratings, for example, of pleasantness and comfortableness (Altarriba et al., 1999; Wallbott & Scherer, 1989; Whissell, 1989). Research on perceived threat from and prejudice toward an outgroup has also utilized survey measures to study emotions such as anxiety (Brader et al., 2008).

The attitude and emotion constructs have sometimes overlapped in HRI research developing new robot-specific acceptance measures, for example, when measuring acceptance based on negative emotions (Nomura, Kanda, et al., 2006; Nomura, Suzuki, et al., 2006). Acceptance of advanced technology such as robots has also been studied using measures previously validated for studying acceptance of other technologies. Based on the social psychological theory of reasoned action and related research, the technology acceptance model was developed for predicting the anticipated end users' successful technology adoption (Davis, 1985). However, considering robots' vastly different nature and functionalities compared to mere technological tools humans can use, these measures might not be the best and should not be the only way to measure acceptance toward coexisting or interactive technology such social robots (Young et al., 2009). As this is an emerging field involving the novel social role positioning of technology, the measurement tools have varied and the search for suitable ones for social and psychological constructs will continue. Considering the weaknesses of cognitive measures of attitude (Peters & Slovic, 2007) and the explicit nature of survey measures, the HRI field could benefit from utilizing more versatile affective measurement designs to study reactions and associated emotions toward the representation of robots at work.

3.4 Identifying positivity and emotions in written text

All measures have their strengths and weakness. While emotion research has measured emotions with physiological and traditional survey measures, research on the more cognitive concepts of attitudes and public opinion has relied heavily on self-ratings in survey measures (Crano & Prislin, 2008). This is also true in HRI research where user studies on specific robot models utilizing convenience samples are common (Naneva et al., 2020; Savela et al., 2018). Furthermore, although some researchers have been interested in validating implicit measures, attitudes most often are measured with explicit measures that rely on people's metacognitive processes to evaluate their attitudes (Albarracín et al., 2008; Crano & Prislin, 2008). While survey research is suitable for examining explicit affective attitudes, there is a demand for other research designs, for example, in the field of HRI (Naneva et al., 2020). Considering surveys' weaknesses, such as response effects (Bassili, 2008), technology-acceptance research could benefit from complementing survey and physiological measures of attitudes and emotions with other less-often used data collection and analysis methods. I argue that one useful research avenue is to use computational social sciences approach to detect implicit attitudes and emotions via automated content analysis of written text.

Before the text analysis, the written form of data must be collected, and surveys can still be useful for this. Respondents can write down the thoughts that ran through their minds during a particular stimulus such as message, as in the thought-listing procedure that has been used for measuring attitudes (Breckler, 1984; Greenwald, 1968). Instead of responding to actual situations, survey participants can also write their responses while imagining a hypothetical scenario. This is a nonactive type of role-playing method or empathy-based stories method (Greenberg & Eskew, 1993; Wallin et al., 2019). It utilizes people's capabilities to empathize and respond to fictional circumstances, and it assumes the reactions are close to or reveal something about the responses to a similar real situation (Sage, 2003). For investigating attitudinal processes rather than behavior, researchers should avoid giving the participants too detailed context information that could confound the results (Greenberg & Eskew, 1993). Instead, respondents should role play and respond to open answer fields as themselves in the hypothetical situation (Greenberg & Eskew, 1993). When combined with an experimental design, this data collection method's strength is the possibility to use randomization to examine causal effects of differently framed scenarios, as in experimental vignette studies (Atzmüller & Steiner, 2010).

There are also various other source options for collecting text-form data, such as fiction and nonfiction literature, scientific publications, newspapers and news websites, and social media. When the researcher is interested in public opinion and the social acceptance of technology such as robots, examining public discussion forums provides an alternative for opinion surveys. While in opinion surveys combining individual attitudes for an overview forms the results, the results derived from analyzing public discussions are more dependent on social factors and the various usages of language (Hoffman et al., 2007). Thus, individual voices might receive substantially more weight (Lewandowsky et al., 2019). Although this is a more biased view on attitudes compared to looking at central tendencies, it might provide a more realistic picture of the socially regulated public opinion compared to collecting essentially private opinions via surveys. Thus, studying naturally occurring discussions over time in social media could grasp the societal pulse on a topic such as robotic technologies.

After collecting the data, the contents of the text corpora must be analyzed with qualitative or quantitative analysis methods. Advances in automated text analysis and utilizing emotional lexicons provide a quantitative means to analyze comprehensive corpora within a short amount of time (Piryani et al., 2017). While texts can include explicit statements, detecting opinions and attitudes is challenging with the computer-aided content analysis because it requires a confirmed attitude target and a subject to which the attitude belongs (Munezero et al., 2014). However, this is not the case with examining affective qualities in written text that could provide information about the underlying emotions and implicit attitudes associated with the topic of conversation.

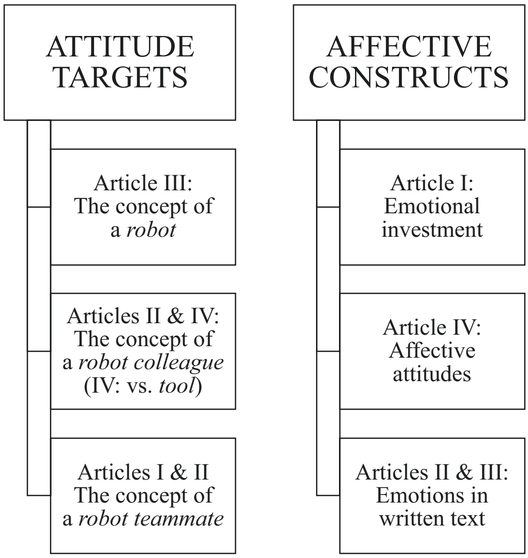
Emotional detection literature provides an overview on the ways to investigate and identify emotions from facial expressions, speech, and writing (Cowie & Cornelius, 2003; Russell et al., 2003). From the different and often interchangeably used affective constructs, emotions can be expressed through language but may not always be detectable through text due to its complexity (Munezero et al., 2014). Although present in the names of the sentiment analysis and opinion mining methods, it is misleading to call affective qualities in written language as sentiments or opinions (Munezero et al., 2014). However, to complement the more explicit affective attitudes measured via traditional survey measures, collecting textual data from survey participants or public discussion forums and analyzing their emotional qualities with affective computing methods could provide a novel perspective on positivity and potential prejudice toward robots.

4 STUDY AIMS AND METHODS

This dissertation reports research on affective attitudes toward and potential prejudice against robots at work. The recent advances in robotics have focused on deploying robots more for social tasks and in social contexts, such as collaborative tasks in work teams, which presents new social and psychological demands for the involved people. Examining workers' and the public's prior judgements before a transition provides knowledge to prevent negative outcomes such as decreased wellbeing.

In this dissertation, I utilized the intergroup threat theory (Stephan & Stephan, 2000) as a theoretical framework for examining realistic and symbolic threats that robots pose and the potential prejudice behind the affective attitudes (Vanman & Kappas, 2019). Based on my review of theoretical and methodological discussions on attitudes and emotions, I conclude that I investigated affective attitudes through focusing on the affective qualities of ingroup identification, attitudes, and positivity in text. Thus, I examined emotional investment, affective attitudes, and positive emotions in text. In the interest of being concise, I will refer to all different types of affective constructs considered in this dissertation as affective attitudes, while acknowledging it describes some of the constructs better than the others. This dissertation's attitude targets were the concepts of robots, robotic tools, robot colleagues, and robot teammates. Based on the previous literature on attitude measurement and mental and social representations, I acknowledge the symbolic representations associated with these concepts and their role in attitude formation. Figure 1 shows the constructs under investigation in this dissertation from all four research articles.

Figure 1. The constructs under investigation in this dissertation.



Data collection methods and appropriate analysis methods were chosen to complement each other because every method has its own strengths and weaknesses. To scrutinize the topic from different viewpoints, I utilized different data types, namely survey experiments, social media data, and longitudinal survey data. I measured the affective attitudes via the survey responses and computational analyses of emotional qualities in written text. The levels of analysis considered included the public's social media discussions and responses to hypothetical workplace scenarios in survey experiments, and the changes in workers' affective attitudes over time. Table 1 shows an overview of the data, methods, and research questions of all four research articles.

Table 1. Overview of the data, methods, and research questions of each study.

	Article I	Article II	Article III	Article IV
RQs/Hs	H1–H4	H5–H8	RQ1–RQ3	H9–H13
Data type (timeframe)	Cross-sectional vignette survey experiments (2019)	Cross-sectional survey experiments with role-playing data collection method (2019, 2020)	Social media data (2006–2018)	Nation-wide longitudinal survey data with four time points (2019–2021)
Observation units and target population (samples)	Survey respondents from U.S. adult population (Study 1: *N* = 1,003; Study 2: *N* = 969)	Survey respondents from U.S. adult population (Study 1: *N* = 1,003; Study 2: *N* = 969, Study 3: *N* = 1,059)	Reddit users' comments (*robot: N* = 3,433,554; *AI: N* = 2,821,614; *automation: N* = 879,092; *bot: N* = 21,559,939; *intelligent agent: N* = 15,119; *software agent N* = 18,324)	Survey respondents from Finnish working population (*N* = 830) with 3,152 observations from four time points
Methods	Descriptive statistics, ANOVA, independent two-sample T-test, OLS regression, single-level mediation	Computerized text analysis (Vader, WKB, SentiStrength, LIWC), descriptive statistics, word cloud, Kruskal-Wallis, OLS regression	Computerized text analysis (Vader, LIWC), descriptive statistics, logistic regression	Descriptive statistics, hybrid multilevel linear regression modelling for within and between participant effects over time
Dependent variables	A 14-item ingroup identification instrument adopted to work team context	Vader, SentiStrength, and LIWC lexicon scores	Vader compound score as continuous and categorical measures (positive text: 0.05<)	Two items measuring affective attitudes toward introducing robots at work
Main independent variables	Experimental group	Experimental group	Scores from LIWC lexicons for *work, home, leisure, social, power, money, focus past, focus present,* and *focus future*	Professional efficacy and cynicism (MBI-GS), technology-use productivity, robot-use self-efficacy (RUSH-3), prior robot use
Control variables	Age, gender, degree in technology, prior robot experience, attitude to robots, personality (BFI-S)	Age, gender, degree in technology, prior robot experience, attitude to robots, personality (BFI-S), robot suitability to own field	Word count, timestamp	COVID-19 pandemic time, occupational field, income level, gender, age, and personality (BFI-S)

4.1 Research aims, questions, and hypotheses

This dissertation aims to gain more knowledge on the social psychological consequences of robotization through investigating the affective attitudes and potential prejudice toward robots focusing on the work domain. The dissertation comprises studies reported in four research articles that examined the phenomena from various perspectives. This dissertation aims to answer the following general research questions:

1. What type of affects are expressed toward robots in the work domain?
2. How do people feel about working with a robot?
3. How does prejudice toward robots arise?

To answer to the general research questions, my objective is to scrutinize the findings from the research articles' diverse research designs. Considering that different concepts associate with their own expectations and preconceptions, the attitude target is considered from the perspectives of the general concept of a robot used colloquially, a tool used at work, a colleague in the same workplace, and an ingroup member of the same work team. I examine people's perceptions of robots at work from the affective perspective considering emotional investment, affective attitudes, and positive emotions in written responses and social media discussions. While taking into consideration the multifaceted nature of attitudes and affects as well as the conceptualization of robots, I expect to gain more understanding of the affective attitudes associated with the concept of a robot, the affective responses people express toward the notion of a robot colleague, and the symbolic and realistic reasons behind prejudice toward robots.

In addition to this dissertation's general research questions, the studies reported together with other authors in the included research articles had their own article-level hypotheses and research questions. **Article I** aimed to examine how having one or more robots on a work team affects the ingroup identification and its dimensions compared to having only humans on the team. Thus, the following hypotheses were pre-registered at the Open Science Framework before collecting the data (Oksanen et al., 2019): Having a robot as an ingroup member decreases ingroup identification (H1) and both of its dimensions: self-definition (H2) and self-investment (H3), and ingroup identification and both self-investment and self-definition decrease when the number of robot members in a group increases (H4). Additional analyses also sought what individual differences exist in identifying with work teams including robots through considering factors of a positive attitude toward robots, prior interactional experience with robots, education in technology, and personality traits, including neuroticism, extraversion, openness, agreeableness, and conscientiousness.

Article II mainly aimed to investigate how positively people react to working with robots based on emotions in written text. Furthermore, additional analyses aimed at exploring the influencing factors behind the reactions. To answer the research questions, we formulated the following hypotheses: People write less positively about working with robots compared to working with other people (H5), people write less positively about working with robots when humans are a minority compared to when robots are a minority in a work group (H6), people write less positively about working with robots when the mutual ingroup is small and requires more interaction (a team vs. an organization; H7), and people with a positive attitude toward robots in general write more positively about working with robots (H8).

Article III aimed to discover how the prevalence and positivity of the comments in social media discussions on robotic technologies varied based on the concept used (robot, automation, AI, bot, intelligent agent, and software agent) and thematic context in which it was used (work, home, leisure, social, power, money, past, present, and future). Thus, the following research questions guided our research. RQ1: How does the use of robotic technology concepts (robot, automation, AI, bot, intelligent agent, and software agent) vary in Reddit discussions? RQ2: How does the positivity in Reddit comments differ among different robotic technology concepts (robot, automation, AI, bot, intelligent agent, and software agent)? RQ3: How does a greater focus on different life domains (work, home, and leisure), motives (social, power, and money), or temporal aspect (past, present, and future) connect to positive comments in Reddit discussions on robotic technologies?

Article IV aimed to examine how various cognitive (perceived cynicism, professional efficacy, technology-enhanced productivity, and robot-use self-efficacy) and behavioral factors (prior experience with robots) have influenced affective attitudes toward robots over time. In addition, our aim was to analyze how the COVID-19 pandemic effected the affective attitudes toward introducing robots at work. We posed the following hypotheses to investigate the connections of psychological wellbeing factors and factors regarding competence and experiences with robots to affective attitudes toward introducing robots at work: High cynicism at work predicts positive affective attitudes toward introducing robots at work (H9), high perceived professional efficacy predicts negative affective attitudes toward introducing robots at work (H10), high perceived technology-use productivity predicts positive affective attitudes toward introducing robots at work (H11), high robot-use self-efficacy predicts positive affective attitudes toward introducing robots at work (H12), and having prior robot interaction experiences predicts positive affective attitudes toward introduction of robots at work (H13).

4.2 Data

4.2.1 Survey experiments

In the first and second survey experiments utilized in **Articles I** and **II**, participants were sorted randomly into three experimental groups. They were asked to imagine a hypothetical workplace 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. No robots were mentioned for the control group that described a work team with four other people. One experimental group described a team with four robot members. In the first survey experiment, the middle group was introduced to a work team of one robot and three human members, while the middle group in the second survey experiment was introduced to a work team with three robots and one human member.

After the vignette assignment in both survey experiments, the participants were asked to respond to questions about how strongly they identified with the hypothetical work team utilizing a 14-item ingroup identification measure (Leach et al., 2008). Following that, they were also asked to write a short social media post about the hypothetical scenario of their first day at a new job. The ingroup identification responses were utilized in **Article I**, and the responses to the role-play task were used in **Article II**. Participants also answered survey questions about sociodemographic information, personality, and prior interactional experience with and a general attitude toward robots.

Article II also utilized a third survey experiment where participants were randomly assigned to four groups. Different to the two previous survey experiments, the members of the shared social group were either colleagues also starting at the job or teammates as in previous survey experiments. Two control groups (only human teammates or colleagues) did not mention robots, but the other two experimental groups were primed with either four robot teammates or four robot colleagues.

The survey experiments were conducted in January 2019 (N = 1,003; 51.11% female; M_{age} = 37.36, SD_{age} = 11.80, range 19–78 years), in April 2019 (N = 969; 51.15% female; M_{age} = 37.15, SD_{age} = 11.35; range 15–94 years), and in April 2020 (N = 1,059; 48.29% male; M_{age} = 37.97, SD_{age} = 11.75, range 18–79 years) by collecting a sample from a U.S. adult population via Amazon's Mechanical Turk. An open-source online software LimeSurvey was utilized for collecting the survey responses. The randomization of the experimental groups was successful based on finding no significant differences in gender, age, and technology degree. Considering data validity and nonnaive participants, the samples were screened for duplicates and abnormal response behavior (Chandler et al., 2014; Chandler et al., 2015; Kennedy et al., 2020).

4.2.2 Social media data

For **Article III**, we collected social media discussions on robotic technologies to focus on the conversations around the concept of a robot. We also identified other related concepts to provide an overview of the discussions on robotic technology concepts while considering the differing representations and emotions with which they are associated (de Groot, 1989; Wagner et al., 1999). The concepts of automation, bot, AI, and software/intelligent agent were chosen to represent both tangible and intangible robotic technologies after considering the definitions for robots and robotic devices and the history and advances of robotization (ISO, 2012; Stone, 2004). To highlight the representations associated with the general concepts and to confine the scope of the study, we excluded terminology that is more specific and focused on the hypernyms.

The data collection was carried out in March 2019 from the Reddit platform, which is one of the most-visited social media platforms in the United States with an increasing number of monthly active users, for example, from 70 million in 2013 to 430 million in 2019 (Auxier & Anderson, 2021; Reddit, n.d.). The Reddit platform was chosen for its successful utilization to examine discussions on various topics because of its multifaceted content (Brett et al., 2019; de Choudhury & De, 2014; Medvedev et al., 2019; Zamani et al., 2019). Based on the large number of comments we collected and analyzed, it proved to be a suitable social media data source for studying discussions about robotic technologies as well.

The identified robot-related concepts were used as seeds in the search criteria for finding the relevant discussions. By analyzing the Reddit corpus of pushshift.io to identify texts referring to the six chosen concepts (Baumgartner et al., 2020), we retrieved 55,254,140 comments for discussions on robots, AI, automation, bots, intelligent agents, and software agents. We excluded duplications from all corpora by the same author to the same subreddit and irrelevant comments from the robot (Mr. Robot: n = 84,867) and AI corpora (AIN'T: n = 71,270). Thus, the final six corpora were the following: robot (N = 3,433,554), AI (N = 2,821,614), automation (N = 879,092), bot (N = 21,559,939), intelligent agent (N = 15,119), and software agent (N = 18,324). For the regression analysis for the comments about bots, we selected 1,000,000 texts randomly from the bot corpus via downsampling.

4.2.3 Longitudinal survey

For the analyses of **Article IV**, we utilized a longitudinal Social Media at Work in Finland Survey. The survey was designed to represent the Finnish working population and the representativeness analysis on sociodemographic factors of the original survey data (N = 1,817; collected in March–April 2019) suggested that the data represented the target population successfully. Due to including the relevant robot-related items needed for the study, we used the four time points after the original data collection in Article IV. The first time point used in the article was collected in September–October 2019 (T1; n = 1,318). Thus, the second time point was collected in March–April 2020 (T2; n = 1,081), the third time point in September–October 2020 (T3; n = 1,152), and the fourth time point in March–April 2021 (T4; n = 1,018). The original participants were recontacted for T3, which explains the larger number of participants compared to T2. The response rates for each time point were acceptable (72.54%–56.03%) and 46.23% of the original participants responded to all surveys (n = 840). From those, only the ones who reported being part of the workforce at least once after the original survey were included in the final sample (n = 830; T1: 44.33% female; M_{age} = 44.33; SD_{age} = 11.09; range = 19–65 years).

4.3 Main variables

4.3.1 Survey measures

The dependent variable in **Article I** was the group identification with a work team. It was measured by adapting Leach and colleagues' (2008) 14-item survey instrument of group-level ingroup identification for the context of a work team. It was developed to measure an individual's social identification with a group, in contrast to personal identities. The 10 statements about the self-investment and four about the self-definition dimensions were rated on a 7-point Likert scale from 1 ("strongly disagree") to 7 ("strongly agree"). We used three dependent variables for the analyses: the whole measure, self-investment, and self-definition.

In **Articles I** and **II**, the main independent variable was the experimental group condition indicating to which hypothetical group composition of human and robot colleagues the participant was introduced. The discrete variable had three possible values in the first two survey experiments. The first value represented the control group, which was not exposed to information about robots, and the last value indicated an experimental group exposed to a description of being assigned to a five-member work team with four robots. In the first survey experiment, the value in the middle indicated a five-member work team with one robot and three other humans, and in the second survey experiment, the middle value indicated a five-member work team with three robots and one other human. However, for the third survey experiment reported only in **Article II**, the experimental group variable had four possible values. Two of them represented the same first and last versions of the experimental conditions from the previous two survey experiments, and two indicated the two new conditions added to the third survey: a scenario describing four robot colleagues at the same organization rather than a work team and an additional control group reflecting the same difference through describing human coworkers in general rather than teammates. Although the values used for the three-point experimental group variables of the first two survey experiments could be interpreted as an ordinal scale, indicating a lack of or an increase of robot teammates (0-1-2), the values in the experimental group variables ultimately reflected categories in a nominal scale.

In **Article IV**, the dependent variable was the affective attitudes toward introducing robots at work. Two items measured comfortableness toward using robots as tools and having robot colleagues (Latikka et al., 2021a) with answer options on a 7-point Likert scale from 1 ("not at all comfortable") to 7 ("very comfortable"). They were used as a two-item sum variable and additionally as one-item measures for comparison in the analyses.

In **Article IV**, the main independent variables were cynicism at work, perceived professional efficacy, technology-use productivity, robot-use self-efficacy, and prior robot use experience. The first two, the negativity toward the significance of one's work and the satisfaction of one's work performance, were measured with five- and six-item subscales of cynicism and professional efficacy of the Maslach Burnout Inventory General Survey (MBI-GS; Maslach et al., 2018). The answer options for both measures ranged from 0 to 6, but for the analyses, we used sum variables with scales of 0–30 and 0–36, respectively. Perceived productivity of technology use was measured with three statements adapted to the context of social media from the productivity subscale of Ragu-Nathan and colleagues' (2008) technostress measure. The answer options ranged from 1 ("disagree completely") to 7 ("agree completely"), but for the analyses, we used a scale with a range of 3–21. Robot-use self-efficacy was measured with statements about the sense of competence in using robots applied from an instrument involving the healthcare work context (RUSH-3; Turja et al., 2019). The answer options ranged from 1 ("disagree completely") to 7 ("agree completely"), and the final scale used had a range of 3–21. Lastly, we measured prior robot use experience by asking participants when they had last used or interacted with robots. For the analyses, we created a dummy variable for all time points, where a value 0 indicated an answer option, "I have never used or interacted with a robot," and a value 1 combined the other options: "During the past week," "During the past month," "During the past half a year," "During past year," and "Over a year ago."

4.3.2 Computational text analysis measures

In **Article II**, the dependent variable was the positivity in the social media posts written as role-play responses for the three survey experiments. The positivity was measured using six different sentiment analysis tools: the WKB valence score (Warriner et al., 2013), VADER compound score (Hutto & Gilbert, 2014), positive and negative measures of SentiStrength (Thelwall et al., 2010), and positive and negative emotion lexicons of LIWC (Pennebaker, Boyd, et al., 2015; Tausczik & Pennebaker, 2010).

In **Article III**, the dependent variable was the positivity in the comments from social media. It was measured with the VADER sentiment analysis tool that we validated for our study through comparing the VADER scores for a random sample of 500 robot and AI comments to the Amazon Mechanical Turk participants' ratings (N = 539). By utilizing the recommended thresholds for the VADER compound score to label each text as negative, neutral, or positive (< −0.05–0.05 <), we created a dummy variable for the main analyses where a value 1 indicated positive comments and a value 0 indicated neutral or negative comments.

In **Article III**, the main independent variables were the nine LIWC lexicon categories (work, home, leisure, social, power, money, focus past, focus present, and focus future). The LIWC assigns each text a score from 0 to 100, a percentage of category-specific lexicon words present in the text, but we rescaled the LIWC variables to 0–10 for our analyses.

4.3.3 Control variables

This dissertation focuses on presenting and combining the main analyses of the four publications, but several additional factors were also considered as controls and reported in detail in the original publications. In the survey experiments of **Articles I** and **II**, the background factors examined in the additional analyses and used as control variables were gender, age, a technology degree, personality traits, prior interactional experience with robots, perceived attitude toward robots, and perceived suitability of robots to one's own field of work. Female was used as a reference category for gender, age was used as a continuous variable, and a dummy variable indicated whether the participant had a degree in technology. Neuroticism, extraversion, openness, agreeableness, and consciousness were measured with a 15-item big five inventory on a 7-point Likert scale (Lang et al., 2011). Prior interactional experience with robots was measured through asking whether participants had used or interacted with a robot and creating a dummy variable for the analyses (1 = Yes, 0 = No/Don't know). Perceived attitude toward robots was measured with self-generated one general item and with six affective, cognitive, and behavioral attitude items based on the applied theoretical assumptions of the tripartite attitude theory (Zanna & Rempel, 2008). All items were measured on 7-point Likert scales (1 = very negative to 7 = very positive; 1 = strongly disagree to 7 = strongly agree). Perceived suitability of robots to the participant's field was measured with one item with a 7-point Likert scale.

In **Article III**, the two control variables used in the models were the comments' word count and creation time. Word frequency ranged from 1 to 46,066 words, where one word could include long sentences combined into one word (e.g., #RespectTheRobot, Stupidrobot). The first comment was created on 6 January 2006 12:28:59 and the last one on 31 October 2018 23:59:56.

In **Article IV**, the control variables included gender, age, occupational field, income level, personality traits, and the COVID-19 pandemic time. Female was used as a reference category for gender, and age was used as a continuous variable. Occupational field was measured with a dummy variable indicating whether the participants worked in a field of "professional, scientific and technical activities" from a list of occupational fields (Official Statistics of Finland, 2008; United Nations, 2008). Income level was measured by asking participants their monthly gross income. Personality traits were measured with a 15-item big five inventory on a 7-point Likert scale (Hahn et al., 2012). A value 1 of the COVID-19 dummy variable indicated time points T2–T4 and value 0 indicated the time point before the pandemic (T1).

4.4 Statistical techniques

4.4.1 Variance analysis

Article I utilized the one-way ANOVA method, eta square effect sizes, independent two-sample T-test, and Cohen's d effect sizes. Equal sample sizes and keeping within the suggested ratio threshold of heterogenous variance provided support for using ANOVA (Dean & Voss, 1999). However, due to the results from the Bartlett's test for equal variances, the Games–Howell multiple comparison test was used as a post hoc analysis for the ingroup identification measure, and Welch's unequal variance test's one-tailed results were used to test the hypotheses about its self-investment and self-definition dimensions. Additionally, we verified the analyses with the nonparametric Kruskal–Wallis test but reported the results from a statistically more powerful one-way ANOVA. The violations of normality in the dependent variable and its sub-scales were found to be minor based on the skewness and kurtosis values and the large sample size (George & Mallery, 2010; Gravetter & Wallnau, 2017; Tabachnick & Fidell, 2013; Waternaux, 1976).

In **Article II**, we used Kruskal–Wallis H test, Dunn's pairwise multiple comparison post hoc test with Bonferroni corrections, and eta square effect sizes. We chose the nonparametric Kruskal–Wallis method due to violations for equal variance (the Bartlett's test) and normality in some of the dependent variables, although the results did not differ from the one-way ANOVA results. Eta square sizes for the Kruskal–Wallis H test were calculated using Barry Cohen's formula (Cohen, 2008). Analyses for both articles were done with Stata 16 software. A dunntest Stata package by Alexis Dinno (2015) was utilized for Dunn's pairwise multiple comparison tests in **Article II**. IBM SPSS Statistics 25 was used for skewness and kurtosis statistics and Games–Howell test results in **Article I**.

4.4.2 Computerized text analysis

For **Article II**, we computed positive and negative scores with SentiStrength (Thelwall et al., 2010), the WKB lexicon (Warriner et al., 2013), and the LIWC 2015 software (Pennebaker, Boyd, et al., 2015). In **Articles II** and **III**, we used a python script with SentimentIntensityAnalyzer from vaderSentiment 3.3.2 to compute VADER compound scores (Hutto & Gilbert, 2014). In **Article III**, we used nine LIWC lexicons (work, home, leisure, social, power, money, focus past, focus present, and focus future) to examine different themes in the social media comments (Pennebaker, Boyd, et al., 2015). For instance, "employment", "labor", and "organization" are examples of words that are markers for the work lexicon (Pennebaker, Booth, et al., 2015). The LIWC measures are previously validated and rely on a word count technique calculating the percentage of the designated words of a given text (Pennebaker, Boyd, et al., 2015; Tausczik & Pennebaker, 2010).

4.4.3 Logistic regression models

In **Article III**, we chose the logistic regression method because the VADER compound score's distribution and its error terms violated the assumptions of linear OLS regression, and because the higher agreement of the human raters with the categorized VADER compound variable in the validation analysis supported the use of a dummy variable suitable for logistic regression. In the article, we reported odds ratios (*OR*s), standard errors for odd ratios (*OR SE*s), average marginal effects (*AME*s), and *p* values for average marginal effects. From the bot corpus, we used a randomly drawn sample of 1,000,000 comments for the regression analysis because the convergence was not achieved.

In the logistic regression models, we used a dummy variable for positive comments (VADER compound score > 0.05) as the dependent variable, and the nine LIWC measures as continuous independent variables with a scale of 0–10. The models predict the likelihood of a comment being positive compared to negative or neutral if its thematic content emphasized one of the LIWC lexicon categories. The *AME* coefficients estimated the average increase or decrease of likelihood for a comment to be positive for each independent variable because they have proved reliable for comparing effects across models (Mood, 2010). Considering the questionable use of statistical significance when using a large dataset, we focused on comparing the directions and effect sizes of the connections (*OR*s and *AME*s). Stata 16 SE was utilized for the analyses.

4.4.4 Between- and within-person multilevel modelling

Article IV utilized hybrid linear multilevel regression modeling, which offers a solution for the weaknesses of both standard random effects and fixed effects (Schunck & Perales, 2017). We reported unstandardized regression coefficients (*B*), their estimated standard errors (*SE B*), and statistical significance (*p*-value). In addition to between-person effects, hybrid models allowed examining between time points if the within-person variation in the independent variables predicted changes in the dependent variable. Thus, the hybrid models provided information about both the static differences between participants and the temporal differences within participants as it computed these simultaneously to the same model while accounting for the included control variables. Main models included 830 participants (3,152 observations), and an additional analysis on the general attitude toward robots that was measured only on time points T2–T4 included 815 participants (2,335 observations).

All statistical analyses were performed with Stata 16 software, and McDonald's omega coefficients were computed with a Stata module (Shaw, 2020) to estimate scale reliability.

4.4.5 Additional analyses, descriptive statistics, and graphics

For the additional analyses of **Articles I** and **II**, we used the OLS regression method and reported standardized beta coefficients (β) and p values. **Article I** additionally reported a single-level mediation analysis result for testing interaction effects, and **Article II** used unstandardized regression coefficients (*B*) and their standard errors (*B SE*), model goodness of fit measure (R^2), model test (*F*), and the model's p value. While we did not detect problematic multicollinearity, Huber–White standard errors (i.e., robust standard errors) were used in cases with heteroscedasticity of residuals concerning **Article I**.

All articles reported descriptive results for the study variables, including means (*M*), standard deviations (*SD*), frequencies (*n*), and percentages (%). In **Article III**, we provided descriptive statistics for both the original bot corpus and its sample, reported descriptive results with 100% stacked bar chart and histograms, and included a figure demonstrating the data collection and inclusion process of robotic technology comments. **Article I** presented descriptive analysis as interval plots with 95% *CI* for the mean. In **Article II**, we utilized Python module for Stata 16, Python WordCloud Generator, and LIWC adjective lexicon to create a word cloud for negative texts (Vader compound $< -.05$) and another one for the adjectives in the negative texts of the role-play experiments.

Stata 16 SE was utilized for the additional analysis, descriptive statistics, and graphics. The first author was responsible for all the final data analyses of the articles.

4.5 Ethical considerations

Although the topic of affective attitudes toward robotic technologies is not a particularly sensitive research topic, other ethical considerations involve this type of research through its process from the first planning phase to data storage, reporting, and public discussions (Evans & Mathur, 2018). Because of this, each study was given ethical consideration appropriate to each study design and data type. To make sure the surveys worked how they were intended, they were first tested using student samples before the final data collection. The Ethics Committee of Tampere Region approved the protocols of the different studies included in this doctoral dissertation. Data integrity and quality checks were conducted throughout the study following the research group's protocol.

The survey experiments reported in **Articles I** and **II** were conducted in English and collected from U.S. respondents via Amazon Mechanical Turk. The participation was voluntary. The social media dataset utilized in **Article III** was collected from the Reddit platform, chosen as a public discussion forum where the users interact in the platform using nicknames. In addition to the comments' text body, we retrieved information about its publication date, author nickname, and the subreddit in which it was published. This did not include identifiable information and the data collected with the robotic technology search terms did not involve sensitive topics. Instead of focusing on individuals, we analyzed the large data sets from a larger scope to obtain insights from robot-related public discussion from a societal perspective. We did not report any individual-level information or results. The survey used in **Article IV** was conducted in Finnish, the research group designed it, and it was collected in collaboration with Norstat through utilizing Norstat's online research panel for recruiting participants. The participation was voluntary.

5 OVERVIEW OF THE MAIN FINDINGS

5.1 Article I: Group identification with robot work team members

Survey experiments reported in **Article I** examined ingroup identification with a work team that included one or more robot members. Based on the results, introducing robots as coworkers of the same work team posed challenges for social identification processes such as emotional attachment to the group. Compared to an all-human team, the ingroup identification and both its dimensions of self-investment and self-definition were significantly lower toward a five-member work team when one of the team members was a robot (H1–H3 supported). Furthermore, we observed a decreasing trend when examining identification toward a work team consisting of three robot members and one human member. The lowest ingroup identification was measured for people who were assigned alone in a work team with four robot members and without other human members. However, we did not find the decreasing trend for self-definition dimension of ingroup identification when comparing teams that both had a robot majority and a human minority group composition (H4 partly supported). This was demonstrated by comparing responses to a work team with three robots and one other human to a team with four robot members, which revealed a small difference only in self-investment. The additional results also showed that individual factors, such as personality, technological expertise, prior experience with robots, and attitudes toward robots in general, affected ingroup identification. People with a positive attitude toward robots had fewer difficulties in identifying with a work team involving robot group members.

The findings suggest that compared to self-definition, self-investment is more sensitive to small numerical changes in a group composition that still reflect a difference between being the only minority member or having one other human member in the group. Defining oneself in respect to the group often relies on cognitive evaluations of comparing oneself with the perceived average group member. The prototype group member does not alter much in the case of a mere numerical increase in majority members. Instead, investing oneself in the group involves affective evaluations that do not consider the group's composition. This emotional investment represents the ingroup identification's affective dimension, which is the focus of this dissertation along with other affective constructs.

5.2 Article II: Emotional reactions to robot colleagues

A series of role-playing experiments reported in **Article II** investigated emotional qualities in written responses to robot colleagues and teammates. In line with Groom and Nass's (2007) argument, people reacted more positively to the idea of working with human than robot colleagues or teammates (H5 supported). Demonstrating a negative effect of another subgroup (Brown, 2011; Carton & Cummings, 2012), the emotional content of the written responses was more positive when robots represented a minority versus majority in the work team composition while the difference was weaker between two work teams with a robot majority (H6 supported). People reacted more positively to sharing a broader work community of the organization with robot colleagues compared to sharing a more intimate work team with robot teammates while the same was not observed for human colleagues versus teammates (H7 supported). In line with the prior research on the connection between general attitudes and reactions to a specific situation (Ivanov et al., 2018; Venkatesh & Davis, 2000), those with a positive attitude toward robots in general wrote more positively about working with robots (H8 supported). The additional results showed that positivity of the written reactions was affected by socio-demographics and individual factors such as personality, technological expertise, and prior experience with robots. Positive attitude toward robots in general was again a strong predictor of reacting positively toward robot colleagues. Based on the additional content analysis results, feelings of oddity and lack of social interaction explained the negative reactions to robot colleagues.

Based on the results, the humans' minority status, a small group size, and individual factors affected the detected emotions negatively. In the context of intergroup threat theory (Stephan & Stephan, 2000), the findings suggest that robot colleagues pose a symbolic threat to human workers. An identity threat another subgroup poses can cause intergroup anxiety and prejudice toward a robot workforce (Brown, 2011; Carton & Cummings, 2012; Vanman & Kappas, 2019). Furthermore, the findings suggest that sharing a close and more interactive social context, such as a work team, with robots poses a greater threat to human workers compared to robot colleagues affiliated in the same organization and broader work community.

5.3 Article III: Emotional talk about robotic technologies on Reddit

Article III utilized computational social sciences to examine positive emotions, life domains, motives, and temporal themes in Reddit social media discussions on robots and related concepts (robot, AI, automation, bot, intelligent agent, and software agent). Robot, along with AI and especially bot, was a dominant concept in social media discussions in the 2006–2018 timeframe. Robot was the most popular of the six concepts before bot surpassed it in 2011. Thus, the use of robotic technology concepts in social media discussions varied over time and depending on the concept (RQ1), which is in line with research on word associations and social representations (de Groot, 1989; Wagner et al., 1999). Robots, along with AI, were discussed more in negative and less in positive comments compared to the other concepts (RQ2). Robots and AI being more often associated with concerns supports the notion that related concepts are associated with different representations that affect the appraisal processes (de Groot, 1989; Wagner et al., 1999). In the context of integrated threat theory (Stephan & Stephan, 2000), stereotypes and negative representations can elicit prejudice. Robots and AI could be perceived as greater threats to humans compared to the other technology concepts (Vanman & Kappas, 2019).

Considering the third research question (RQ3), the positivity in future-oriented discussions and the conversations around an older concept of a robot being no more positive compared to the newer concepts provide contradictory support for notions of mere exposure effect, familiarity principle, and fear of the unknown (Carleton, 2016; Reis et al., 2011; Zajonc, 1968). The study also did not find support for negativity in discussions about social relations (de Graaf et al., 2019; Savela et al., 2018; Taipale et al., 2015) or economy and work (Dekker et al., 2017). Although work was discussed more positively than the home domain was, the comments related to work were still less positive compared to those about leisure activities, which may not involve technology entering personal spaces or replacing humans. Discussions about power were less positive, which is in line with previous findings about the decreasing sense of control (Latikka et al., 2021a). Considering the positivity in economic and work discussions, this finding implies that the power dynamic does not pose a realistic but rather a symbolic threat that could inflict prejudice toward robots (Vanman & Kappas, 2019).

5.4 Article IV: Affective attitudes toward robots at work

Article IV reports findings from a longitudinal study that examined within-between effects of Finnish workers' psychological wellbeing and affective attitudes toward robots at work. The results showed that increased cynicism at work (H9) and low perceived professional efficacy (H10), strong technology-use productivity beliefs (H11) and robot-use self-efficacy (H12), and prior user experiences with robots (H13) predicted positivity toward robots at work during the timeframe (2019–2021). Affective attitudes of men, introverts, disagreeable, high-income earners, and workers from the science and technology fields were more positive. In addition, people in general were more positive toward introducing robots at work during the COVID-19 pandemic than before it.

Workers with high professional efficacy and optimism toward their work might perceive introducing robots at work as more threatening for their satisfying work life, which is in line with our theoretical argumentation based on integrated threat theory (Stephan et al., 2008; Stephan & Stephan, 2000; Vanman & Kappas, 2019). The results were also in line with previous on research technology acceptance (Venkatesh & Davis, 1996; Venkatesh & Davis, 2000), robot-use self-efficacy (Latikka et al., 2019; Latikka et al., 2021b; Turja et al., 2020), and the theories explaining the positive effect of exposure to the attitude target (Paluck et al., 2019; Reis et al., 2011; Zajonc, 1968); although we did not find support for positive within-person effect based on prior robot interaction experiences with robot colleagues. This could be due to more firsthand interaction experiences with robotic tools than with robot colleagues.

Table 2 shows the summary of the findings from the four research articles included in this dissertation.

Table 2. Summary of the findings from all four articles.

Article ***RQs/Hs***	**Main results**	**Additional results**
Article I: *H1–4 supported*	Having a robot on the work team had a negative impact on ingroup 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 general attitude toward robots, technological expertise, and to some extent, prior experience with robots. 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.
Article II: *H5–H8 supported*	Prejudice: Negative emotions about working with robots. Prejudice increases if a. minority status (more robots than humans in a group) b. close group (team vs. organization) c. negative attitude toward robots in general.	Written reactions were more positive for female, young and technologically educated, agreeable personalities, and those with no prior experience with robots. Positive attitude toward robots in general was a stronger predictor of positive writings than robot's suitability to the job. Findings suggest more negative reactions stem from feelings of oddity in an unusual situation and the lack of social interaction.
Article III: *RQ1–RQ3*	Compared to *automation and intelligent/ software agent*, concepts *bot*, *robot* and *AI* were used most often in Reddit discussions and the latter two less often in positive context. Comments addressing themes of *leisure*, *money*, and *future* were associated with positive and *home*, *power*, and *past* with negative comments. Comments with domestic vocabulary were less likely and leisure vocabulary more likely positive compared to work vocabulary.	From the perspective of the integrated threat theory, our findings support a realistic threat posed by robotic technologies to humans' private space, authority, or autonomy. Results on social, leisure, and future vocabularies suggest low symbolic threat. Results on work, money, and power lexicons do not support the notion of realistic economic threat but rather that human autonomy and control over robotic technologies is a more prevalent threat present in social media discussions. Our findings propose that robots and especially AI are perceived most threatening to humans from the different robotic technologies as they threaten the power balance of humans' authority over technology.
Article IV: *H9–H13*	Increased cynicism toward individuals' own work, robot-use self-efficacy, and prior user experiences with robots predicted increased positivity over time toward introducing robots at work. Workers with higher perceived technology-use productivity, robot-use self-efficacy, and prior user experiences with robots were more and those with higher perceived professional efficacy less positive toward introducing robots at work.	Participants were more positive toward introducing robots at work during the COVID-19 pandemic than before it. The affective attitudes of men, introverts, critical personalities, workers in science and technology fields, and high-income earners were more positive toward introducing robots at work.

6 DISCUSSION

This dissertation aimed to contribute to the understanding on people's expectations and the potential social psychological consequences of introducing new-generation robots at work. This was studied from different perspectives the research articles offered that together contributed to answering this dissertation's general research questions.

1. What type of affects are expressed toward robots in the work domain?

The emotional qualities in public social media discussions on Reddit in 2006–2018 revealed that robots are part of highly positive discussions about leisure activities, slightly positive discussions about the work domain, and negative discussions about the home domain. Thus, social media users expressed more positivity in comments addressing robots and work rather than the home domain, but they were more negative in their robot comments about work than leisure. People expressed positive emotions when talking about robots in the context of money and future, while robots and power or past orientation were discussed more negatively. In addition, the concepts of robots and AI were used more often in negative discussions compared to other related concepts, such as bot or autonomation. This might be due to the former robotic technology concepts having a stronger association with social agency compared to the latter concepts.

In addition to examining social media discussions, the findings from the survey studies reveal expressions of feeling a sense of unfamiliarity, strangeness, uncomfortableness, and emotional detachment toward robots at work. Based on the longitudinal study, workers' affective attitudes toward robots in the work domain have been relatively neutral with a slight positive trend during 2019–2021. The positive trend seems to be stronger for workers who are having increasingly cynic thoughts about their job, while the workers that are confident in their skills and feel that their job is rewarding have more negative affective attitudes toward robots in the work domain. The findings suggest that people feel uncomfortable with robots especially in cases where robots are introduced as autonomous and social actors, such as colleagues or teammates.

2. How do people feel about working with a robot?

People preferred working with other human workers or using robots as tools and were more uncomfortable with the idea of working with a robot. Robot colleagues were considered strange and disrupting to the familiar situations and social processes. Based on the results, there are also notable differences in whether robots are represented as colleagues in the same workplace or as a teammate of the same work team. The latter concept has connotations of working alongside and more closely with human workers. Thus, the expectations differed based on the titles that robots received which had consequences on people's reactions.

Emotional investment and written reactions toward robots were more positive if workers were not alone with robots at work and could continue working with other human workers. Discontent workers who became cynic toward their work and did not feel rewarded or confident about their own professional capabilities perceived robot colleagues as more pleasant and less threatening. This might be due to a robot workforce offering them a relief in the work life in which they were unsatisfied. Favoritism toward using robots as tools rather than working with a robot colleague also highlights the strong connotation of the latter with social agency and its impact on potential prejudice. This coincides with finding stronger negativity around the concepts of robot and AI compared to the other robotic technology concepts examined.

3. How does prejudice toward robots arise?

The findings suggest that robots, especially as coworkers for humans, pose a disruption to the current power dynamic and social processes. Introducing a robot as a colleague rather than as a technical tool has significant implications on people's expectations and potential prejudice. Furthermore, sharing a work team with robot colleagues disrupts the ingroup dynamic as it introduces nonhuman outgroup members as ingroup members of the team. Feelings such as lack of authority over technology, strangeness due to the unfamiliar situation, and uncomfortableness with the idea of working alongside robots seem to threaten the human workers even when robots do not replace them.

Based on the findings, prejudice can occur when human workers are content with their job and their own performance in it and thus a robot workforce would endanger the continuation of the favored situation. When the workers' social needs are met and their psychological wellbeing is sound, the workers are motivated to preserve their current work environment and are less comfortable with the idea of robot colleagues. In contrast, workers who have become cynic toward their work and the sufficiency of their own professional capabilities do not find a robot workforce as a threat to their living, but rather as a relief to their unsatisfying work life. However, higher positivity in economy discussions on robots compared to conversations regarding power implies that losing power over technology is a more significant factor in prejudice toward robots than endangering people's livelihoods.

The findings show that people react more negatively to a robot when it is represented using concepts embedded with expectations about a social and autonomous actor, such as colleagues, coworkers, or teammates. The idea of working closely with a robot as a team member is even more threatening compared to having robot colleagues employed in the same workplace. Negativity toward robots at work increases further when workers are alone with robot teammates compared to sharing the experience with other human workers. If robots have a majority status inside a work team where human workers represent the minority, robots could be seen as threatening outgroup members and prejudice toward them might arise, even though robots and human workers share a common ingroup.

6.1 Theoretical and practical implications

Vanman and Kappas (2019) proposed that intergroup threat theory, which is traditionally used to investigate prejudice toward human outgroups (Stephan et al., 2008; Stephan & Stephan, 2000), could be useful in explaining potential prejudice toward robots. This dissertation's findings support this notion and report potential prejudice toward robots especially in situations where robots receive social roles and titles that humans previously received. People seem to be threatened by robots especially when they are framed as resembling humans (Yogeeswaran et al., 2016). While highlighting a situational threat, previous empirical findings on perceived situational and attitudinal threat that autonomous technology poses also support Vanman and Kappas's (2019) notion and demonstrate that realistic and symbolic threats decrease acceptance (Stein et al., 2019).

Higher negativity toward power and home themes in social media discussions about robots could stem from threats such as those to humans' safety and control over technology. Negative affective attitudes toward a robot workforce expressed by workers who are content with their current work life demonstrate that robot colleagues could pose a status threat. These observations points toward the presence of realistic threats. However, not finding higher negativity in social media robot discussions about work and money provides no support for the realistic economic threat that is often the topic of conversation about robots (e.g., Acemoglu & Restrepo, 2020; Bessen, 2019). As follows, the overall results in this dissertation emphasize robots as presenting a symbolic threat to humans (Vanman & Kappas, 2019). The higher negativity in discussions about power could also be interpreted as a symbolic threat from the perspectives of feeling inferior and a decreased sense of autonomy. This is in line with findings suggesting that some people react more positively to robots that are positioned as servants (Allan et al., 2021). The higher positivity toward robots at work versus the home domain might be due to workers encountering robots (Turja & Oksanen, 2019). However, discussing robots more negatively within the home context compared to work or leisure themes could also be interpreted as a symbolic threat from the perspective of sharing social spaces that are more personal and intimate with technology.

From the different symbolic threats, this dissertation's findings highlight a symbolic threat robots pose to human identity and social processes (Vanman & Kappas, 2019; Yogeeswaran et al., 2016). Robot colleagues were considered strange and less appropriate ingroup members compared to humans. The negativity increased when robots were perceived to enter a closer social space without the presence of other humans. Although hoping technology will free them from work, people's fears of losing their identity and becoming alienated from other people seem to be relevant threats and sources of prejudice. These themes are represented in fiction and speculative non-fiction popular works (Cave & Dihal, 2019), which have been argued to have an impact on the design and deployment of robotic technology and the attitudes and emotional responses such as consumers' fears (Cave & Dihal, 2019; Küster et al., 2021). Similar findings have also been reported from the customer perspective on HRI research, as feelings of eeriness and threat to the human identity caused customers' discomfort toward humanoid service robots (Mende et al., 2019).

The findings discussed above contribute to using the intergroup threat theory as a framework to examine potential prejudice toward robots (Vanman & Kappas, 2019). In addition, this dissertation presented a novel theoretical and methodological contribution for investigating emotional qualities of ingroup identity, attitudes, and writings as affective attitudes toward robots at work. Examining positivity toward robots from these different perspectives offered a comprehensive overview on the affective attitudes toward the symbolic representations of robots, robotic tools, robot colleagues, and robot teammates. This dissertation contributed to the theoretical debate over the similarities and differences between the constructs of attitude and emotion through comparing the different dependent variables and their affective qualities. It also provided a methodological contribution to the discussion on measuring affective attitudes from written text and combining computational social sciences with traditional survey research.

This dissertation's practical contribution is that people are not ready to face work situations alone with robots that are introduced as colleagues but are not overall negative about having robots in the work domain. Workers could find robot colleagues or teammates as intimidating but might appreciate the offer to use robots as tools to ease their workload. Robots could be offered as a relief to a challenging work life or as a safety measure to minimize health risks during pandemics. To avoid the potential prejudice toward social robots, it could be sensible not to use titles with inherent social roles emphasizing that they are autonomous replacements for human workers. Instead, paying attention to workers' wellbeing and ensuring their sense of autonomy and control over technology should prove beneficial when implementing new advanced robotic solutions. Thus, this dissertation offers insights on the social impact of how robots could affect social relations and humans' psychological wellbeing (Lin et al., 2011).

6.2 Strengths, limitations, and future directions

In addition to the theoretical and practical insights that contribute to the HRI research, this doctoral dissertation makes a strong methodological contribution to the field of social psychology because it combined traditional survey methods together with advanced experimental and longitudinal designs and computational social science methods. The research articles utilized diverse research designs and perspectives to examine people's affective expressions toward robots at work. Two research articles (**Articles I** and **II**) reported results from a series of survey experiments collected from the U.S. adult population. By examining reactions toward hypothetical robot colleague scenarios, they offered causal information about the potential social psychological consequences from the perspective of two constructs: ingroup identification and emotions in written text. Furthermore, **Article II** introduced a novel research design that combined survey research and an experimental design with role-playing data collection and sentiment analysis methods.

Article III widened the scope of the investigation notably in several aspects because, for example, it compared the work domain with home and leisure domains, social lexicons with power and money lexicons, and robot discussions with comments on related concepts, such as AI and automation. It also exploited a large data set encompassing the whole comment history of Reddit until 2018 that mention robotic technologies, that is, for example, close to 3.5 million social media comments on robots. Thus, it expanded the methodological perspective from **Article II** further toward computational social sciences. Finally, **Article IV** advanced the causal investigations in this dissertation from the survey experiments of **Articles I** and **II** to a longitudinal design utilizing four time points (2019–2021) from a nation-wide survey data sample of the Finnish working population. Combining longitudinal and experimental designs, role-playing data collection, big data, and computational social sciences is this dissertation's significant strength and provides a multifaceted overview on people's affects toward robots at work.

Every research design has its own strengths and weaknesses. As technologically highly advanced countries (Qureshi et al., 2020), the United States and Finland were assessed to be appropriate sources for data involving robotization. While some researchers have argued that Amazon Mechanical Turk is a useful source to collect quality survey responses from U.S. respondents for studies with novel experimental designs (Hauser & Schwarz, 2016; Thomas & Clifford, 2017), the biased representation in some sociodemographics, such as education and marital status (Smith et al., 2016), makes it a challenging source to collect representative data of the adult U.S. population from. Collecting public discussion data from one social media platform, however large the quantity of data, has a similar weakness in representation. Data collected from Reddit has been used for social media research on perceptions of specific topics because of their relatively high quality and comprehensive content (Brett et al., 2019; de Choudhury & De, 2014; Medvedev et al., 2019; Zamani et al., 2019). Although in 2018 Reddit was the fifth most-visited social media platform in the United States with more than 330 million active users monthly (Auxier & Anderson, 2021; Reddit, n.d.), the discussions on it might not represent public opinion of a nation-wide population. In addition, while they could also be considered as a strength of the research designs included in this dissertation, using a two-item attitude measure in **Article IV**, automated sentiment analysis in **Articles II** and **III**, and hypothetical scenarios instead of laboratory or field study designs to measure affects toward robots at work do not provide an all-inclusive perspective on the phenomenon.

Future studies could utilize the intergroup threat theory to further examine and compare the different types of threats a robot workforce might pose in certain conditions. In addition to the comparison between robots as colleagues or tools, investigating people's perceptions toward robots as assistants could provide more insight into the discussion on the implied social roles of robots from the perspective of authority over technology. Future studies could also consider research designs that include people's exposure to existing models of new-generation robots with advanced social features. Measuring attitudinal and affective constructs could involve physiological and behavioral responses combined with validated and comprehensive survey measures. Researchers in social psychology and related fields could also implement automated data collection and analysis methods more widely to study socially relevant phenomena. Collaborating with computing science researchers offers a multidisciplinary view on the study matter, and becoming more familiar and competent with computational social scientific methods will advance the field of social psychology and what can be studied within it.

6.3 Conclusion

This dissertation aimed to investigate people's expectations and the potential social psychological consequences of introducing new-generation robots at work. Based on the results, people are not overall negative toward robots in the work domain but express more negativity toward robots at work compared to the leisure domain. The negative affects increased the more closeness and social agency the robot received through introducing it as a colleague rather than a tool or introducing it as a teammate rather than a more distant colleague. The robot workforce threatens human workers' social processes and agency, and thus, poses a symbolic threat to humans. This highlights the importance of how new-generation robots with advanced social features are introduced and implemented. The potential social psychological consequences of such endeavours can be mitigated through careful framing and paying attention to human workers' social and psychological needs.

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I

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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

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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.

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, 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, p. 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.

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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.

1. 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 (Ashforth & Mael, 1989; Hogg et al., 2004; Tajfel, Billig, Bundy, & Flament, 1971). 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, Leach et al. (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 et al., 2012).

2. 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 (Ashforth & Mael, 1989; Hogg et al., 2004; Tajfel et al., 1971), 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 et al., 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).

3. 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 et al., 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 (Ashforth & Mael, 1989; Hogg et al., 2004; Tajfel et al., 1971), 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 et al., 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 et al., 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, extraversion, 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 and 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*.

4. Study 1

4.1. 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 et al. (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) 0.01 and for Cohen's d effect sizes 0.2 will be considered as a small effect, 0.06 and 0.5 as a medium effect, and 0.14 and 0.8 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, $M_{\text{age}} = 37.36$ years, $SD_{\text{age}} = 11.80$ 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 et al. (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 = 0.94) and self-definition (α = 0.89).

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* = 0.08). Also, the self-investment (skewness = – 0.42, *SE* = 0.08) and self-definition (skewness = – 0.34, *SE* = 0.08) 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 = – 0.26, SE = 0.15), but better for self-investment (kurtosis = – 0.06, SE = 0.15) and the whole measure (kurtosis = – 0.12, SE = 0.15).

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 = 0.88), extraversion (α = 0.86), openness (α = 0.79), agreeableness (α = 0.68), conscientiousness (α = 0.74).

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, pp. 267–298; 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.

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					
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		

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		

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.

5. 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 ($F(2,1002) = 65.35$, $p < .001$).

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 ± .10, $p < .001$) and the all human team (– 1.03 ± .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 ± .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 ($\eta_p^2 = 0.15$) and medium to imagining a team with one robot ($\eta_p^2 = 0.10$). Small effect was found between a control group and group asked to imagine a team with one robot ($\eta_p^2 = 0.01$). Previous analyses support the first hypothesis (H1).

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 = 0.2). 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 = 0.9). 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 = 0.2). 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 = 0.7). 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 = 0.5). 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 (β = – .12, $p = .006$) and the control group (β = – 0.18, $p = .003$). A positive relationship to higher identification was found in the experiment groups and the control group for extraversion (β = .15, $p = .001$; β = 0.21, $p = .001$), openness (β = 0.15, $p = .001$; β = 0.26, $p < .001$), agreeableness (β = 0.21, $p < .001$; β = 0.31, $p < .001$), and conscientiousness (β = 0.11, $p = .007$; β = 0.24, $p < .001$). In addition, having a degree in technology (β = 0.15, $p < .001$) and positive attitude towards robots (β = 0.46, $p < .001$) 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: β = – .07, $p = .017$; four robots: β = – 0.38, $p < .001$). The interaction between the experiment group and positive attitude towards robots was statistically significant when comparing the control group to four robot teammates (β = .40, $p = .004$) but not when comparing to one-robot experiment group (β = 0.27, $p = .075$). No statistically significant interactions were found between experiment group and age, gender, technology education, prior experience with robots, or personality traits.

6. 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

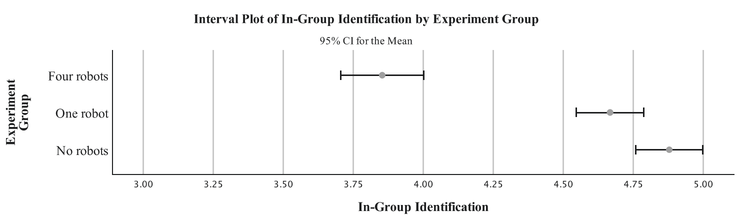

Fig. 1. *In-Group Identification means (95% CI) in a scale of 1–7* by *Experimental group in Study 1 (N = 1003).*

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.

7. 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.

7.1. 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, $M_{\text{age}} = 37.15$ years, $SD_{\text{age}} = 11.35$ 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 1 min. 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 et al. (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 ($\alpha = 0.97$) and the two sub-scales: self-investment ($\alpha = 0.95$) and self-definition ($\alpha = 0.94$).

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 = – 0.28, $SE = 0.08$). Also, the self-investment (skewness = – 0.36, $SE = 0.08$) and self-definition (skewness = – 0.21, $SE = 0.08$) 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 = – 0.94, SE = 0.16), but moderate for self-investment (kurtosis = – 0.53, SE = 0.16) and the whole measure (kurtosis = – 0.62, SE = 0.16).

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 ($\alpha = 0.84$), extroversion ($\alpha = 0.82$), openness ($\alpha = 0.79$), agreeableness ($\alpha = 0.63$), conscientiousness ($\alpha = 0.69$).

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

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					
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		

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.

8. 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 ± .11, $p < .001$) and in the team consisting of three robots (– 0.60 ± .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 (– 0.16 ± .12, $p = .390$) and eta square effect ($\eta_p^2 = 0.00$). There was a small eta square effect when comparing the control group to a group imagining a team with three robots ($\eta_p^2 = 0.05$) and a medium size effect compared to a group of four robots ($\eta_p^2 = 0.07$).

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.

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 (0.0) and a one-tailed Welch's *t*-test, $t(608.06) = 0.36$, $p = .361$. 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 = 0.7) or the team with four robots ($t[607.32] = 9.67$, $p < .001$, Cohen's d = 0.8), 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 = 0.3. 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 = 0.4. 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 = 0.1.

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 extraversion (experimental groups: β = .29, $p < .001$; control group: β = 0.19, $p = .001$), openness (β = 0.17, $p < .001$; β = 0.28, $p < .001$), agreeableness (β = 0.11, $p = .013$; β = 0.20, $p = .001$), and among the control group for conscientiousness (β = 0.17, $p = .004$), but not in the experimental groups (β = – 0.07, $p = .074$). In addition, having a degree in technology (β = 0.34, $p < .001$), prior interactional experience with robots (β = 0.11, $p = .006$), and positive attitude towards robots (β = 0.45, $p < .001$) 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 = – 0.14, $p < .001$) or four (β = – 0.21, $p < .001$) 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 = 0.41, $p = .003$, respectively). A statistically significant interaction was also found for at least two experiment groups and technology education (β = 0.13, $p = .003$; β = 0.06, $p = .184$), female gender (β = – 0.13, $p = .018$; β = – 0.10, $p = .070$), extraversion (β = 0.14, $p = .135$; β = 0.25, $p = .010$), and conscientiousness (β = – 0.49, $p = .006$; β = – 0.57, $p = .002$), 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 = 0.24, $p < .001$) and both of its dimensions: self-investment (β = 0.20, $p < .001$) and self-definition (β = 0.28, $p < .001$). 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 = 0.05, $p = .025$) and self-investment (β = 0.06, $p = .018$), but for self-definition it remained statistically

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		

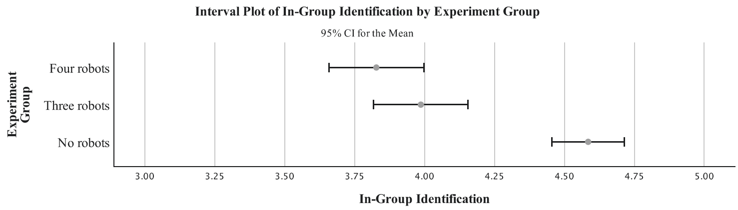

Fig. 2. *In-Group Identification means (95% CI) in a scale of 1–7* by *Experimental group in Study 2 (N = 969).*

nonsignificant (β = 0.04, 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.

9. 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.

10. 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 et al., 2006) and the results regarding neuroticism and extraversion are is in line with the few studies investigating personality and human-robot interaction (Robert, 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 ((Robert, 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.

11. 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 et al., 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 and 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 behavior (see, e.g., Atzmüller & Steiner, 2010), appropriately designed vignette experiments are robust predictors of actual behavior and intentions (Aguinis & Bradley, 2014; Evans et al., 2015; Hainmueller et al., 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.

12. 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; LePine, 2005; Van Knippenberg, 2000) and presumably concerns the issue of robot teams as well.

CRediT authorship contribution statement

Nina Savela: Conceptualization, Methodology, Investigation, Data curation, Formal analysis, Visualization, Writing - original draft, Writing - review & editing. **Markus Kaakinen:** Conceptualization, Methodology, Writing - review & editing. **Noora Ellonen:** Conceptualization, Methodology, Writing - review & editing. **Atte Oksanen:** Project administration, Funding acquisition, Supervision, Conceptualization, Methodology, Investigation, Data curation, Writing - review & editing.

Declaration of competing interest

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

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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 Stronglyagree):

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			

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Research Article

Emotional reactions to robot colleagues in a role-playing experiment

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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 coworkers 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 coworkers 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, $M_{\text{age}} = 37.36$ years, $SD_{\text{age}} = 11.80$, 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 ($Mdn_{\text{age}} = 35$ 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 ($Mdn_{\text{age}} = 38$ 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 non-active 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^2_H) 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, $p < .001$, $\eta^2_H = .09$), WKB valence score (χ^2 with ties [2, $N = 991$] = 49.66, $p < .001$, $\eta^2_H = .05$), SentiStrength positive sentiment score (χ^2 with ties [2, $N = 1003$] = 48.88, $p < .001$, $\eta^2_H = .05$), SentiStrength negative sentiment score (χ^2 with ties [2, $N = 1003$] = 30.52, $p < .001$, $\eta^2_H = .03$), LIWC positive emotion (χ^2 with ties [2, $N = 1003$] = 53.24, $p < .001$, $\eta^2_H = .05$), and LIWC negative emotion (χ^2 with ties [2, $N = 1003$] = 42.48, $p < .001$, $\eta^2_H = .04$). The effect size was small in negative scores of SentiStrength and intermediate in all other measures (Cohen, 1988).

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			

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, $p < .001$, $\eta^2_H = .14$), WKB valence score (χ^2 with ties [2, $N = 952$] = 94.58, $p < .001$, $\eta^2_H = .10$), SentiStrength positive sentiment score (χ^2 with ties [2, $N = 969$] = 88.27, $p < .001$, $\eta^2_H = .09$), SentiStrength negative sentiment score (χ^2 with ties [2, $N = 969$] = 30.17, $p < .001$, $\eta^2_H = .03$), LIWC positive emotion (χ^2 with ties [2, $N = 969$] = 110.18, $p < .001$, $\eta^2_H = .11$), and LIWC negative emotion (χ^2 with ties [2, $N = 969$] = 41.21, $p < .001$, $\eta^2_H = .04$).

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 coworkers 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, $p < .001$, $\eta^2_H = .03$), WKB valence score (χ^2 with ties [1, $N = 551$] = 16.39, $p < .001$, $\eta^2_H = .03$), SentiStrength positive sentiment score (χ^2 with ties [1, $N = 558$] = 9.54, $p = .002$, $\eta^2_H = .02$), and LIWC positive emotion (χ^2 with ties [1, $N = 558$] = 16.17, $p < .001$, $\eta^2_H = .03$).

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, $p = .029$, $\eta^2_H = .01$), the WKB valence score (χ^2 with ties [1, $N = 539$] = 4.37, $p = .037$, $\eta^2_H = .01$), and SentiStrength positive score (χ^2 with ties [1, $N = 549$] = 4.31, $p = .038$, $\eta^2_H = .01$). 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, $M_{\text{age}} = 37.46$ years, $SD_{\text{age}} = 11.60$ 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 (α = .84–.81), extraversion (α = .86–.78), openness (α = .80–.82), agreeableness (α = .61–.58), and conscientiousness (α = .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

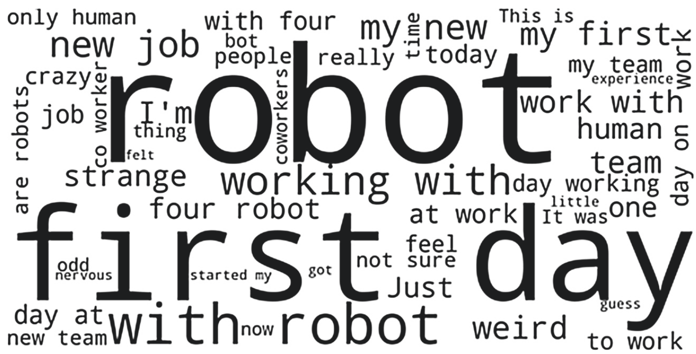

Fig. 1. Word cloud generated from experimental condition participants' negative texts.
Note: Texts: $n = 253$, word count: 5353.

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 ($N = 1837$).

	Model 1 ($n = 1814$)			Model 2 ($n = 1814$)			Model 3 ($n = 1155$)		
Measure	*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	supported	supported	supported	supported
Prejudice increases if…				
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.

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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 on next page*)

(*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)

	Model 4 ($n = 1155$)		
Measure	*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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PUBLICATION III

Emotional talk about robotic technologies on Reddit: Sentiment analysis of life domains, motives, and temporal themes

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Abstract
This study grounded on computational social sciences and social psychology investigated sentiment and life domains, motivational, and temporal themes in social media discussions about robotic technologies. We retrieved text comments from the *Reddit* social media platform in March 2019 based on the following six robotic technology concepts: *robot* ($N = 3,433,554$), *AI* ($N = 2,821,614$), *automation* ($N = 879,092$), *bot* ($N = 21,559,939$), *intelligent agent* ($N = 15,119$), and *software agent* ($N = 18,324$). The comments were processed using VADER and LIWC text analysis tools and analyzed further with logistic regression models. Compared to the other four concepts, *robot* and *AI* were used less often in positive context. Comments addressing themes of *leisure, money*, and *future* were associated with positive and *home, power*, and *past* with negative comments. The results show how the context and terminology affect the emotionality in robotic technology conversations.

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Keywords
Robotic technologies, social media, sentiment analysis

Discussions about robotic technologies and whether they represent an advancement or a threat for the future of humanity have interested societies across time and around various advanced technology inventions since the beginning of industrial automation. Sometimes, the message is that robots and artificial intelligence (AI) will help societies progress by supplementing or assisting humans and easing their burden (i.e. Tucker, 2018). Other times, the headlines stress that advanced robotic technologies will inevitably infiltrate our homes and workplace, function autonomously as social actors, and replace humans and steal their jobs (i.e. Gardels, 2018). In state-of-the-art discussions on robotic technology, the general public often has the role of receiving news, with interviews of experts for insights on the recent advancements in, for example, machine learning and new generation social robots. However, considering that the masses ultimately have the critical role of accepting or resisting changes that affect their everyday lives, attention should be given to discussions in which public opinion and emotions toward robotic technologies on the societal level are expressed.

Surveys are a widely used method to capture the public's attitudes toward robotic technologies (Naneva et al., 2020). However, surveys utilize questions and statements predesigned by researchers and, therefore, are not suited for studying socially regulated public discussions. Rather than being just a collection of individuals' opinions, public opinion formation is affected by communication and social factors (Hoffman et al., 2007), and it can sometimes be significantly influenced by the voices of few (Lewandowsky et al., 2019). Thus, another way to grasp the societal pulse on a topic and its development over time is to examine naturally occurring discussions taking place on social media platforms. Understanding public opinion and emotional language in discussions about robot technologies is crucial because socially shared norms are likely to be persistent and spread (Farrow et al., 2017) and because norms and attitudes influence user behavior (Heerink et al., 2010; Venkatesh and Davis, 2000). Although some investigations on AI and robot discussions on news and social media have been conducted (Carter et al., 2020; Fast and Horvitz, 2017; Io and Lee, 2020; Javaheri et al., 2020; Lee and Toombs, 2020; Sinha et al., 2020), more rigorous comparison between sentiments about different robotic technology concepts and thematic contexts is needed.

In this study, we utilized computational tools to investigate sentiment in social media discussions on robotic technologies. Our aim was to discover how the prevalence and positivity of the comments varied based on the concept used (*robot, automation, AI, bot, intelligent agent, software agent*). Because discussions on different robotic technologies in different contexts are likely to vary (Savela et al., 2018; Taipale et al., 2015; Wittenbrink et al., 2001), we also compared the discussions focusing on different life domains (*work, home, leisure*), motives (*social, power, money*), and temporal themes (*past, present, future*). Theoretically, our study is grounded in the social psychological processes of social representations and natural language processing of emotions and attitudes, while also considering theories on basic psychological needs and prejudice when examining the connection of context on linguistic expressions in social media. This is the first study to use life domain, motive, and temporal lexicons to investigate social media discussions on robotic technologies. Our research will expand the existing literature on human–robot interaction and technology acceptance by utilizing automated linguistic methods to analyze public opinion on robots.

Using text analysis to identify emotions and attitudes toward robotic technologies

Research on attitudes and social acceptance of robots has mainly relied on surveys with self-reported measures and on user studies with convenience samples focusing on certain technology products (Naneva et al., 2020; Savela et al., 2018). These types of studies are well suited to uncovering the explicit emotions and attitudes people hold and are able to express on demand, but researchers have called for other types of measures in the field of acceptance of robots (Naneva et al., 2020). One option is to analyze informal conversations in a natural setting such as social media, which provides affective content to examine as it is a popular way to receive and share information (Sun et al., 2015). Social media platforms are societally important discussion forums and channels to share opinions and emotions. As such, they are a rich source of implicit attitudes and emotional reactions that can help us to understand the opinion formation processes and social factors behind them (Goldenberg et al., 2020; Kanavos et al., 2014; Munezero et al., 2014; Sullivan, 2015). For example, emotional reactions could be affected by the choices in terminology and representations they activate (de Groot, 1989; Moscovici, 1988; Smith, 1998; Wagner et al., 1999).

In addition to the relevance of the social context, collective emotions and what they can reveal about attitudes toward topic such as robotic technologies are interesting in themselves. Considering that most of our knowledge on public opinion originates from survey studies (Hofman et al., 2021) and that emotions are connected to cognitive attitudes and behavior (Peters and Slovic, 2007), investigating the acceptance of robotic technologies through affective attitudes in written language is also needed. Computational social sciences provide methods for such investigations (Chang et al., 2014; Edelmann et al., 2020; Lazer et al., 2020). As important societal and behavioral issues are widely discussed in social media, such data offer a possibility for natural language processing of public discussions around the concepts under investigation, such as robotics. As the target of interest is emotional expressions in public discussion, the emotional orientation of comments on social media can be analyzed as socially constrained expressions of affect (Munezero et al., 2014).

Researchers have argued that social media conversations reveal collective emotions and attitudes that are constructed and maintained socially and are a part of the social context where they are expressed (Goldenberg et al., 2020; Kanavos et al., 2014). In a way, the new era of computational linguistics leans on a social psychological research tradition that stresses the significance of collective conceptions carried through social representations (Moscovici, 1988), while a more cognitive approach to representations describes how mental representations are activated from individual's memory (Smith, 1998). Investigations of implicit attitudes have utilized mental representations and word associations to reveal subconscious attitudes that are not necessarily readily available to the individual (see, for example, de Groot, 1989; Wagner et al., 1999), although the certainty of whether the attitudes discovered this way are in fact unconscious has been questioned (Fazio and Olson, 2003). Still, word associations highlight the significance of representations and semantics behind the chosen words and exact concepts the attitude is targeted at.

Following the previous line of reasoning, it can be argued that different concepts of the same topic might trigger different emotions and attitudes and, for example, different expressions of sentiment in social media conversations. Considering the topic of robotic technologies, all the different but related concepts have individual origins and certain histories of how and in which contexts they have been used. For example, a *robot* can be technically defined as a programmable machine that can manipulate its environment (ISO 8373, 2012). The word originated from a Czech play in 1920, where it was used as a supplement for the word *automation* to describe mechanical slaves that were played by human actors (Stone, 2004). Robotic devices and artificial beings have, however, been part of mythologies since long before that and have been known in history as, for example, machines or automata (Stone, 2004). Its origin and depiction in cinema may have influenced the representations people have in mind when they use the word *robot*, compared to other related concepts. In addition to the etymology and culturally shared fictive imagery, social representations of robotic technologies are influenced by today's existing robot devices. As the appearances and names of certain products and models become part of the representations of robots, they also influence public discussions on the topic.

Besides the usage history and potential connotations associated with different concepts, opinions, and emotional expressions on subjects such as advanced technologies are likely to depend on context. Although researchers have argued that explicitly measured attitudes are stable through time and contexts (Buhrmester et al., 2011), contextual cues have been found to affect implicitly measured attitudes (Wittenbrink et al., 2001). Fazio and Olson (2003) specify that the flexibility of attitudes is likely to be greater in sensitive subjects for which people have greater motivation to mask their true opinions. Therefore, context-specific variation is likely to be found in emotional and attitudinal expressions in social situations such as on social media, where natural language is influenced by social norms (Hynes and Wilson, 2016; Spears et al., 2002).

Acceptance of robotic technologies in different contexts

Previous literature has found that robots are generally accepted, especially in domains that are monotonous, dangerous, or require challenging skills from humans (Naneva et al., 2020; Savela et al., 2018; Taipale et al., 2015; Takayama et al., 2008). Although this seems to be different in the case of social robots (Naneva et al., 2020), the integration of robots into social contexts and leisure activities has been met with some suspicion (Savela et al., 2018; Taipale et al., 2015; Takayama et al., 2008). Researchers have argued that this skepticism is related to domestic and work environments that require social interaction and where robots replace humans (de Graaf et al., 2019; Savela et al., 2021a, 2021b). However, interaction with a robot or artificial intelligence instead of a human in an online environment received less negative reception in one study (Oksanen et al., 2020).

While some studies have examined the processes and influencing factors involved in the acceptance of domestic robots (Smarr et al., 2014; Sung et al., 2010), rigorous studies comparing work, home, and leisure domains remain scarce. In addition to potential uncertainty toward social interaction with robots (Savela et al., 2021b), negative views of robots might stem from fears of decreased control (Latikka et al., 2021) or worsening economic situation (Dekker et al., 2017). The effect of economic considerations on opinions of robots seems to depend on the individual's perspective; those at risk of being replaced by robots are likely to talk about robots differently than those emphasizing the efficiency and economic benefits of automation of jobs (Berg et al., 2018; Dekker et al., 2017).

In addition to life domains and motivational contexts, discussions of robotic technologies could vary depending on the temporal focus of the discussion. Talking about future technologies shifts the focus on readiness to accept robotic technologies not yet in use or that may be invented in the future. Because familiarity with technology in a certain context can increase its attractiveness and acceptance (Reis et al., 2011; Taipale et al., 2015; Zajonc, 1968), fear of the unknown is likely to cause uncertainty or even anxiety in discussions about unfamiliar entities such as advanced technology (Carleton, 2016). Similarly, it could be argued that positivity toward robotic technologies will increase in time due to increasing familiarity, and apprehensive discussions more likely involve newer technologies. Although contradicting this argument, a large-scale survey on European citizen's opinions reported decreasing acceptance of robots between 2012 and 2017 (Gnambs and Appel, 2019).

Research overview

This study utilizes computational social science framework and methods to investigate sentiment in social media discussions of robotic technologies and the connection of positivity with different life domain, motivational, and temporal themes. The main broader theoretical framework of our research is social psychological theories about language and representations (de Groot, 1989; Moscovici, 1988; Smith, 1998; Wagner et al., 1999), as investigating attitudes and emotions in text is highly dependent on linguistic choices and conceptions. As certain robotic technology concepts might prove to be more dominant or more integrated in general discussions, examining changes in usage over time will reveal conceptual trends of robotic technology. For this reason, our first research question maps out the usage trends of six robotic technology concepts (*robot, automation, AI, bot, intelligent agent, software agent*).

Based on integrated threat theory (Stephan and Stephan, 2000; Stephan et al., 2008), negative stereotypes can affect attitudes negatively and cause prejudice. Considering both this and research arguing that language affects people's appraisal processes (de Groot, 1989; Wagner et al., 1999), different concepts of robotic technology could be linked to different social and mental representations that are in turn likely to be associated with certain emotions and attitudes. Therefore, our second research question examines differences in sentiment orientation between discussions around various robotic technology concepts.

The main components of integrated threat theory, namely realistic and symbolic threat (Stephan and Stephan, 2000), represent the potential for negativity to be caused by a threat to realistic capital, such as income or power, or symbolic property, such as social identity. Vanman and Kappas (2019) argue that these threats could be behind the acceptance of robots, as the fear of losing one's job to robots or anxiety toward robots taking the place of humans as social actors could be interpreted as realistic and symbolic threats to humans. Robotic technology could therefore be a threat to basic human needs, such as social relatedness to others (Baumeister and Leary, 1995; Ryan and Deci, 2000) and competence and autonomy (Ryan and Deci, 2000). To consider human motives and perception of potential threat to intrinsic needs, we analyzed sentiments in robotic technology discussions and compared them with linguistic focus on social, power, and financial motives. Considering the significance of context in acceptance of robots (Savela et al., 2018; Taipale et al., 2015) and in social media discussions in general (Hynes and Wilson, 2016; Spears et al., 2002; Wittenbrink et al., 2001), we also analyzed how sentiments in robotic technology discussions are associated with linguistic focus on life domains of *work, home*, and *leisure*. Finally, we examined the difference in sentiment by temporal focus (*past, present*, and *future*).

Given the broad viewpoint of our study on different themes, we pose research questions for our explorative study design rather than hypotheses. The research questions are as follows:

1. How does the usage of robotic technology concepts (*robot, automation, AI, bot, intelligent agent, software agent*) vary in Reddit discussions?
2. How does the positivity in Reddit comments differ among different robotic technology concepts (*robot, automation, AI, bot, intelligent agent, software agent*)?
3. How is a greater focus on different life domains (*work, home, leisure*), motives (*social, power, money*), or temporal aspect (*past, present, future*) connected to positive comments in Reddit discussions on robotic technologies?

Method

Procedure

To answer our research questions, we collected data from the Reddit social media platform in March 2019. Reddit was the fifth most visited social media platform in the United States and had more than 330 million active users monthly in 2018 and has grown rapidly in popularity since (https://www.redditinc.com/). It has been a popular source of research data for its versatile and expansive content and relatively high quality (Medvedev et al., 2019; Zamani et al., 2019) and has been previously utilized for investigating discussions and perceptions of specific phenomena (Brett et al., 2019; De Choudhury and De, 2014). Reddit was chosen as the source of social media data for our study because it contained discussions related to different robotic technologies on multiple viewpoints in various channels and subgroups.

Figure 1 presents the data collection and inclusion process in a diagram. Our premise was to investigate social media discussions around the concept of *robot*, but we also

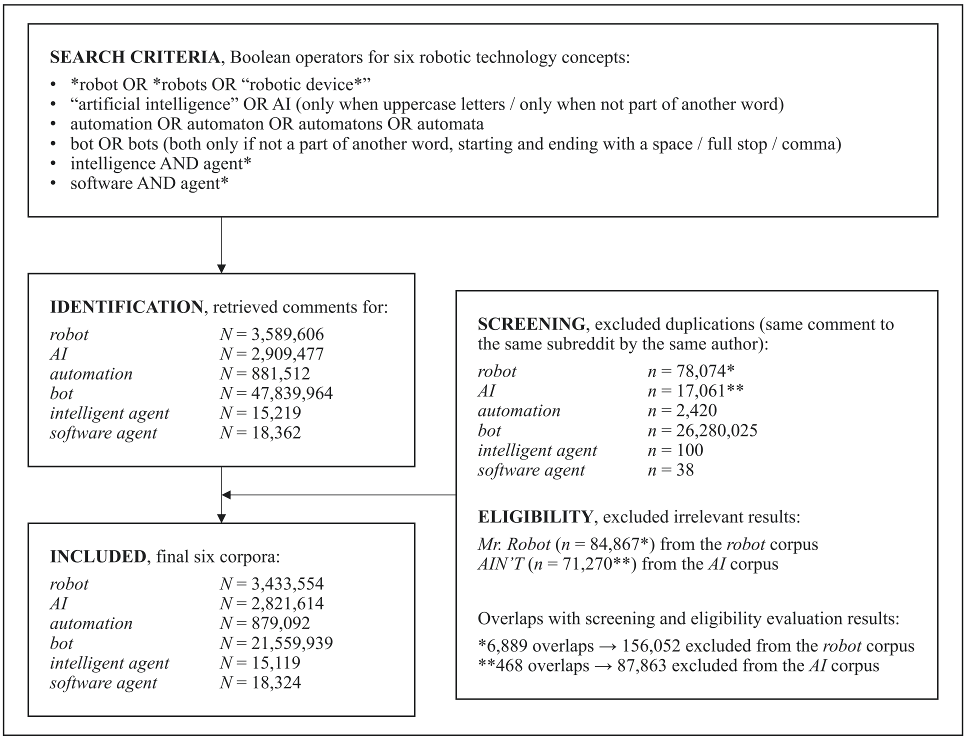

Figure 1. Data collection and inclusion process of robotic technology comments in Reddit.

needed to identify relative concepts for comparisons and to have a better overview on technologies related to *robots*. As a starting point, we utilized the definition and vocabulary for robots and robotic devices by International Organization of Standardization (ISO 8373, 2012), which emphasize that robots have some degree of autonomy and actuated mechanism with programmable axes while robotic devices lack either. Automation and its declensions were chosen to consider the predecessor of the concept of *robot*, as *robot* has been argued to replace the previously used *automaton* (Stone, 2004). *AI, software/intelligent agent*, and *bot* were chosen to represent advanced technology like robots without actuated mechanism that do not operate in the physical world. In line with the rationale that different words may evoke different emotions because language affects people's appraisal processes (de Groot, 1989; Wagner et al., 1999), all concepts were treated as their own topics, instead of combining them into artificial topics created by researchers themselves. For the same reason, we restricted our focus on hypernyms. Based on the examination of the definitions and etymology and on preliminary familiarization of the conversations in subreddits, we identified relevant robot-related concepts as seeds and formulated search criteria to find the relevant texts (see Figure 1).

Second, we analyzed the Reddit corpus of pushshift.io to identify texts referring to the selected terms (Baumgartner et al., 2020). We retrieved 3,589,606 comments for the concept of *robot*; 2,909,477 for *AI*; 881,512 for *automation*; 47,839,964 for *bot*; 15,219 for *intelligent agent*; and 18,362 for *software agent*.

We prepared the corpora for further analysis by excluding duplications that were identical comments by the same author to the same subreddit. In addition, we excluded comments found by identification of the phrase *Mr. Robot* (n = 84,867) from the *robot* corpus, since a reference solely to the name of this particular TV-show does not refer to technology, and comments found by identification of the capitalized expression *AIN'T* (n = 71,270) from the *AI* corpus. Exclusion of duplications and irrelevant comments resulted in the final six corpora: *robot* (N = 3,433,554), *AI* (N = 2,821,614), *automation* (N = 879,092), *bot* (N = 21,559,939), *intelligent agent* (N = 15,119), and *software agent* (N = 18,324). The number of distinct comment IDs (n = 27,824,212) showed that there was very little overlap between the different corpora (N = 28,727,642). The comments were submitted by 2,810,035 authors in 137,344 different subreddits, AskReddit (n = 2,088,865) being the most prevalent channel for robotic technology discussions based on the number of hits for our key concepts. We also used downsampling and selected 1,000,000 texts randomly from the *bot* corpus to be used in the regression analysis.

We processed the content of the comments with the Valence Aware Dictionary for Sentiment Reasoning (VADER; Gilbert and Hutto, 2014), a sentiment analysis tool that is among the best performing in social media text benchmarks (Ribeiro et al., 2016), to assess the positivity of the comments. We also used the Linguistic Inquiry and Word Count (LIWC) text analysis software (Pennebaker et al., 2015; Tausczik and Pennebaker, 2010) and its lexicons to analyze LIWC's categories *work, home, leisure, social, power, money, focus past, focus present*, and *focus future*.

Measures

Descriptive statistics of the study variables are reported in Table 1. The main dependent variable of this study is the VADER compound score. Using the thresholds recommended for VADER, we created a categorical variable that labeled each text as positive ($0.05<$), neutral, or negative (<-0.05). A dummy variable indicating positive comments with a value 1 and neutral or negative with a value 0 was used as the final dependent variable in the analyses reported in results. Descriptive statistics of the final dependent variable for all six corpora are reported in Table 1 and the original VADER compound score statistics in Table 2.

To use the VADER sentiment analysis results as an outcome variable in our study, we validated it for our datasets collected from Reddit. We tested the validity of the dependent variable of VADER compound score using a random sample of 500 robot and AI comments and participants (N = 539) from Amazon Mechanical Turk. Human raters rated the positivity or negativity of 20 comments on a scale from −4 to 4. These were rescaled to a scale of −1 to 1 to allow comparison of the mean score from human raters with the VADER compound score for the same comment. Among the 500 comments, 67.60% of VADER compound scores were located within ±0.5 points of the mean score of human raters, suggesting relatively close agreement. Here, rather than an exact match, we aimed to verify a same direction and similar strength, considering the different original scales and scoring style of humans compared to the VADER compound score. In

Table 1. Descriptive statistics for positive comments: six corpora (robots, AI, automation, bot, intelligent agent, software agent).

	Robot		AI		Automation	
	n	%	*n*	%	*n*	%
VADER compound	3,433,554	100.00	2,821,614	100.00	879,092	100.00
0 (negative/neutral)	1,686,883	49.13	1,210,792	42.91	325,233	37.00
1 (positive >.05)	1,746,671	50.87	1,610,822	57.09	553,859	63.00
	Bot		**Intelligent agent**		**Software agent**	
	n	%	*n*	%	*n*	%
VADER compound	21,559,939	100.00	15,119	100.00	18,324	100.00
0 (negative/neutral)	7,821,211	36.28	3,990	26.39	5,817	31.75
1 (positive >.05)	13,738,728	63.72	11,129	73.61	12,507	68.25
VADER compound	1,000,000	100.00				
0 (negative/neutral)	362,358	36.24				
1 (positive >.05)	637,642	63.76				

Comments categorized as positive based on VADER compound score (>0.05).

addition, however, only 34.60% of the VADER compound scores fell between the CI 95% of the mean score from human raters.

For comparing categorization to positive comments instead of continuous variables, we also created two dummy variables indicating positive comments from human raters' mean score and from the VADER compound score (>.05). Among the 500 comments, 61.40% received the same value from human raters and VADER, and Cohen's kappa shows fair agreement ($\kappa = .224$) when comparing the positive dummy variables.

Table 2 reports descriptive statistics of the main independent variables of the study, the six LIWC lexicon categories (*work, home, leisure, social, power, money, focus past, focus present*, and *focus future*). In each category, raw LIWC output gives each comment a score from 1 to 100 that represents the percentage of category-specific lexicon words present in the text. For our analysis, we rescaled the LIWC variables to 1–10.

Finally, Table 3 shows descriptive analysis of the two control variables used in the models: word count and time created. Word frequency ranged from 1 to 46,066 words, where one word can include long sentences combined into one word (e.g. #RespectTheRobot, Stupidrobot). The first comment was created on 6 January 2006 12:28:59 and the last one on 31 October 2018 23:59:56.

Statistical techniques

We chose to use logistic regression analysis because the assumptions of linear regression (ordinary least squares) were violated due to the distribution of the VADER compound score and its error terms. In addition, higher agreement based on the validation analysis between human raters and VADER compound score categorized as positive comments

Table 2. Descriptive statistics for sentiment analyses variables of VADER compound and LIWC categories: six corpora (robots, AI, automation, bot, intelligent agent, software agent).

	Robot (N = 3,433,554)				AI (N = 2,821,614)				Automation (N = 879,092)			
	Md	*M*	*SD*	Range	*Md*	*M*	*SD*	Range	*Md*	*M*	*SD*	Range
VADER compound	0.08	0.14	0.58	−1–1	0.29	0.18	0.64	−1–1	0.42	0.27	0.61	−1–1
LIWC work	0.00	0.19	0.32	0–10	0.12	0.21	0.29	0–8.00	0.38	0.47	0.43	0–8.00
LIWC home	0.00	0.02	0.12	0–10	0.00	0.01	0.06	0–5.00	0.00	0.03	0.12	0–5.00
LIWC leisure	0.00	0.13	0.28	0–10	0.01	0.16	0.25	0–6.67	0.00	0.09	0.19	0–5.00
LIWC social	0.75	0.82	0.68	0–10	0.68	0.73	0.50	0–8.00	0.62	0.66	0.44	0–6.67
LIWC power	0.11	0.23	0.36	0–10	0.20	0.25	0.29	0–6.67	0.22	0.26	0.26	0–5.00
LIWC money	0.00	0.06	0.19	0–10	0.00	0.05	0.14	0–6.67	0.04	0.17	0.26	0–6.67
LIWC past	0.10	0.26	0.37	0–10	0.14	0.24	0.32	0–7.50	0.14	0.21	0.26	0–6.67
LIWC present	1.02	1.05	0.69	0–8.00	1.08	1.09	0.53	0–10	1.11	1.11	0.49	0–7.50
LIWC future	0.00	0.12	0.24	0–6.67	0.04	0.13	0.21	0–6.67	0.10	0.16	0.22	0–6.67
	Bot (N = 21,559,939)				Intelligent agent (N = 15,119)				Software agent (N = 18,324)			
	Md	*M*	*SD*	Range	*Md*	*M*	*SD*	Range	*Md*	*M*	*SD*	Range
VADER compound	0.44	0.31	0.51	−1–1	0.84	0.42	0.73	−1–1	0.67	0.34	0.70	−1–1
LIWC work	0.12	0.15	0.20	0–8.94	0.29	0.36	0.27	0–3.34	0.46	0.53	0.34	0–5.00
LIWC home	0.00	0.01	0.05	0–6.67	0.00	0.01	0.04	0–1.25	0.00	0.03	0.07	0–1.91
LIWC leisure	0.15	0.20	0.24	0–9.38	0.03	0.07	0.12	0–1.51	0.04	0.09	0.14	0–2.45
LIWC social	0.78	0.79	0.51	0–9.72	0.79	0.82	0.40	0–9.55	0.70	0.75	0.39	0–4.17
LIWC power	0.15	0.19	0.25	0–9.56	0.22	0.25	0.19	0–3.18	0.21	0.24	0.18	0–2.78
LIWC money	0.00	0.05	0.15	0–7.50	0.01	0.06	0.13	0–1.64	0.08	0.15	0.20	0–2.35
LIWC past	0.13	0.19	0.26	0–8.76	0.18	0.24	0.22	0–5.48	0.18	0.24	0.24	0–1.77
LIWC present	0.69	0.75	0.56	0–8.89	1.04	1.02	0.38	0–6.97	0.96	0.94	0.41	0–3.33
LIWC future	0.00	0.06	0.14	0–6.67	0.08	0.10	0.11	0–1.47	0.08	0.10	0.11	0–2.00

(*Continued*)

Table 2. (Continued)

	Sample: Bot (n = 1,000,000)			
	Md	*M*	*SD*	Range
VADER compound	0.44	0.31	0.51	–1–1
LIWC work	0.12	0.15	0.20	0–8.94
LIWC home	0.00	0.01	0.05	0–5.00
LIWC leisure	0.15	0.20	0.24	0–8.94
LIWC social	0.78	0.79	0.51	0–9.40
LIWC power	0.15	0.19	0.25	0–6.67
LIWC money	0.00	0.05	0.15	0–6.67
LIWC past	0.13	0.19	0.26	0–6.67
LIWC present	0.69	0.75	0.56	0–7.50
LIWC future	0.00	0.06	0.13	0–6.67

Table 3. Descriptive statistics for word count and time control variables: six corpora (robots, AI, automation, bot, intelligent agent, software agent).

	Word count				Timestamp (date)
	Md	*M*	*SD*	Range	Range
Robot (*N* = 3,433,554)	38	92.64	167.30	1–6007	1136892374–1541030392 (10 January 2006 to 31 October 2018)
AI (*N* = 2,821,614)	61	112.51	165.81	1–5628	1137113202–1541030394 (13 January 2006 to 31 October 2018)
Automation (*N* = 879,092)	78	136.59	181.35	1–5890	1140482994–1541030300 (21 February 2006 to 31 October 2018)
Bot (*N* = 21,559,939; *n* = 1,000,000)	88; 88	118.65; 118.61	124.91; 124.50	1–28,694; 1–4768	1136550539–1541030396; 1143697390–1541030357 (6 January 2006 to 31 October 2018; 30 March 2006 to 31 October 2018)
Intelligent agent (*N* = 15,119)	242	392.76	542.08	3–46,066	1140866167–1541029453 (25 February 2006 to 31 October 2018)
Software agent (*N* = 18,324)	208	349.15	381.16	3–5901	1142293353–1541029760 (13 March 2006 to 31 October 2018)

provided further support for running analyses with the dummy variable. We report odds ratios (*OR*s), standard errors for odd ratios (*OR SE*s), average marginal effects (*AME*s), and *p* values for average marginal effects. With the original *bot* corpus, the regression analysis did not achieve convergence. Instead, we drew a random sample of 1,000,000 comments from the *bot* corpus for the logistic regression models. Descriptive statistics are provided for both the original corpus and the sample.

In the logistic regression models, we used LIWC variables as continuous independent variables with a scale from 1 to 10. For the dependent variable, we used a categorical dummy variable of comments categorized as positive based on VADER compound score (>0.05). With a dependent variable with two groups (positive; not positive = negative/neutral), the models predict the likelihood of a comment being positive if its thematic content emphasizes one of the six LIWC lexicon categories. Thus, the idea of the average marginal effects is to estimate the average increase or decrease of likelihood for a comment to be positive for each independent variable.

Considering how easy it is to find statistically significant results with large datasets, our main analyses aimed at demonstrating the associations with effect sizes (*OR*s and *AME*s) and comparing the directions of the effects of related thematic variables. Our analytical approach has been previously established and *AME* coefficients are useful and highly reliable for comparing effects across models (Mood, 2010).

We used a python script with SentimentIntensityAnalyzer from vaderSentiment 3.3.2 to produce VADER compound scores and LIWC 2015 software to produce nine LIWC category scores (*work, home, leisure, social, power, money, focus past, focus present*, and *focus future*) for our six corpora. Stata 16 SE was used for the analysis and graphics.

Results

Descriptive statistics of the comments in the six corpora show that the concepts of *robot* and *AI* occurred in similar frequency in the Reddit discussions (*N* = 3,433,554; *N* = 2,821,614), followed by *automation* (*N* = 879,092). However, the most popular concept of the corpora was *bot* (*N* = 21,559,939), while *intelligent agent* (*N* = 15,119) and *software agent* (*N* = 18,324) were the least popular concepts used in the 2006–2018 timeframe.

Yearly occurrences of the six robotic technology concepts in Reddit comments are reported in Figure 2. The differences in volume of the comments can be seen from the vastly different scales of the histograms of each corpus. Based on yearly frequencies, *robot* was the most popular concept of the six until 2010, with *bot* surpassing it in 2011; the popularity of *AI* increased, but it remained the third-place trend among these concepts during 2006–2018. Usage of the six concepts per year revealed acceleration over time for the words *bot, automation*, and *AI*. Their recent popularity can be seen in their proportion of comments dated after 2013 (94.85%, 91.30%, 88.76%, respectively) compared to the three other concepts *robot, software agent*, and *intelligent agent* (83.45%, 80.05%, 75.77%, respectively). Besides being the most frequently occurring concept in the 2006–2011 corpora overall, *bot* was also the most increasingly used concept in Reddit discussions during the timeframe, thus representing the new trending concept of robotic technologies.

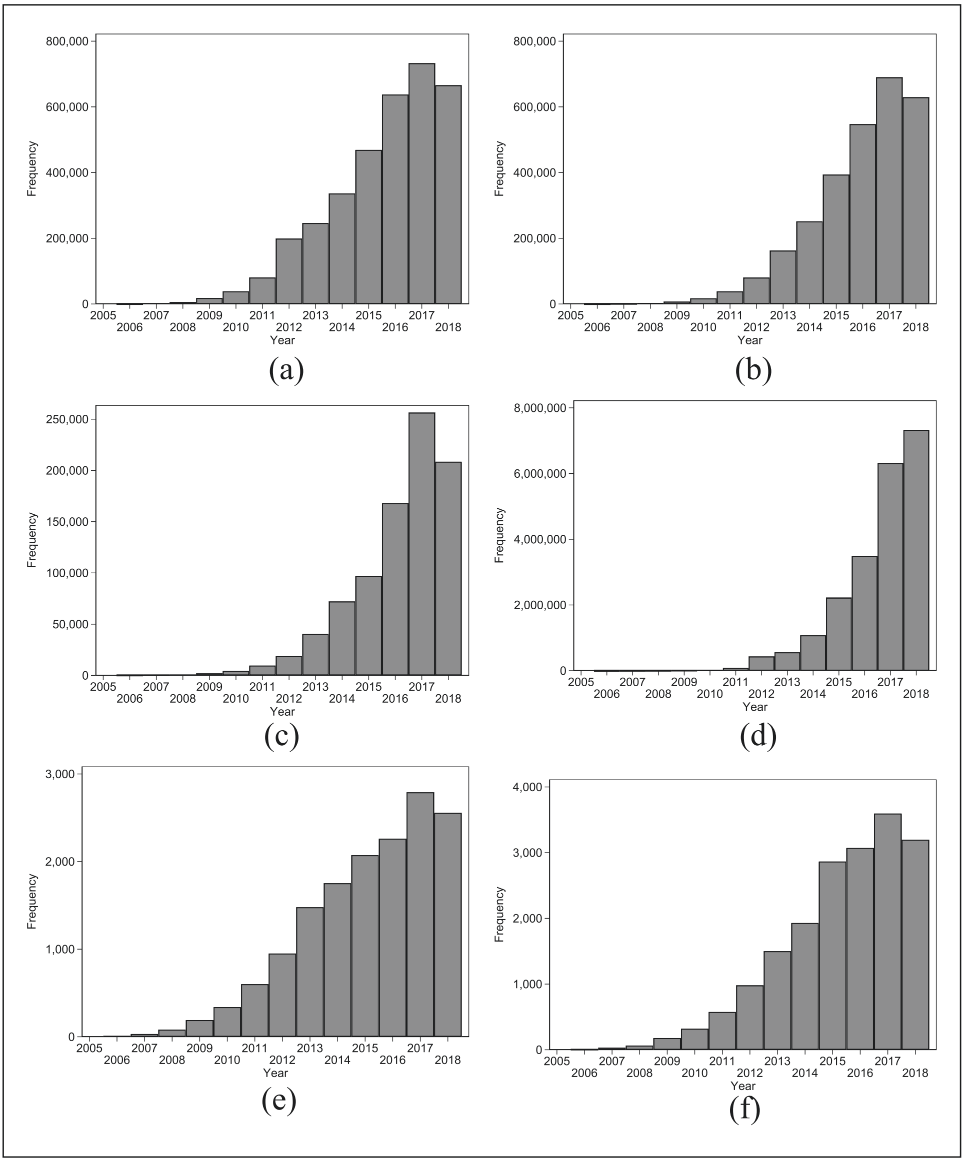

Figure 2. Histograms of Reddit comments referring to robotic technology by year (2006–2018): (a) robot, (b) AI, (c) automation, (d) bot, (e) intelligent agent, and (f) software agent.
The last comments were from 31 October 2018, and hence the data collected did not cover all of 2018.

Based on the descriptive statistics on VADER sentiment analysis results reported in Table 1 and Figure 3, the concepts of *robot* and *AI* were used less often in positive (50.87%, 57.09%) and more often in negative (30.84%, 33.87%) contexts compared to the other concepts' proportions of positive (63.00–73.61%) and negative (18.73–27.91%) comments. The largest proportions of positive (73.61%, 68.25%) and smallest proportions of neutral comments (0.88%, 3.84%) were identified for the *intelligent agent* and

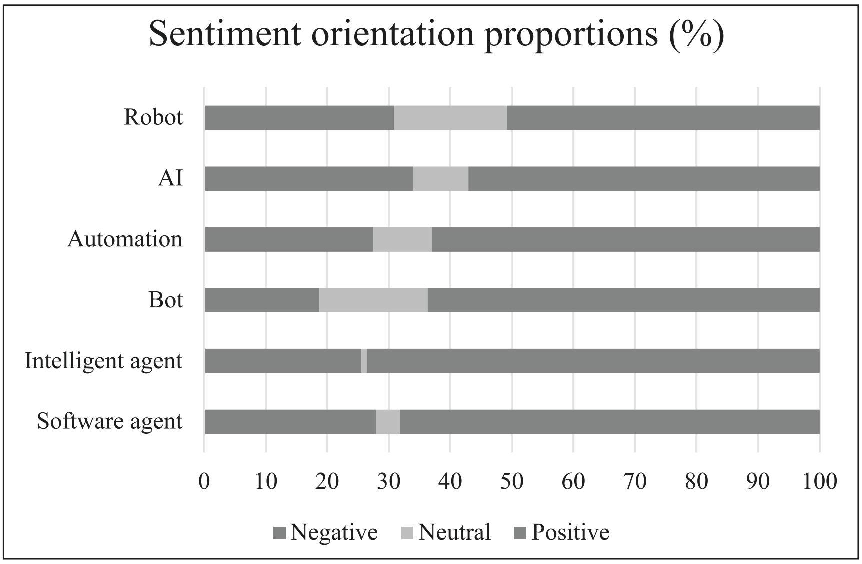

Figure 3. Proportions of negative, neutral, and positive comments in Reddit (2006–2018) by six robotic technology concepts.
Categorized as negative (<-0.05), neutral, and positive (>0.05) based on VADER compound score.

software agent corpora, suggesting they were less often used in casual or neutral discussions and more often in emotional discussions, especially positive ones, than were the other four concepts. The smallest proportion of negative comments was found in the *bot* corpus (18.73%). Comments categorized as neutral were most often found in the *bot* (17.55%) and *robot* (18.29%) corpora.

Results of the logistic regression analyses are reported in Table 4. For each corpus, Model 1 compared three different life domains (*work, home, leisure*). We found that comments were less likely to be positive if they used LIWC *home* vocabulary (AME = −0.510 to 0.047, $p < .001$) compared to LIWC *work* (AME = −0.009 to 0.230, $p < .001$) or LIWC *leisure* (AME = −0.042 to 0.243, $p < .001$) vocabularies, the statistically nonsignificant result of LIWC *home* lexicon in the *software agent* corpus being the only exception.

Model 2 of each corpus predicts positivity of the comments by three different motivational contexts (*social, power, money*). The relationship of the LIWC *social* lexicon with positivity was small (AME = 0.002–0.019, p = .000–.002) or statistically nonsignificant, except the slight positive connection in the *bot* corpus ($AME = 0.089$, $p < .001$) and negative connection in the *intelligent agent* corpus ($AME = -0.098$, $p < .001$). Apart from the *bot* corpus (LIWC power: $AME = 0.242$, $p < .001$; LIWC money: $AME = -0.112$, $p < .001$), robotic technology comments using LIWC *power* lexicon (AME = −0.223 to −0.035, $p < .001$) words were less likely and LIWC *money* lexicon (AME = 0.011 to 0.178, $p < .001$) words more likely to be positive.

Finally, comparing three temporal aspects (*past, present, future*) in Model 3 of each corpus revealed that, with the exception of the *bot* corpus ($AME = 0.113$, $p < .001$),

Table 4. Logistic regression models predicting positive comments by six robotic technology concepts.

		Robot (N = 3,433,554)			AI (N = 2,821,614)			Automation (N = 879,092)		
		OR	*SE OR*	*AME*	*OR*	*SE OR*	*AME*	*OR*	*SE OR*	*AME*
Model 1	LIWC work	1.31	0.00	0.067***	1.72	0.01	0.130***	0.96	0.01	−0.009***
	LIWC home	0.86	0.01	–0.038***	0.68	0.02	−0.092***	1.23	0.02	0.047***
	LIWC leisure	1.61	0.01	0.116***	2.50	0.01	0.219***	2.90	0.04	0.243***
Model 2	LIWC social	1.08	0.00	0.019***	1.01	0.00	0.002**	1.02	0.01	0.005***
	LIWC power	0.87	0.00	–0.035***	0.73	0.00	−0.076***	0.76	0.01	–0.063***
	LIWC money	1.61	0.01	0.117***	2.09	0.02	0.178***	1.05	0.01	0.011***
Model 3	LIWC past	0.99	0.00	–0.003***	0.87	0.00	–0.032***	0.89	0.01	–0.026***
	LIWC present	1.08	0.00	0.018***	1.04	0.00	0.009***	1.08	0.00	0.017***
	LIWC future	1.13	0.01	0.030***	1.31	0.01	0.066***	0.75	0.01	−0.065***
		Bot (n = 1,000,000 sample)			Intelligent agent (N = 15,119)			Software agent (N = 18,324)		
		OR	*SE OR*	*AME*	*OR*	*SE OR*	*AME*	*OR*	*SE OR*	*AME*
Model 1	LIWC work	2.05	0.02	0.159***	3.36	0.28	0.230***	1.27	0.06	0.052***
	LIWC home	0.48	0.02	–0.164***	0.07	0.03	−0.510***	1.42	0.33	0.076
	LIWC leisure	0.83	0.01	–0.042***	3.20	0.59	0.221***	2.47	0.31	0.195***
Model 2	LIWC social	1.51	0.01	0.089***	0.60	0.03	−0.098***	1.05	0.04	0.011
	LIWC power	3.06	0.03	0.242***	0.31	0.03	−0.223***	0.49	0.04	–0.152***
	LIWC money	0.60	0.01	–0.112***	2.33	0.38	0.160***	2.28	0.20	0.177***
Model 3	LIWC past	1.67	0.01	0.113***	0.47	0.04	–0.146***	0.48	0.03	–0.158***
	LIWC present	1.32	0.01	0.061***	1.02	0.05	0.004	1.38	0.06	0.069***
	LIWC future	1.43	0.02	0.079***	2.39	0.44	0.168***	2.56	0.40	0.200***

AME: average marginal effect; OR: odds ratio; SE: standard error.
Dependent variable: Comments categorized as positive based on VADER compound score (>0.05). Independent variables: Contextual focus (*work, home, leisure*) in Model 1, motivational focus (*social, power, money*) in Model 2, and temporal focus (*past, present, future*) in Model 3. Models were controlled by word count and the time when the comment was created.
$^{**}p < .01$; $^{***}p < .001$.

comments using the LIWC *past* lexicon (*AME* = –0.158 to −0.003, $p < .001$) were less likely to be categorized as positive consistently across the robotic technology corpora. The relationship of LIWC *present* category with positivity was small or nonexistent, except the slight positive connection in the *bot* and *software agent* corpora. With the exception of the *automation* corpus, comments using LIWC *future* vocabulary were more likely to be categorized as positive across the different robotic technology concepts.

Summary and concluding discussion

This study utilized computational tools to investigate sentiment and life domain, motivational, and temporal themes in Reddit social media discussions on six concepts related to robotic technologies (*robot, AI, automation, bot, intelligent agent, software agent*). The study was grounded on computational social sciences and social psychologies theories on language and representations. The comments were processed using VADER and LIWC sentiment analysis tools and the sentiment results were then analyzed both descriptively and further with logistic regression models. During the timeframe of 2006–2018, *AI* became the third most used concept in Reddit discussions, *robot* being the most popular concept until the popularity of *bot* rapidly increased and surpassed it in 2011. Compared to the four other concepts, the concepts of *robot* and *AI* were used less often in positive comments. In addition, we found comments addressing themes of *leisure, money*, and *future* to be linked to positive and *home, power*, and *past* to negative comments.

As social psychological theories on language and representations suggest (de Groot, 1989; Wagner et al., 1999), the usage of robotic technology concepts in social media discussions vary depending on the concept. *Robot* and *AI*, and especially *bot*, were found to be more dominant concepts in social media discussions compared to *automation, intelligent agent*, and *software agent*. Yearly occurrence analysis revealed accelerating usage over time of the concepts of *bot, automation*, and *AI*. Based both on increasing yearly frequencies and popularity of the concept in Reddit discussions during the timeframe overall, *bot* was the new trending concept of robotic technologies. However, the results suggest that the concepts of *robot* and *AI* were also fairly popular topics discussed in Reddit forums. Thus, the occurrences of robotic technology in Reddit discussions varied depending on the concept and over time, answering our first research question.

Considering our second research question and research arguing that language affects people's appraisal processes (de Groot, 1989; Wagner et al., 1999), we examined sentiment orientation between discussions around different robotic technology concepts. We found that *robot* and *AI* occurred more often in negative and less often in positive comments than the four other concepts, which suggests that *robot* and *AI* are associated with more negative conceptions and concerns. Based on integrated threat theory (Stephan and Stephan, 2000), negative representations and stereotypes can affect attitudes negatively. Following the reasoning of integrated threat theory used in the context of robotic technology (Vanman and Kappas, 2019), *robot* and *AI* could be perceived as the robotic technologies most threatening to humans from the perspective of realistic or symbolic threats. Examining sentiments and changes in usage over time revealed that *intelligent agent* and *software agent* were less integrated in discussions in general and in discussions that were free of strong emotional or attitudinal tendencies. In contrast, comments referring to *bots* and *robots* were most often categorized as neutral, and as they were also the most frequently occurring concepts overall in 2006–2018 Reddit discussions, it could be argued that they are the most integrated robotic terminology of the six concepts in casual social media conversations.

Guided by our third research question, we scrutinized the connections of sentiment in robotic technology discussions and different contextual themes: life domains, motives, and temporal focus. We found that comments were less likely to be positive if they used domestic vocabulary compared to work or especially leisure vocabularies. This was in line with previous research on domestic environments (de Graaf et al., 2019). In contrast to this, Taipale et al. (2015) found in a previous study that the introduction of robots into leisure activities or social domains was less likely to receive positive reception than their introduction into work domains, where their use was more familiar. However, a study by Oksanen et al. (2020) reported a positive reaction to interacting with a robot or artificial intelligence in a gamified online environment, which can be considered belonging to leisure activities.

Robots in social domains and social interaction with robotic technology have received skepticism in previous literature, especially when robots were intended to replace humans (de Graaf et al., 2019; Savela et al., 2018, 2021a, 2021b; Taipale et al., 2015). However, this study did not find support for a negative relationship between social vocabulary and positive comments. In line with previous findings regarding the relationship between acceptance of robots and decreasing sense of control (Latikka et al., 2021), comments using power vocabulary were less likely to be categorized as positive. Economic vocabulary had an opposite connection, which is somewhat in contrast with the previous findings regarding fear of one's own decreasing economic situation (Dekker et al., 2017) but can be understood from the perspective of efficiency and the economic benefits of automation of jobs (Berg et al., 2018).

In contrast to arguments about familiarity and mere exposure effect and fear of the unknown (Carleton, 2016; Reis et al., 2011; Zajonc, 1968), comments using a past tense lexicon were less likely positive and comments using future tense more likely positive across the different robotic technology concepts. Thus, the result of emotional and attitudinal language on social media suggests that fear of the unknown does not decrease the readiness to envision and talk about new robotic technologies of the future with positive expectations. This is also strengthened by the fact that although *robot* has been a dominant part of robotic technology discussions in Reddit longer than *bot* and *AI*, we found no evidence that the sentiment in *robot* comments overall would have turned more positive than newer and thus less familiar concepts.

Theoretical contributions and implications for practice

Our research demonstrates how the usage of robotic technology concepts in discussions of one social media platform vary over time and based on the concept, and how certain concepts (*robot, AI*) are linked with more negative emotions and attitudes, as identified through automated text analysis. Different robotic technology concepts being associated with different representation of certain emotions highlights the significance of language used and thus supports social psychological theories about language (de Groot, 1989; Moscovici, 1988; Smith, 1998; Wagner et al., 1999). Thus, our research contributes to the linguistic research on robotic technology.

Our findings on the different life domain, motivational, and temporal contexts contribute to understanding the reasons and theoretical basis behind the acceptance of robotic technology. The themes of *home, power*, and *past focus* being associated with more negative sentiment implies that robotic technologies pose a rather realistic threat in the perspective of integrated threat theory, such as a threat to humans' private space, authority, or autonomy (Vanman and Kappas, 2019). No vast differences in texts focusing on *social* terminology and the focus on *leisure* and *future* terminologies being strongly connected to positive comments furthermore suggests low symbolic threat. However, our results do not support the notion of realistic economic threat posed by robotic technology as we found no evidence on higher negativity in texts on work and money. The negative association with discussions about *power* implies that human autonomy and control over robotic technologies is a more prevalent threat present in social media discussions. Thus, our findings propose that robots and especially artificial intelligence are perceived most threatening to humans from the different robotic technologies as they threaten the power balance of humans' authority over technology.

These findings on how robotic technologies are discussed in social media also have societal and practical implications on the development of advanced technology. Based on Reddit comments, it seems that people do not talk as negatively about robotic technology and even express positivity in discussions focusing on *leisure, work, money*, and *future*. However, the negative findings regarding discussions on *power* and *home* contexts suggest that technology developers and policy makers should place attention and effort on enabling people to retain their sense of autonomy over technology and sense of security about technology entering their private life domain of home environment. Investing on leisure domain and preserving human autonomy and control over robotic technologies should prove to be beneficial when developing sustainable advanced technology.

Limitations, strengths, and future research direction

Our data were limited to Reddit platform discussions and may not apply to discussions in other social media environments and cannot be generalized to all people. Regardless of our automated inspection and randomized manual checks of the data for potential sources of skewness, social media big data have its limitations in terms of validity and reliability. For example, informant reliability is weakened by the phenomenon of bots generating text content in social media platforms. Although duplicated comments were excluded from the data used for analyses to avoid skewness of the results based on repeated posting, because of the search word for the *bot* corpus and its large size compared to the other corpora, we should be careful not to overestimate the popularity of bot discussions over other robotic technologies. It should also be noted that a word such as "bot," for example, has multiple meanings in different contexts and interesting context-specific information cannot be observed when treating them as a one category.

Choosing the six concepts related to robotic technology also has its limitations. We chose to restrict our focus on hypernyms that represent the key concepts in themselves, instead of including, for example, certain robot types, brands, or models. Adding extra terms was judged problematic by our research team as it increases the number of discussions and even then, there might be something left out. The rationale for our approach was that we were interested in emotional language in the conversations using these main keywords specifically. It should also be noted that the six concepts do not equally relate to the concept of robot but instead have their own etymology and discussions on the definition. This is demonstrated well in the discussions about defining the social role in the concept of "agent" (Jennings et al., 1998; Maes, 1995). Our findings contribute to the discussion on how to use and interpret the six concepts related to robotic technology from the perspective of how they are used in casual discourse on the Internet.

As shown in our descriptive statistics, emotions and attitudes toward certain technologies have evolved during the span of our study. For this reason, we controlled for the confounding effect of time, the comments were posted in our logistic regression models. In the descriptive statistics, we chose to focus on yearly frequencies to observe the overall trends for the timespan of 12 years and for getting an overview that is not affected by monthly or daily occurrences. Future studies could examine the impact of specific events on the use of certain concept in social media and sentiments related to these discussions.

Although our data included the available comments of the whole population of Reddit users, without randomized experiments big data and other observational studies are limited in not providing verification for causal effects (Hoerl et al., 2014). However, descriptive observations are the foundation of predictive and explanatory investigations and provide beneficial insights (Hofman et al., 2021). Thus, utilizing average marginal effects of inferential statistics in addition to descriptive analysis methods gives strength to our findings from the comparisons between themes, but future research should investigate the generalizability of the findings in other public discussions and further study the associations using data and methods more suited to examine causality. It can be argued that identifying emotions or attitudes from text offers different information to that obtained through explicit measurement methods. For this reason, future research should investigate whether explicit measurements such as surveys reveal similar connections between different robotic technology concepts and life domain, motivational, and temporal themes. We verified the validity of the VADER tool for identifying positive comments in our data using human raters. Future research should continue to develop automated content analysis tools and their reliability for social scientific research. Our research contributes to the use of computational tools in public opinion mining in social psychological research in the context of robotic technology.

Conclusion

The results shed light on how terminology and thematic contexts affect the emotionality of robot conversations on social media. Based on our findings, *bot, robot*, and *AI* are popular concepts in public social media discussions, the latter two discussed less often in positive comments than *bot, automation, intelligent agent*, or *software agent*. The results show that robotic technologies are more likely to be found in positive context when discussed about themes such as *leisure, money*, and *future*, while discussions about *home, power*, and *past* themes are more often associated with negative or neutral comments on robotic technologies. This implies that robotic technologies are not talked as positively in discussions about home context, power dynamics, or past time, but are likely to be a part of positive discussions when talking about leisure activities, economic issues, or the future. Our findings advance our understanding on emotional talk about robotic technologies, how they are discussed in social media and in what contexts. In addition, the study advances the use of tools from computation social science for studying emotional expression and public opinion in social media. Gaining knowledge of the emotions of the public in more natural and organic environments is also relevant to legislation and the experts developing new applications for technology. Negative emotions and resistance may challenge the desired benefits from the introduction of robots into new domains, whereas social acceptance and positive expectations could guide the most beneficial and sustainable utilization of new technology.

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PUBLICATION IV

Affective attitudes toward robots at work: A population-wide four-wave survey study

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Affective Attitudes Toward Robots at Work: A Population-Wide Four-Wave Survey Study

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Abstract
Robotization of work is progressing fast globally, and the process has accelerated during the COVID-19 pandemic. Utilizing integrated threat theory as a theoretical framework, this study investigated affective attitudes toward introducing robots at work using a four timepoint data ($n = 830$) from a Finnish working population longitudinal study. We used hybrid multilevel linear regression modelling to study within and between participant effects over time. Participants were more positive toward introducing robots at work during the COVID-19 pandemic than before it. Increased cynicism toward individuals' own work, robot-use self-efficacy, and prior user experiences with robots predicted positivity toward introducing robots at work over time. Workers with higher perceived professional efficacy were less and those with higher perceived technology-use productivity, robot-use self-efficacy, and prior user experiences with robots were more positive toward introducing robots at work. In addition, the affective attitudes of men, introverts, critical personalities, workers in science and technology fields, and high-income earners were more positive. Robotization of work life is influenced by workers' psychological well-being factors and perceived as a welcomed change in the social distancing reality of the pandemic.

Keywords Robot · Work · Attitude · Well-being · Longitudinal

1 Introduction

Recent social distancing measures due to the COVID-19 pandemic have been argued to further increase the use of robots in the work life [1–3]. For a number of years, automation and robots have been utilized in fields such as manufacturing and agriculture [4, 5], but the interest in introducing robots to fields more involved with social interaction with humans is prominent [6]. Robot coworkers and team members working alongside human workers are becoming a reality rather than science fiction due to the enhanced features of service robots, such as interaction, collaboration, and sociability [7, 8], and the increasing number of collaboration robots being deployed in businesses [9]. Because of this, the current work life might face novel psychological demands along with these new generation robots. Thus, there is a need for longitudinal investigations on workers' perceptions of robots and how these perceptions are connected to workers' psychological well-being in general.

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Sheridan [10] proposed that one of the challenges in human–robot interaction is whether robots can generate jobs and enhance the sense of self-worth instead of taking away jobs and work tasks from humans and diminishing their sense of self-worth. From the perspective of intergroup threat described in integrated threat theory [11, 12], these examples could be seen as realistic and symbolic threats robots pose [13]. Perceiving robots as threatening outgroup members could increase prejudice toward robots. To fully utilize robots in everyday work life and to successfully collaborate with them, social psychological processes such as attitudes, trust, and being comfortable with interacting with robots are essential [14–16].

Previously, attitudes toward robots have often been studied via user studies of relatively small samples and survey studies of cross-sectional data. Although some large-scale survey studies exist [17, 18], as do cross-cultural studies [6, 19] and user studies utilizing iterative design and multiple timepoints [6, 20], longitudinal survey studies with representative samples have not yet been conducted. Our study aims to fill this gap and investigates the impact of workers' psychological well-being factors on affective attitudes toward robots at work. We utilize a longitudinal survey dataset (2019–2021)

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designed to represent the Finnish working population and examine the trends in attitudes and user experiences over time. This is the first study to examine attitudes toward robots with population-wide longitudinal survey research.

1.1 Attitudes Toward Robots at Work

Previous research demonstrated that people's attitudes toward robots were generally relatively positive [6, 21, 22]. However, it should be noted that people tend to respond more positively in surveys due to acquiescence bias [23] and in face-to-face situations such as field interviews due to social desirability [24]. Based on one large-scale opinion survey, European citizens' positivity toward robots decreased during 2012–2017 [17]. The potential negativity toward robots at work context has been argued to relate to a fear of losing one's income due to robot automation replacing humans for the sake of efficiency [25, 26] and to a discomfort due to social processes in interacting with robots [27].

Studies examining the relationship of psychological well-being and factors related to attitudes toward robots are still scarce and report mixed results. One small study ($N = 53$) from the surgical field found that a group of surgical trainees with high risk of burnout perceived training on robotic surgery as less interesting and important, and they were not anticipating using robotic surgery in future practice [28]. Some studies have found a positive relationship between low worker well-being and perceptions of advanced technology. One mixed-methods study by Brougham and Haar [29] tested awareness of advanced technology and its connection to different job and well-being factors on 120 employees and found that turnover intentions, cynicism, and depression were positively associated with workers' beliefs that their jobs were replaceable by technology such as robots and artificial intelligence (AI). Similarly, another team of researchers found AI awareness to be connected to job burnout [30]. While Kong et al. [30] found no such connection with career competencies, Brougham and Haar [29] found organizational commitment and career satisfaction to be negatively associated with participants' beliefs that advanced technology could replace their job.

These previous findings suggest that discontented workers might have positive perceptions of robots at work, while contented workers might be more threatened by the idea of a robot doing their work tasks and potentially replacing them. Although operating with cross-sectional data, these studies were designed to analyze if the pre-awareness of robotization of their work predicted workers' well-being, rather than examining the impact of well-being factors on attitudes toward robots. Some evidence from a user study of older adults implied a positive connection between low life satisfaction and negative attitudes toward interacting with robots [31]. However, the relationship between psychological well-being factors and attitudes toward robots could be different for those performing work tasks compared to subjects of work such as patients being cared for. The connection of psychological well-being measures on affective attitudes toward using or interacting with robots at work has not been previously studied.

As the pandemic has been proposed to have an impact on people's attitudes toward information technology [3], the potential reasons behind the assumed attitude shift highlight the connection of technology's perceived benefits to attitudes toward it and the need to investigate these connections. Technology acceptance research has identified several factors, such as job relevance, output quality, and result demonstrability, addressing the benefits of a certain technology and their connections to the technology's perceived usefulness, and further to the attitude toward using it [32, 33]. Although these constructs involve the same technology, it is possible that positively perceived outcomes of one technology could affect attitudes toward other technologies. Studies support the notion that general interest in technology and its development is connected to positive attitudes toward robots [34, 35].

Robot-use self-efficacy beliefs concern people's confidence in their own abilities to use robots [36, 37] and are a technology-specific form of the concept of perceived self-efficacy [38]. Recent studies on robot-use self-efficacy beliefs have demonstrated a positive association with general attitudes toward robots [35] and a readiness for robotization among healthcare workers [34, 39]. Self-efficacy beliefs are dynamic and can be altered by the context and change over time as information and experience are gained [40]. However, no prior studies have investigated the longitudinal relationship between perceived robot-use self-efficacy and affective attitudes toward robots.

Because familiarity with an attitude object can increase its attractiveness and decrease anxiety [41–43], positive attitudes toward robots could increase after having more encounters with robots. Indeed, people with firsthand experience of using robots have demonstrated more positive attitudes toward robots compared to those without prior experience [35].

From other background factors, previous research has found a positive connection between education in technology and positive attitudes toward robots [37, 44]. Although human–robot interaction literature on income remains scarce, some previous studies suggested that low-income earners were less comfortable with robots in public places [45] but perceived them more suitable to their own field of work [46]. In technology adoption literature, gender and age are argued to be important confounding factors [47] and some studies have found men and younger people to have a more positive attitude toward robots [45, 48, 49]. Previous research on personality traits has found high extraversion to be connected to higher trust and willingness to interact with robots [50]. Consistent findings for other personality traits remain scarcer in human–robot interaction literature, but some evidence implies that neurotic [37, 50] and conscientious people and people not as open to experiences are more uncomfortable with interacting with robots [50, 51].

The COVID-19 pandemic has been argued to increase the robotization of workplaces [1], which can refer to introducing robots as tools for workers to utilize or as a robot workforce for human workers to work alongside of and potentially be replaced by. Unprecedented times including social distancing measures may have influenced people's attitudes toward robots. The benefits of utilizing robots to reduce human contact and the spread of viruses has been proposed to outweigh the concerns over privacy issues and potential job loss and to help boost the adoption of robots [52]. Thus, researchers have called for investigations on the impact of the COVID-19 pandemic on people's attitudes toward robots and replacing human contact with machine contact [2] and how the deployment of robots affects organizations [3]. The ongoing COVID-19 pandemic has been stated to have a positive impact on the acceptance of other information technology, such as online services [3], but evidence of its influence on people's perceptions about robotization of work is needed.

1.2 Theoretical Background and Hypotheses Development

The theoretical framework of our research consists of theories on intergroup threat, strain, and attitude processes. Because attitude and comfort can be viewed as emotive factors influencing trust in automation [15], we designed our study to examine how various cognitive (perceived cynicism, professional efficacy, technology-enhanced productivity, and robot-use self-efficacy) and behavioral factors (prior experience with robots) have influenced affective attitudes toward robots during the 2019–2021 timeframe. In addition, our aim was to analyze how the COVID-19 pandemic impacted the affective attitudes toward introducing robots at work. We posed five hypotheses to investigate the connections of psychological well-being factors and factors regarding competence and experiences with robots to affective attitudes toward introducing robots at work. From the different aspects of robotization of work, our study focuses on the ideas of introducing robots as tools for workers to utilize and as a robot workforce for human workers to work alongside of.

Integrated threat theory states that realistic or symbolic threats can provoke negativity [11, 12]. If robots pose a threat to workers' livelihoods (realistic threat), this might increase uncomfortableness and prejudice toward interacting with robots at work [13]. In contrast, if technology is perceived as a relief from an unsatisfying job, as a source of productivity, or as a solution for the need for social distancing and therefore benefits workers themselves, robots might not be perceived as threatening.

H1a High cynicism at work predicts positive affective attitudes toward introducing robots at work.

H1b High perceived professional efficacy predicts negative affective attitudes toward introducing robots at work.

Venkatesh and Davis [32, 33] have theorized that facilitative factors, such as job relevance, output quality, and result demonstrability, are connected to perceived usefulness of technology, which further affects the attitude toward using technology and the use intention. Therefore, positively perceived task outcomes and other technology-use productivity beliefs likely affect the attitude toward the same technology. However, it could be argued to facilitate favorable expectations on other information technologies as well. Thus, people who make positive cognitive appraisals on technology use in general based on its perceived benefits on work productivity might also have more positive attitudes toward introducing robots at work.

H2 High perceived technology-use productivity predicts positive affective attitudes toward introducing robots at work.

The concept of perceived self-efficacy is a central component of social cognitive theory [53] and depicts individuals' beliefs in their own capabilities to accomplish tasks and attain goals [38]. Self-efficacy beliefs shape the way people think, feel, behave, and motivate themselves, and thus can affect how people approach novel situations and tasks [54], such as deploying robots at work. Those with high confidence in their abilities to use robots at work are likely to perceive such technology more positively [34, 35, 39].

H3 High robot-use self-efficacy predicts positive affective attitudes toward introducing robots at work.

Contact hypothesis [55], fear of the unknown [41], familiarity principle [42], and mere-exposure effect [43] suggest that interaction experiences with the attitude target enhances the positivity toward it. For this reason, we expected that people with previous robot interaction experience would have more positive affective attitudes toward robots compared to those with no experience and that this effect is also found in within-person changes.

H4 Having prior robot interaction experiences predicts positive affective attitudes toward introduction of robots at work.

In addition to the main hypotheses and the explored impact of the COVID-19 pandemic, we designed our study to include background factors of the science and technology field, income level, gender, age, and personality traits as control variables.

2 Method

2.1 Participants and Procedure

For the analyses, we utilized a longitudinal Social Media at Work in Finland Survey, which was designed to represent the Finnish working population. The survey was designed by the research group and collected in collaboration with Norstat, utilizing Norstat's online research panel for recruiting participants via diverse offline and online sources. Participants did not receive direct financial compensation, but they can reclaim rewards with points they received from participating in the surveys. Data integrity and quality checks were conducted throughout the study following the research group's protocol. The local Academic Ethics Committee did not find ethical problems in the research. The survey was conducted in Finnish, and the participation was voluntary.

The original survey was collected in March–April 2019 from 1,817 participants, the data being representative by age and gender, covering diversely different occupational fields and regions of Finland. For the present study, we used the four timepoints followed by the first data collection because robot-related questions relevant to the present study were added after the original survey. The first timepoint included in this study (T1; $n = 1{,}318$) was collected in September–October 2019, and the second timepoint (T2; $n = 1{,}081$) in March–April 2020. After that the original participants were recontacted. The third timepoint included in this study (T3; $n = 1{,}152$) was collected in September–October 2020, and the fourth timepoint (T4; $n = 1{,}018$) in March–April 2021. Of the original survey respondents, 46.23% participated in all five surveys ($n = 840$) and the response rates were relatively high for all timepoints (T1: 72.54%; T2: 59.49%; T3: 63.40%; T4: 56.03%). The final sample used in this study ($n = 830$) consisted of respondents who answered to all timepoints and who were working during at least one timepoint after the original survey collected in spring 2019 (44.33% female; $M_{\text{age}} = 44.33$; $SD = 11.09$; Range = 19–65). The response time medians of the surveys were 15.3–16.9 min.

2.2 Measures

This study's main dependent variable is affective attitudes toward introducing robots at work. To consider the workers' well-being in the context of affective attitudes toward robots at work, we utilized subscales of burnout measure (cynicism and professional efficacy) and technostress measure (productivity) relevant to our research questions. Other main independent variables include robot-use self-efficacy and prior robot-use experience. Control variables include the COVID-19 pandemic time variable, occupation in the science and technology field, income, gender, age, and five personality traits (extraversion, conscientiousness, openness, agreeableness, and neuroticism). Descriptive statistics of all measures are presented in Table 1 and Pearson correlation coefficients for all the study variables are provided in appendices (Appendix).

2.2.1 Affective Attitudes Toward Introducing Robots at Work

The dependent variable was measured with two items used in previous research [37]: "How would you feel about using a robot as a work equipment?" and "How would you feel about having a robot as a colleague?" We provided answer options on a 7-point Likert scale from 1 ("not at all comfortable") to 7 ("very comfortable"). For the analysis, we used both items as 1-item measures and as a 2-item sum variable with highly correlated items in all four timepoints (T1: $r = 0.75$; T2: $r = 0.77$; T3: $r = 0.76$; T4: $r = 0.79$).

2.2.2 Cynicism at Work

The cynicism at work context refers to a negative attitude or indifference toward work due to a loss of interest in work and the sense of meaning it entails [56]. Cynicism at work was measured utilizing the 5-item cynicism subscale of the Maslach Burnout Inventory General Survey (MBI-GS) [56], which includes statements such as "I have become less enthusiastic about my work." The answer options ranged from 0 to 6. We created a sum variable with a range of 0–30 that had a good internal consistency at all timepoints (T1: $\omega = 0.82$; T2: $\omega = 0.80$; T3: $\omega = 0.82$; T4: $\omega = 0.82$).

2.2.3 Professional Efficacy

Professional efficacy refers to workers' satisfaction on their occupational accomplishments and feelings of effectiveness at work [56]. Perceived professional efficacy was measured utilizing the 6-item professional efficacy subscale of the MBI-GS [56], including statements such as "In my opinion I am good at my job." The answer options ranged from 0 to 6. We created a sum variable with a range of 0–36 that had a good internal consistency in all timepoints (T1: $\omega = 0.89$; T2: $\omega = 0.89$; T3: $\omega = 0.90$; T4: $\omega = 0.89$).

2.2.4 Technology-Use Productivity

To measure perceived productivity of technology use, we utilized items from Ragu-Nathan et al.'s [57] technostress measure's productivity subscale. The three statements about productivity beliefs were adapted to the context of social media: "Social media helps to improve the quality of my work," "Social media helps me to accomplish more work than would otherwise be possible," and "Social media helps me to perform my job better." The answer options ranged from 1

Table 1 Descriptive statistics of the study variables

Continuous variables	Range	T1		T2		T3		T4		Within-person
		M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*SD*
Affective attitudes toward introduction of robots…	2–14	6.72	3.30	7.13	3.29	7.31	3.33	7.61	3.37	1.61
As a tool at work	1–7	3.64	1.71	3.88	1.73	3.96	1.74	4.07	1.73	0.91
As a colleague	1–7	3.09	1.82	3.25	1.77	3.35	1.81	3.53	1.84	0.92
Cynicism at work	0–30	14.40	7.15	14.02	6.86	14.05	6.93	14.32	7.07	3.69
Professional efficacy	0–36	27.61	6.81	27.41	6.81	27.07	6.99	26.98	6.93	3.65
Technology-use productivity	3–21	7.35	4.52	7.65	4.60	7.64	4.56	7.50	4.59	2.38
Robot-use self-efficacy	3–21	15.62	4.44	15.71	4.32	15.68	4.40	15.67	4.35	2.08
General attitude toward robots	1–7			4.41	1.31	4.47	1.30	4.58	1.31	
Income	1–8	3.71	1.53							
Age	19–65	44.33	11.09							
Extroversion	3–21			13.43	4.35					
Conscientiousness	5–21			15.61	3.04					
Openness	3–21			14.70	3.36					
Agreeableness	3–21			14.40	3.01					
Neuroticism	3–21			11.70	3.61					
Categorical variables	Coding	*n*	%	*n*	%	*n*	%	*n*	%	
Prior robot-use experience	0/1	322	38.80	420	50.60	437	52.65	460	55.42	0.31
During COVID-19	0/1	0	0	830	100	830	100	830	100	
Science and technology field								42	5.06	
Female	0/1	362	43.61							
n		830[a]		830[a]		830[a]		830[a]		3,320[1]

We report means and standard deviations for the continuous study variables and frequencies and proportions for the categorical variables
[a]The observations for the variables of cynicism at work and professional efficacy are lower ($n = 3{,}152$; T1: 817, T2: 798, T3: 769, T4: 768) due to some participants ($n = 97$) not working at one or more timepoints

("disagree completely") to 7 ("agree completely"). The final scale had a range of 3–21 and its internal consistency was excellent at all timepoints (T1: ω = 0.95; T2: ω = 0.95; T3: ω = 0.95; T4: ω = 0.95).

2.2.5 Robot-Use Self-Efficacy

We utilized a robot-use self-efficacy measure applied from RUSH-3 [36] to examine respondents' perceived abilities to use robots. Items included questions such as, "I'm confident in my ability to learn how to use robots in order to guide others to do the same." The answer options ranged from 1 ("disagree completely") to 7 ("agree completely"). The final scale had a range of 3–21 and its internal consistency was excellent at all timepoints (T1: ω = 0.93; T2: ω = 0.93; T3: ω = 0.94; T4: ω = 0.93).

2.2.6 Prior Robot-Use Experience

To measure participants' prior robot-use experience, we asked them, "When have you last used or interacted with a robot?" and provided them the following answer options: "I have never used or interacted with a robot," "During the past week," "During the past month," "During the past half a year," "During past year," and "Over a year ago." For the analyses, we created a dummy variable for all timepoints indicating if the participant had interacted with a robot at all (the last five answer options).

2.2.7 Control Measures

Control variables were measured in one timepoint and included variables for the COVID-19 pandemic time, occupational field, income level, gender, age, and personality traits. To account for the significance of the unusual times of the COVID-19 pandemic, we created a "During COVID-19" dummy variable where value 1 was assigned to timepoints T2–T4, value 0 referencing the timepoint before the pandemic (T1).

Occupational field was surveyed utilizing a list of Standard Industrial Classification TOL 2008 [58] that is derived from the list of International Standard Industrial Classification of All Economic Activities (ISIC) [59]. For the analysis, we used a dummy variable indicating whether the participants worked in a field within "professional, scientific and technical activities," hereafter referred to as "science and technology field." No differences were found for other occupational fields. Income level was measured by asking participants their monthly gross income. Income variable had eight values: below 1,000€ (1); 1,000–1,999€ (2); 2,000–2,999€ (3); 3,000–3,999€ (4); 4,000–4,999€ (5); 5,000–5,999€ (6); 6,000–6,999€ (7); and over 7,000€ (8). Female was used as a reference category for gender, and age was used as a continuous variable.

We used the 15-item big five personality inquiry [60] to measure the personality traits. Answer options to the statements varied from 1 to 7, and thus the final range for the sum variables of each trait was 3–21. The internal consistency of the scales was good for extraversion ($\omega = 0.87$), and acceptable for conscientiousness ($\omega = 0.70$), openness ($\omega = 0.71$), agreeableness ($\omega = 0.60$), and neuroticism ($\omega = 0.71$).

2.3 Statistical Techniques

All statistical analyses were performed with Stata 16 software and McDonald's omega coefficients were computed with a Stata module [61] to estimate scale reliability. Table 1 reports descriptive results for the study variables including means (M), standard deviations (SD), frequencies (n), and proportions (%). In addition to descriptive statistics, we computed hybrid linear multilevel regression models using Stata's hybrid command—an approach considered to combine the strengths of standard random effects and fixed effects surpassing their weaknesses [62]. For these main analysis models (see Table 2), we report unstandardized regression coefficients (B), their estimated standard errors ($SE\ B$), and statistical significance (p value).

With the hybrid models, we tested whether the within-person variation in cynicism at work, professional efficacy beliefs, perceived technology-use productivity, robot-use self-efficacy beliefs, or prior robot-use interaction experience between timepoints predicted changes in affective attitudes toward robots as equipment or colleagues. In addition to the dynamic differences over time, the hybrid models provide figures for static differences between participants. Thus, we report both within-effects for the main independent variables and between-effect associations computed simultaneously for the same variables and the control variables measured at one timepoint. Main models included 830 participants and 3,152 observations, and an additional analysis on general attitude toward robots (timepoints T2–T4) included 815 participants and 2,335 observations.

3 Results

Based on our descriptive results, positive attitudes toward robots have increased during the COVID-19 pandemic (see Table 1). Affective attitudes toward using robots as tools at work ($B = 0.33$, $p < 0.001$) and toward robot colleagues ($B = 0.29$, $p < 0.001$) were more positive during the COVID-19 pandemic era than before it (T2–T4 vs. T1). This increasing trend could also be seen in the general attitude towards robots (T2 vs. T4: $B = 0.17$, $p = 0.009$) that was measured during the COVID-19 (T2–T4). A similar trend was observed for prior user experiences with robots (T2–T4 vs. T1: $B = 0.14$, $p < 0.001$), but for robot-use self-efficacy, the slight increase from before the COVID-19 era was not statistically significant. No statistically significant changes between timepoints were observed for cynicism at work, professional efficacy beliefs, or perceived technology-use productivity during our study's timeframe.

The main results based on the hybrid models are presented in Table 2. We found within-person effects for cynicism at work ($B = 0.03$, $p = 0.006$), robot-use self-efficacy ($B = 0.14$, $p < 0.001$), and prior robot-use experience ($B = 0.32$, $p = 0.010$), meaning that the temporal increase in these during the T1–T4 timepoints predicted more positive affective attitudes toward introducing robots at work. However, it should be noted that although the within-person effect for cynicism at work was significant over the four timepoints, the regression coefficient was small. Similar results were found for a robot as a tool at work and as a colleague for cynicism and robot-use self-efficacy, but in terms of prior robot-use experience, the result remained statistically significant only in the case of affective attitude toward robots as tools at work. We also found between-person effects for professional efficacy beliefs ($B = -0.06$, $p = 0.004$), perceived technology-use productivity ($B = 0.12$, $p < 0.001$), robot-use self-efficacy beliefs ($B = 0.35$, $p < 0.001$), and prior robot-use experience ($B = 1.33$, $p < 0.001$). Similar results were found for a robot as a tool at work and as a colleague.

In addition, adding a general attitude toward robots variable (measured only in T2–T4) in the model showed similar results and demonstrated that the general attitude toward robots is a strong predictor of the context-specific affective attitudes toward introducing robots at work based on both within-person effects ($B = 0.74$, $p < 0.001$) and between-person effects ($B = 1.67$, $p < 0.001$). It is notable that the small within-person effect of cynicism at work is slightly

Table 2 Hybrid multilevel models predicting affective attitudes toward introducing robots at work

	Tool or colleague			Tool			Colleague		
	B	*SE (B)*	*p*	*B*	*SE (B)*	*p*	*B*	*SE (B)*	*p*
Within-person variables									
Cynicism at work	0.03	0.01	.006	0.01	0.01	.033	0.01	0.01	.007
Professional efficacy	− 0.01	0.01	.184	0.00	0.01	.401	− 0.01	0.01	.123
Technology-use productivity	0.01	0.01	.502	0.01	0.01	.500	0.00	0.01	.609
Robot-use self-efficacy	0.14	0.02	< .001	0.08	0.01	< .001	0.07	0.01	< .001
Prior robot-use experience	0.32	0.12	.010	0.19	0.07	.007	0.13	0.07	.060
Between-person variables									
Cynicism at work	− 0.02	0.02	.215	− 0.01	0.01	.211	− 0.01	0.01	.271
Professional efficacy	− 0.06	0.02	.004	− 0.02	0.01	.038	− 0.03	0.01	< .001
Technology-use productivity	0.12	0.02	< .001	0.05	0.01	< .001	0.07	0.01	< .001
Robot-use self-efficacy	0.35	0.02	< .001	0.19	0.01	< .001	0.16	0.01	< .001
Prior robot-use experience	1.33	0.23	< .001	0.79	0.11	< .001	0.54	0.13	< .001
Controls									
During COVID-19	0.56	0.08	< .001	0.30	0.04	< .001	0.26	0.05	< .001
Science and technology field	0.69	0.31	.026	0.20	0.15	.182	0.49	0.18	.008
Income	0.14	0.06	.015	0.06	0.03	.025	0.08	0.03	.019
Female	− 0.54	0.17	.002	− 0.37	0.09	< .001	− 0.18	0.10	.069
Age	0.01	0.01	.362	0.00	0.00	.905	0.01	0.00	.132
Extraversion	− 0.08	0.02	< .001	− 0.04	0.01	< .001	− 0.05	0.01	.001
Conscientiousness	− 0.03	0.03	.322	− 0.02	0.02	.178	− 0.01	0.02	.544
Openness	0.02	0.03	.526	0.00	0.01	.921	0.02	0.02	.232
Agreeableness	− 0.07	0.03	.020	− 0.02	0.01	.138	− 0.05	0.02	.004
Neuroticism	0.02	0.03	.380	0.02	0.01	.135	0.00	0.01	.813

stronger during the COVID-19 timepoints ($B = 0.04$, $p = 0.001$) and remains statistically significant ($B = 0.03$, $p = 0.006$) even after a strong predictor of general attitude toward robots is added to the model.

The affective attitudes toward introducing robots at work were significantly more positive during the COVID-19 pandemic era (T2–T4) than before it ($B = 0.56$, $p < 0.001$). Based on the between-person effect results for background factors, workers from the science and technology field were more positive toward robot colleagues ($B = 0.49, p = 0.008$), higher income was associated with more positive affective attitudes toward robots introduced as tools or as colleagues ($B = 0.14, p = 0.015$), and women were less positive toward using robots as tools at work ($B = -0.37, p < 0.001$). In addition, extraversion was negatively associated with positivity toward introducing robots at work ($B = -0.08$, $p < 0.001$) and for agreeableness, a similar connection was found only for affective attitude toward the idea of having a robot colleague ($B = -0.05, p = 0.004$). No differences were found based on age and the personality traits of conscientiousness, openness to experiences, and neuroticism.

4 Discussion

This Finnish longitudinal study on working populations investigated the within-between participant effects of workers' psychological well-being factors on their affective attitudes toward introducing robots at work. The results showed that people were more positive toward introducing robots at work during the COVID-19 pandemic than before it. Increased cynicism at work, robot-use self-efficacy, and prior user experiences with robots predicted positivity toward introducing robots at work over time. People with higher perceived professional efficacy were less and those with higher scores in technology-use productivity beliefs, robot-use self-efficacy, and prior user experiences with robots were more positive toward introducing robots at work. In addition, the affective attitudes of women, extroverts, and agreeable respondents were more negative, and workers in the science and technology field and with higher income were more positive, providing more evidence on background factors in the field of human–robot interaction.

The results partly supported hypothesis H1a, confirming that an increase in cynicism at work had a small positive effect on the positivity toward introducing robots at work. The results based on between-person effects confirmed H1b, meaning that workers with higher perceived professional efficacy had more negative affective attitudes toward introducing robots at work. Similarly, we found support from between-person effects for H2, confirming that workers with higher perceived technology-use productivity were more positive toward introducing robots at work. These were in line with our theoretical argumentation based on integrated threat theory [11–13] and the technology acceptance model [32, 33].

The findings also supported our other hypotheses confirming that high robot-use self-efficacy (H3) and having prior robot interaction experiences (H4) predicted positive affective attitudes toward introducing robots at work. These results were in line with previous research on robot-use self-efficacy [34, 35, 39] and the theories explaining the positive impact of exposure to the attitude target [42, 43, 55]. We found connections for both between the workers and in changes within them over time, except we did not find a statistically significant within-person effect between prior robot interaction experiences and affective attitude toward robot colleagues. Considering the currently deployed robot technologies, this could be due to the firsthand interaction experiences likely involving robots as tools rather than as colleagues.

These associations might exist because the COVID-19 pandemic has changed the ways of working, the work per se, and normal interaction possibilities. A large proportion of employees have also worked remotely and were pushed to take a notable digital leap [63]. Hence, individuals' professional and emotional connection to their work, colleagues, and employer may have suffered and increased cynicism at work and altered employees' affective attitudes toward robots to more positive to aiding these gaps. This could also be the case for workers self-doubting their abilities to handle the work and seeing robots as a relief for their burden. However, becoming more familiar with and more confident in utilizing robotic technology at work significantly increases workers' positive affective attitudes toward robots at work. Those workers who see and believe in the positive productivity possibilities of traditional technology, such as social media, could also be more inclined to appreciate and interact with robots and other advanced technologies.

In addition to our main hypotheses, we sought to investigate the impact of the COVID-19 pandemic on people's attitudes toward robots. In line with what other researchers have proposed [1–3, 52], the affective attitudes toward introducing robots at work were remarkably more positive during the COVID-19 pandemic than before it. During the timeframe between September 2019 and April 2021, we observed a slight increase in affective attitudes toward introducing robots at work, general attitude towards robots (March 2020–April 2021), robot-use self-efficacy, and having prior user experiences with robots. In addition to the potential benefits in preventing human contact and the spread of viruses, the changes in attitudes could be due to increased faith in the usefulness of technology in general as especially knowledge workers have relied more on communication technology during the COVID-19 pandemic. In addition, the suggested enhancement of robotization of workplaces during the pandemic [1] can be indirectly observed from the fact that increasingly more respondents had at least some encounters with robots across the span of our study's timeframe.

In line with previous findings [37, 44], respondents from science and technology were more comfortable with the idea of having a robot as a colleague. Consistent with one previous study [45], we found that people with a higher income were more positive toward introducing robots at work, contributing to the scarce evidence on human–robot literature about the relationship between income and attitudes toward robots. Another previous study found low-income earners to perceive robots as more suitable to their own field of work [46]. This somewhat different finding could be due to an essentially different outcome variable. For instance, manual workers with a low income could consider robots suitable for doing their job while simultaneously being uncomfortable with robots deploying into their workplace and potentially replacing them. In contrast, high-income earners, and knowledge workers from the fields of science and technology, for example, might feel that the possibility of robots replacing them is rather unlikely and thus robot coworkers do not make them as uncomfortable.

Although some studies have found women to be more negative toward robots [48, 49, 64], other studies have found no difference based on gender [45]. Our study expands the literature in finding that women's uncomfortableness was directed at using a robot as a tool rather than having them as colleagues, which is in line with the notion that the potential gender differences depend on the robot type [45]. Along with some previous findings [45], we found no relationship between age and the affective attitudes measure.

In contrast to some evidence on previous research [50], we found introverted people to be more positive toward introducing robots at work and agreeable individuals less comfortable with the idea of having a robot colleague. However, this was somewhat in line with a previous study on U.S. respondents where a similar relationship remained statistically insignificant [37]. Other personality traits were not connected to our affective attitudes measure. Considering that our study's target population involved people from a specific cultural background and life domain, namely the Finnish working population, more research on the relationships of personality traits with the attitudes toward robots is needed.

4.1 Theoretical Contributions and Implications

Our research expands the current technology acceptance literature on psychological well-being factors, which have been previously understudied in the context of attitudes toward robots. Our results on perceived technology-use productivity supports the findings from previous research [34, 35] suggesting that positive evaluations of technology in general are connected to positive attitudes toward robots. Because this relationship between attitude toward a specific technology and attitude toward other technologies or technology in general is not represented in technology acceptance models [32, 33], it should be noted and further investigated. Our additional analysis results also verify a connection between attitude toward robots in general and attitude toward interacting with a robot in specific situations, such as at work, which is in line with previous findings [27, 65]. Our study makes a similar notion on technology acceptance models and psychological well-being factors, such as work burnout when used in the work context. Furthermore, positive attitudes toward and perceived benefits in using a new technology predicts usage motivation and intention to continue using the technology [66, 67].

In addition, our study illuminates the mechanisms in which the unusual situation a pandemic causes could alter the sense of threat technology is provoking and affect the attitudes toward it. Based on integrated threat theory [11, 12], realistic and symbolic threats can provoke negativity and promote prejudice. Vanman and Kappas [13] have proposed that integrated threat theory could be used to explain negativity toward robots as well. Our results support the notion in a sense that workers who were cynical toward their own abilities and the relevance of their work might have perceived robots at work as less threatening because they saw robots as a relief from an unsatisfying job. Thus, they might have seen robots as a realistic advantage rather than a threat, which increased their positivity toward robots. In contrast, low-income earners and those confident in their work skills might experience robots as a realistic threat that could take away their valued jobs from them. In addition, robot colleagues could pose a symbolic threat for compassionate and extraverted workers who would rather interact with human workers.

Considering the importance of language and representations [68, 69], introducing robots as colleagues instead of technical tools is associated with different expectations and can have significantly different social and power implications. In addition to the potential symbolic threat and prejudice that perceiving robots as social actors might provoke, the slightly less positive affective attitude toward robots as colleagues on average could be due to unfamiliarity. People are less likely to have experience with interacting with social robots than using robotic technologies as tools, which could make them more comfortable with the idea of using robots as tools at work based on theoretical arguments of contact hypothesis [55], familiarity principle [42], mere exposure effect [43], and fear of the unknown [41].

4.2 Implications for Practice

Considering the implications of our results for further robotization of work life, policy makers and employers should pay more attention to workers' psychological well-being in general. Our results imply that workers expressing cynicism toward their work and professional abilities, which are dimensions of work burnout, could be more enthusiastic to obtain robots to lessen their burden at work. Even though high cynicism at work and low professional efficacy would lead to viewing robots at work more positively, introducing robots should not be done while neglecting workers' well-being because this could have a negative societal impact and increase negativity toward robotization. Attention should be given to prevent cynicism at work and burnout in general by reinforcing the abilities and resources with actions, such as giving employees opportunities to influence and control their work, workload, and hours; enhancing stress management skills and possibilities for recovery; and fostering workplace support [70, 71]. A more sustainable way for mitigating adopting robots at work is to educate and familiarize workers with robots. In line with previous research [35], our results also highlight the importance of enabling successful encounters with robots and improving workers' confidence in their abilities to use advanced technology, for example by providing adequate training.

Our results indicated that there are individual differences in affective attitudes toward robots that need to be considered. Low-income earners might perceive robots at work more threatening than those with secure income and therefore robotization should be handled delicately. On average, women might be more hesitant to use robots as tools, but no other differences based on gender or age were found. This study's results also imply that robot colleagues cause more discomfort for outgoing and compassionate workers, but reserved and rational or critical workers might react more positively. It could be beneficial to direct the opportunities to interact with robots at work to those who are more interested and willing to do so while allowing more hesitant workers the choice not to and the time to adjust to the change.

4.3 Strengths, Limitations and Future Research Direction

A significant strength of our study was to utilize nationally representative large-scale survey data of a working population with a four-point longitudinal design and multiple validated measures for well-being and psychological factors. Using hybrid linear regression models and computing within- and between-person effects simultaneously also provides strength for our findings. However, the results found in the Finnish working population are not directly generalizable to other populations with different cultural backgrounds. Future research should validate our results with nationally representative samples collected from other countries. In addition, although responses on the idea of having robots at work offer valuable information about the potential consequences before they are realized, field studies with advanced robots utilizing versatile affective measurements would be an important future research avenue.

5 Conclusions

This was the first large-scale longitudinal study conducted in human–robot interaction research on positive attitudes toward robots. Our study is also among the few to consider well-being factors on technology acceptance. Our results based on nationally representative data on Finnish workers suggest that robotization of work life is judged as a positive transformation by dissatisfied and insecure workers who think that using technology is productive and beneficial. Workers with increased work-related stress based on cynicism toward their work and professional abilities might consider the robot workforce a relief, whereas people with a high sense of competence and pride in their own work perceive robotization of work more negatively. In addition to workers' well-being and psychological factors, individual differences in personality and socio-demographics influence attitudes toward robots in the work context. Our findings also show that introducing robots at work is perceived increasingly positively during COVID-19 and times of social distancing. The results imply that distressing times and troubled workers are seeking solutions from technology and anticipating robotization of work life more positively.

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Availability of Data and Material The data that support the findings of this study are available from the corresponding author upon reasonable request.

Code Availability Not applicable.

Declarations

Conflict of interest The authors do not have a conflict of interest to declare.

Ethical Approval The Academic Ethics Committee of the Tampere Region stated prior data collection that the research project did not include any ethical problems.

Consent to Participate Participation in the study was completely voluntary and participants were informed about their opportunity to withdraw from the study.

Appendix

See Table 3.

Table 3 Pearson Correlation Coefficients of the Study Variables

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1. Robots at work-attitudes[a] T1	1																
2. Robots at work-attitudes[a]T2	**.69**	1															
3. Robots at work-attitudes[a]T3	**.71**	**.71**	1														
4. Robots at work-attitudes[a]T4	**.66**	**.69**	**.75**	1													
5. Cynicism at work T1	.04	.03	.03	.03	1												
6. Cynicism at work T2	.00	.00	−.02	−.02	**.63**	1											
7. Cynicism at work T3	.00	.00	.03	.01	**.61**	**.66**	1										
8. Cynicism at work T4	.01	−.03	−.02	−.02	**.56**	**.64**	**.66**	1									
9. Professional efficacy T1	−.03	.01	.01	.01	−**.28**	−**.25**	−**.25**	−**.22**	1								
10. Professional efficacy T2	−.05	−.02	−.02	−.05	−**.27**	−**.21**	−**.24**	−**.18**	**.66**	1							
11. Professional efficacy T3	−.06	−.01	−.03	−.05	−**.26**	−**.27**	−**.24**	−**.24**	**.59**	**.61**	1						
12. Professional efficacy T4	−.06	−.01	−.01	−.01	−**.26**	−**.24**	−**.29**	−**.24**	**.58**	**.63**	**.65**	1					
13. Technology-use productivity T1	**.20**	**.17**	**.18**	**.14**	.00	−.03	−.04	−.07	.03	.03	.01	.03	1				
14. Technology-use productivity T2	**.22**	**.20**	**.21**	**.23**	.02	−.02	−.04	−.05	.05	.04	.02	.04	**.66**	1			
15. Technology-use productivity T3	**.20**	**.16**	**.20**	**.19**	.03	−.01	−.03	−.01	.04	.03	.03	.03	**.62**	**.65**	1		
16. Technology-use productivity T4	**.19**	**.16**	**.18**	**.19**	.00	−.05	−.06	−.05	.06	**.09**	.05	.06	**.61**	**.62**	**.68**	1	
17. Robot-use self-efficacy T1	**.42**	**.42**	**.42**	**.39**	−**.08**	−**.08**	−.05	−.04	**.20**	**.20**	**.17**	**.16**	**.13**	**.15**	**.09**	**.12**	1
18. Robot-use self-efficacy T2	**.33**	**.42**	**.41**	**.39**	−**.08**	−**.08**	−.03	−.05	**.17**	**.23**	**.14**	**.14**	**.07**	**.14**	**.09**	**.08**	**.71**
19. Robot-use self-efficacy T3	**.33**	**.38**	**.47**	**.41**	−**.08**	−**.07**	−.06	−**.08**	**.18**	**.18**	**.21**	**.21**	**.13**	**.15**	**.13**	**.13**	**.68**
20. Robot-use self-efficacy T4	**.35**	**.36**	**.41**	**.44**	−**.12**	−**.11**	−.07	−**.10**	**.17**	**.21**	**.18**	**.24**	**.10**	**.15**	**.08**	**.09**	**.68**
21. Prior robot-use experience T1	**.29**	**.24**	**.27**	**.26**	.04	.02	−.01	−.04	−.01	−.03	.00	−.02	**.18**	**.14**	**.16**	**.16**	**.21**

Table 3 (continued)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
22. Prior robot-use experience T2	**.26**	**.28**	**.28**	**.25**	.06	.01	.00	–.04	–.01	.01	–.01	–.03	**.12**	**.17**	**.18**	**.16**	**.17**
23. Prior robot-use experience T3	**.19**	**.22**	**.25**	**.20**	.05	.04	.04	.02	.04	**.07**	.07	.04	**.12**	**.13**	**.19**	**.19**	**.16**
24. Prior robot-use experience T4	**.19**	**.19**	**.21**	**.22**	.06	.00	.05	.00	.02	.00	.01	–.02	**.11**	**.12**	**.18**	**.18**	**.16**
25. General robot attitude[b] T1	**.52**	**.66**	**.59**	**.56**	–.03	**–.11**	**–.11**	**–.10**	.05	.01	.07	.06	**.15**	**.19**	**.15**	**.13**	**.38**
26. General robot attitude[b] T2	**.55**	**.60**	**.70**	**.61**	–.02	**–.11**	–.07	**–.08**	**.12**	**.08**	**.07**	**.08**	**.14**	**.21**	**.18**	**.16**	**.41**
27. General robot attitude[b] T3	**.54**	**.58**	**.59**	**.70**	–.06	**–.10**	–.05	–.05	.05	.01	.04	**.08**	**.15**	**.20**	**.17**	**.17**	**.39**
28. Science and technology field	**.09**	**.14**	**.14**	**.17**	–.02	–.03	–.03	.02	–.01	**–.08**	–.06	–.06	.02	.02	.01	.03	**.11**
29. Income	**.17**	**.21**	**.18**	**.20**	–.04	–.06	–.03	–.03	**.08**	**.09**	.07	.06	.06	**.08**	.05	.06	**.14**
30. Female	**–.19**	**–.17**	**–.17**	**–.15**	.00	.03	.04	–.02	.05	**.11**	**.09**	**.11**	.00	–.01	.02	–.02	**–.08**
31. Age	**–.12**	**–.11**	**–.12**	**–.12**	–.01	–.02	–.04	–.01	**.13**	**.15**	**.20**	**.14**	**–.16**	**–.20**	**–.16**	**–.16**	**–.12**
32. Extraversion	**.12**	**.09**	.06	.06	.00	–.04	–.07	–.02	**.19**	**.29**	**.20**	**.20**	**.13**	**.15**	**.08**	**.15**	**.18**
33. Conscientiousness	**–.11**	–.04	**–.07**	**–.09**	**–.16**	**–.13**	**–.14**	**–.13**	**.30**	**.40**	**.30**	**.29**	–.05	–.03	–.06	–.03	**.07**
34. Openness	**–.11**	**–.10**	**–.09**	–.06	**–.17**	**–.18**	**–.19**	**–.16**	**.21**	**.27**	**.22**	**.26**	**.14**	**.10**	**.07**	**.16**	.05
35. Agreeableness	**–.10**	–.06	–.06	–.07	**–.20**	**–.17**	**–.23**	**–.19**	**.12**	**.20**	**.13**	**.20**	.04	.05	.04	**.08**	.03
36. Neuroticism	.01	.02	–.01	–.01	**.22**	**.25**	**.25**	**.17**	**–.14**	**–.13**	**–.12**	**–.12**	.00	.06	.03	.02	**–.13**

18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36

1. Robots at work-attitudes[a]T1
2. Robots at work-attitudes[a]T2
3. Robots at work-attitudes[a] T3
4. Robots at work-attitudes[a] T4

Table 3 (continued)

	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36
5. Cynicism at work T1																			
6. Cynicism at work T2																			
7. Cynicism at work T3																			
8. Cynicism at work T4																			
9. Professional efficacy T1																			
10. Professional efficacy T2																			
11. Professional efficacy T3																			
12. Professional efficacy T4																			
13. Technology-use productivity T1																			
14. Technology-use productivity T2																			
15. Technology-use productivity T3																			
16. Technology-use productivity T4																			
17. Robot-use self-efficacy T1																			
18. Robot-use self-efficacy T2	1																		
19. Robot-use self-efficacy T3	**.71**	1																	
20. Robot-use self-efficacy T4	**.70**	**.71**	1																
21. Prior robot-use experience T1	**.19**	**.17**	**.19**	1															
22. Prior robot-use experience T2	**.18**	**.17**	**.18**	**.50**	1														
23. Prior robot-use experience T3	**.22**	**.19**	**.18**	**.42**	**.57**	1													
24. Prior robot-use experience T4	**.16**	**.17**	**.20**	**.45**	**.52**	**.56**	1												
25. General robot attitude[b] T1	**.37**	**.38**	**.34**	**.20**	**.26**	**.21**	**.17**	1											
26. General robot attitude[b] T2	**.39**	**.44**	**.42**	**.18**	**.20**	**.20**	**.14**	**.69**	1										

Table 3 (continued)

	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36
27. General robot attitude[b] T3	**.34**	**.37**	**.43**	**.17**	**.18**	**.15**	**.16**	**.66**	**.68**	1									
28. Science and technology field	**.10**	**.12**	**.11**	**.09**	**.09**	.04	.05	**.16**	**.14**	**.11**	1								
29. Income	**.13**	**.13**	**.13**	**.18**	**.23**	**.20**	**.15**	**.23**	**.22**	**.18**	**.08**	1							
30. Female	–**.07**	–.04	–.01	–**.13**	–.04	.00	.00	–**.21**	–**.18**	–**.17**	–**.12**	–**.30**	1						
31. Age	–**.18**	–**.15**	–**.19**	–**.12**	–**.09**	–.06	–**.07**	–.04	–**.07**	–.05	–.06	**.09**	.01	1					
32. Extraversion	**.17**	**.15**	**.14**	**.12**	.03	**.07**	.07	**.12**	**.10**	**.13**	.06	.04	–.06	**.10**	1				
33. Conscientiousness	**.10**	.06	**.07**	–.05	–**.07**	–.02	–.04	–.03	–.05	–.06	–.04	.02	**.08**	**.10**	**.19**	1			
34. Openness	.07	**.07**	**.08**	**.13**	.04	.04	**.07**	–.05	–.03	–.03	–.04	.01	**.07**	.04	**.22**	**.20**	1		
35. Agreeableness	.06	.05	**.10**	.03	.02	.03	.02	.03	–.01	.00	–.05	.01	**.08**	.02	**.14**	**.26**	**.24**	1	
36. Neuroticism	–**.08**	–**.11**	–**.09**	–**.09**	.02	.03	.04	–**.09**	–.06	–.05	.01	–**.17**	**.23**	–**.10**	–.04	–.05	–**.29**	–**.16**	1

p values < .05 are indicated with bold font

[a]Affective Attitudes Toward Introducing Robots at Work-variable

[b]General attitude toward robots -variable (measured only T2–T4)

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