Human-Robot Teams – Paving the Way for the Teams of the Future

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Summary

Thanks to advances in artificial intelligence and robotics, robots, and especially social robots that can naturally interact with humans, are now found in more and more areas of our lives. At the same time, teams have been the norm in organizations for decades. To bring these two circumstances together, this dissertation addresses the use of social robots together with humans in teams, so-called human-robot teams (HRTs).

This work aims to advance knowledge about HRTs and important underlying mechanisms in the establishment of such teams, thereby providing insights in two aspects. First, a structured and universal definition of HRTs is derived from the various perspectives of extant research, and based on a comprehensive literature overview, important characteristics and influencing factors of HRTs as well as research gaps in HRT research are identified. Second, insights into the underlying mechanisms of the establishment of human-robot teams are provided for settings with social robots in two different team roles: team assistant and lower-level (team) manager.

For this purpose, this dissertation contains three research studies that cover the currently largely unexplored area of social robots' use in organizational teams at both the employee and lower-level manager levels. The first study (conceptual study) provides a foundation for this dissertation and beyond by developing a structured and universal definition of HRTs. It also structures extant research on HRTs and proposes an agenda for future research on HRTs based on research gaps identified in a comprehensive literature review that includes 194 studies on HRTs.

The second and third studies (empirical studies 1 and 2) use empirical online studies to address two of the research gaps identified in the conceptual study. They examine the underlying mechanisms in decisions for social robots in two different team roles: team assistant (empirical study 1) and team manager (empirical study 2). By looking at expectations and experiences of taskwork-/performance-related and teamwork-related/relational features of social robots using polynomial regressions and response surface analyses, these studies rely on expectation disconfirmation theory to provide a detailed investigation of the underlying mechanisms of organizational decisions for social robots.

Empirical study 1 thereby shows that for teamwork, positive disconfirmation and high levels of experiences lead to higher acceptance of humanoid and android robotic team assistants, and similar results emerge for a humanoid robot’s taskwork skills. In contrast, for taskwork skills of android team assistants, high levels of positive disconfirmation lead to lower robot acceptance.

For robotic lower-level managers, empirical study 2 shows that there are discrepancies in the evaluation of performance-related usefulness and relational attitude. While for usefulness a slight overfulfilment of expectations leads to a positive impact on the readiness to work with, before evaluations decrease with greater overfulfillment, for attitude increasing positive experiences are associated with (decreasing) positive evaluations of readiness.

In summary, this dissertation contributes to scientific research on HRTs by advancing the understanding of HRTs, providing a structured and universal definition of HRTs, and suggesting avenues for future research. The systematic investigation of underlying mechanisms for the selection of different types of social robots for different team roles provides a holistic view of this new form of organizational teams. In addition to the research contributions, this thesis also provides practical guidance for the successful establishment of HRTs in organizations.

Zusammenfassung

Dank Fortschritten im Bereich der künstlichen Intelligenz und der Robotik sind Roboter, und insbesondere soziale Roboter, die auf natürliche Weise mit Menschen interagieren können, heute in immer mehr Bereichen unseres Lebens anzutreffen. Gleichzeitig setzen Unternehmen schon seit Jahrzehnten gezielt auf teambasierte Arbeitskonzepte. Um diese beiden Gegebenheiten nun zusammenzubringen, befasst sich diese Dissertation mit dem Einsatz von sozialen Robotern zusammen mit Menschen in Teams, sogenannten Mensch-Roboter-Teams (engl. Human-Robot Teams, HRTs).

Diese Arbeit zielt darauf ab, das Wissen über HRTs und wichtige zugrundeliegende Mechanismen bei der Bildung solcher Teams zu erweitern und dadurch Erkenntnisse in zweierlei Hinsicht zu liefern. Erstens wird eine strukturierte und allgemeingültige Definition von HRTs aus den verschiedenen Perspektiven der bisherigen Forschung abgeleitet und auf Basis eines umfassenden Literaturüberblicks werden wichtige Merkmale und Einflussfaktoren von HRTs sowie Forschungslücken in der Forschung an HRTs aufgezeigt. Zweitens werden Einblicke in die zugrundeliegenden Mechanismen bei der Etablierung von Mensch-Roboter-Teams für Szenarien mit sozialen Robotern in zwei verschiedenen Teamrollen - Teamassistent und Teammanager - gegeben.

Zu diesem Zweck enthält diese Dissertation drei Forschungsstudien, die das derzeit weitgehend unerforschte Gebiet des Einsatzes sozialer Roboter in Organisationsteams sowohl auf der Mitarbeiter- als auch der Teammanagerebene abdecken. Die erste Forschungsstudie (konzeptionelle Studie) liefert eine Grundlage für diese Dissertation und darüber hinaus, indem sie eine strukturierte und universelle Definition von HRTs entwickelt. Weiterhin wird die bisherige Forschung zu HRTs strukturiert und eine Agenda für die künftige Forschung zu HRTs vorgeschlagen, die auf Forschungslücken beruht, die in einer umfassenden Literaturübersicht mit 194 Studien zu HRTs ermittelt wurden.

Die zweite und dritte Forschungsstudie (empirische Studien 1 und 2) nutzen empirische Online-Studien, um zwei der in der konzeptionellen Studie identifizierten Forschungslücken zu adressieren. Sie untersuchen die zugrundeliegenden Mechanismen bei Entscheidungen für soziale Roboter in zwei verschiedenen Teamrollen: Teamassistent (empirische Studie 1) und Teammanager (empirische Studie 2). Durch die Betrachtung von Erwartungen und Erfahrungen in Bezug auf aufgaben-/leistungsbezogene und teamarbeitsbezogene/relationale Merkmale von sozialen Robotern mittels polynomieller Regressionen und Response-Surface-Analysen stützen sich diese Studien auf die Expectation Disconfirmation Theory, um eine

detaillierte Untersuchung der zugrunde liegenden Mechanismen von unternehmerischen Entscheidungen für soziale Roboter zu ermöglichen.

Die empirische Studie 1 zeigt dabei, dass bei teamarbeitsbezogenen Merkmalen positive Diskonfirmation und ein hohes Niveau an Erfahrungen zu einer höheren Akzeptanz von humanoiden und androiden robotischen Teamassistenten führen, und dass ähnliche Ergebnisse für die aufgabenbezogenen Merkmale eines humanoiden Roboters zu beobachten sind. Im Gegensatz dazu führt ein hohes Maß an positiver Diskonfirmation bei den aufgabenbezogenen merkmalen von androiden Teamassistenten zu einer geringeren Roboterakzeptanz.

Für robotische Teammanager zeigt die empirische Studie 2, dass es Diskrepanzen bei der Bewertung der leistungsbezogenen Nützlichkeit und der relationalen Einstellung gegenüber sozialen Robotern gibt. Während bei der Nützlichkeit eine leichte Übererfüllung der Erwartungen zu einem positiven Effekt auf die Bereitschaft zur Zusammenarbeit führt, bevor die Bewertungen bei größerer Übererfüllung abnehmen, sind bei der Einstelllung gegenüber sozialen Robotern zunehmende positive Erfahrungen mit (abnehmenden) positiven Bewertungen der Bereitschaft verbunden.

Insgesamt trägt diese Dissertation zur Forschung an HRTs bei, indem sie das Verständnis von HRTs erweitert, eine strukturierte und universelle Definition von HRTs liefert und Wege für zukünftige Forschungen aufzeigt. Die systematische Untersuchung der zugrundeliegenden Mechanismen für die Auswahl verschiedener Typen von sozialen Robotern für unterschiedliche Teamrollen ermöglicht eine ganzheitliche Betrachtung dieser neuen Form von Organisationsteams. Neben den wissenschaftlichen Beiträgen liefert diese Arbeit auch praktische Anhaltspunkte für die erfolgreiche Implementierung von HRTs in Organisationen.

Table of Contents

List of Figures

List of Tables

List of Abbreviations

AI	Artificial Intelligence
ANOVA	Analysis of Variance
C	Cross-sectional
CASA	Computers are Social Actors
Cat.	Category
cf.	confer/conferatur (compare)
COVID-19	Coronavirus Disease 2019
EDT	Expectation Disconfirmation Theory
EU	European Union
e.g.	exempli gratia (for example)
et al.	et alii (and others)
f	Female
GUI	Graphical User Interface
H	Hypothesis
HIT	Human Intelligence Task
HR	Human Resources
HRC	Human-Robot Collaboration
HRI	Human-Robot Interaction
HRT	Human-Robot Team
i.e.	id est (that is to say)
IMOI	Input-Mediator-Output-Input
IPO	Input-Process-Output
IS	Information Systems
ISO	International Organization for Standardization
IT	Information Technology
L	Longitudinal
m	Male
MTurk	Amazon Mechanical Turk
NASA	National Aeronautics and Space Administration
n.i.	No information provided by author(s)
M	Mean
n	Sample Size
n.s.	Not Significant
p	Significance Level

Ph.D.	Doctor of Philosophy
POMDP	Partially Observable Markov Decision Processes
RQ	Research Question
RSA	Response Surface Analysis
S	Social Interaction
SD	Standard Deviation
T	Task Interaction
T + S	Task & Social Interaction
TAM	Technology Acceptance Model
UAV	Unmanned Aerial Vehicle
UGV	Unmanned Ground Vehicle
US	United States of America
USAR	Urban Search and Rescue
vs.	Versus

1 Introduction

Current advancements in artificial intelligence are enabling this technology to be used in more and more application contexts (Maedche et al., 2019). AI is becoming an ubiquitous facet of our daily lives and, thanks to the advancements, is even able to become "human-aware" and interact with humans on an eye-level, for example in teams (Korteling et al., 2021; Seeber et al., 2020; Tewari, 2022; van den Bosch et al., 2019).

At the same time, robots are increasingly penetrating multiple areas of our lives. They have been in the focus of research (Lasota et al., 2014; Lozano-Pérez, 1983; Mori, 1970; Z. Pan et al., 2012; Preising et al., 1991; Wolf & Stock-Homburg, 2020), media (Alvarez Satorre, 2017; Boffey, 1983; Ford, 2015; Stylianou et al., 2015), and popular culture (e.g., R2-D2, T-800, or WALL-E; I. Phillips, 2015) for years, even decades. They have made their way into our professional (International Federation of Robotics, 2021; Wood, 2021) and personal lives (2018; Sung et al., 2007; Weiss et al., 2009) and continue to be an advancing technology.

Given this combination of recent promising developments, one might expect mixed human-robot teams (HRTs), in which humans collaborate with robots (Wolf & Stock-Homburg, 2020), to be a natural next step. However, these teams are not yet a widespread reality in the occupational context and remain aspirations thanks to their potentials, for example, to increase efficiency of teams (Gombolay, Gutierrez, et al., 2015). This dissertation therefore aims to advance knowledge about HRTs and provide insights into the path to these teams of the future.

1.1 Motivation and Research Questions

In the professional organizational context – the focus of this dissertation – the emphasis has traditionally been on functional industrial robots, which are used in industrial automation applications, such as manufacturing (ISO 8373; International Organization for Standardization, 2012), and are viewed more as tools than teammates (Tsai et al., 2022). In this context, a wide range of research has been conducted to better understand this type of robots and resulting implications of usage (Graetz & Michaels, 2018; Hoeniger, 1998; Ji & Wang, 2019). For instance, it has been shown that industrial robots help increase labor productivity (ABB, 2021; Dauth, 2017; Graetz & Michaels, 2018).

In more recent years, another type of robots has emerged and gained prominence: social robots. Social robots have the ability to interact naturally with humans using speech, gestures, and facial expressions (Breazeal, 2003; Breazeal & Scassellati, 1999). In addition to using these natural cues, social robots can also, for example, perceive and/or express emotions, establish social relationships, and communicate with interpretive dialogues (Fong et al., 2003; Stock-Homburg, 2022). Social robots also tend to have a human-like appearance, for example with a head, arms, and legs (so-called humanoid robots; Mende et al., 2019), and sometimes even aim to be indistinguishable from humans (so-called android robots; MacDorman & Ishiguro, 2005). With advances and innovations in robotics and artificial intelligence (AI), the scope of social robots has expanded drastically over the last years (Hildesheim & Michelsen, 2021; Leite et al., 2013; Leite et al., 2009). Thanks to this, today, social robots cover a wide range of applications in many aspects of our lives, from elder care (Kidd et al., 2006) to retail (C. Schmitt et al., 2017; Subero-Navarro et al., 2022), education (Belpaeme et al., 2018), and private households (Weiss et al., 2009).

However, social robots enabled through AI, used widely in organizational teams to collaborate and interact with humans, are still the future and not the current reality in organizations. This is despite the fact that social robots have already been shown to increase the efficiency of HRTs in experimental laboratory settings (Breazeal et al., 2005; Hoffman & Breazeal, 2007) and thus could have a similar potential as industrial robots.

The usage of social robots in organizations can further address another important issue: Driven by an aging workforce in many Western countries (OECD, 2019) and a skilled worker scarcity, in particular for technical skills (Bessen, 2014; Bughin et al., 2018; Smit et al., 2020), organizations are increasingly struggling with unfilled positions (Christian, 2022). The scale of these developments is significant: The European working-age population is likely to decrease by 13.5 million (about 4 percent) by 2030 due to demographic change (Smit et al., 2020). At the same time, more than half of the European workforce will face significant change: Some 94 million workers are expected to require reskilling (Smit et al., 2020). Thanks to their expanding skill sets and thus potential areas of application, social robots could provide much-needed relief in this war for talent for companies that are currently unable to fill their vacancies.

Finally, in addition to developments in robotics and the workforce, the working world in general is changing: General automation and digitization, and not least developments such as the COVID 19 pandemic, have drastically changed the way work is done in organizations (Gartner, 2020). The trend is toward more flexible working models, new skills are needed in dealing with technologies, and a new awareness of safety is required (e.g., with regard to risks of infection in the workplace) (Carlsen, 2020; Kretchmer, 2020; World Economic Forum, 2020a; Zahidi, 2020). Social robots could be beneficial in the face of these challenges by taking over tasks from human colleagues to support and thus helping companies become future-proof in the long run.

While extensive research has been conducted on broader areas such as human-robot interaction (HRI) and human-robot collaboration (HRC), e.g., in customer contact (Merkle, 2021), research on HRTs remains an emerging field. A growing interest into the topic is evident through the significant increase in publications in recent years (see Figure 1-1). In contrast, research on all-human work teams goes back almost a century (Mathieu et al., 2018). There are extensive studies and rich findings that help to understand how teams function and what, for example, their success factors are (R. Stock, 2004, 2005). For HRTs, however, this knowledge is currently lacking in many places: Existing research comes from a variety of backgrounds and has several research gaps due to the narrow focus on specific aspects of HRTs (Wolf & Stock-Homburg, 2020). As a result, while there is a body of research on HRTs, it lacks consistency and structure. In particular, when considering HRTs in organizational contexts, there is a lack of a sound understanding of what constitutes these teams, how they are formed, and what important characteristics and influencing factors are.

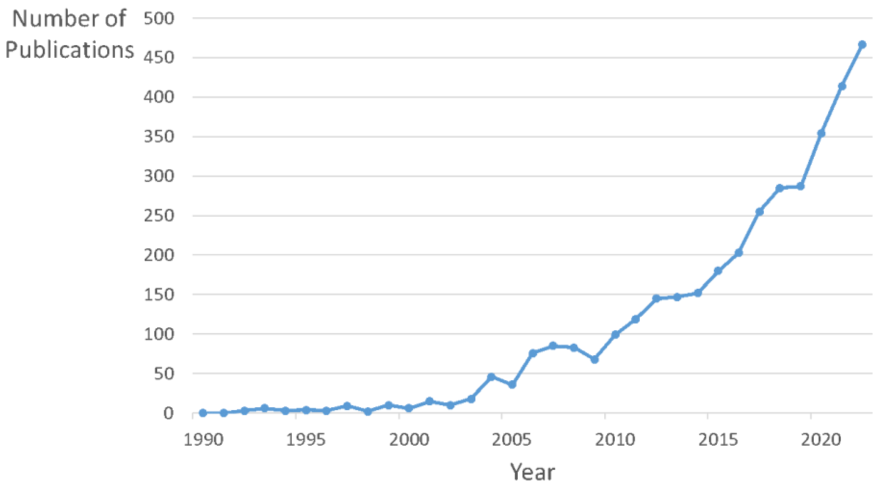


Figure 1-1. Number of Publications on Human-Robot Teams 1990 to 2022 (Source: Search on Google Scholar for Search Term "human-robot team")

To help address the gaps in research on HRTs, the focus of this dissertation is on the inwards directed use of social robots enabled through AI in organizational teams (see Figure 1-2). The main goal is to advance knowledge about HRTs and provide insights into the path to these teams of the future. In doing so, the thesis raises three overarching research questions (RQs).

Researchers studying HRTs come from a variety of disciplines and have different research foci (Wolf & Stock-Homburg, 2020). As a result, they take different perspectives, so there is no universal definition of HRTs and no structured understanding of fundamental characteristics, processes, and influencing factors of HRTs. Therefore, in order to avoid the jingle fallacy – according to which different things are understood by the same name (Marsh et al., 2019) – for

HRTs, obtain an overview of extant research on HRTs, and identify avenues for future research on HRTs, the first overarching research question of this dissertation is:

1. *How are human-robot teams (HRTs) defined and what are important characteristics and influencing factors?*

One aspect that is virtually completely missing from HRT research is the fact that robots do not magically appear in teams. Extant research tends to be either conceptual in nature or is concerned with pre-existing HRTs (Wolf & Stock-Homburg, 2022). The part of the research that deals with robot selection usually focuses on the selection of industrial robots (e.g., Ketipi et al., 2014; Koulouriotis & Ketipi, 2014). To my knowledge, there is only one study that considers an avatar selection scenario (Trainer et al., 2020). However, the focus of this study is not on an organizational context and it also focuses on virtual social avatars instead of physically embodied robots.

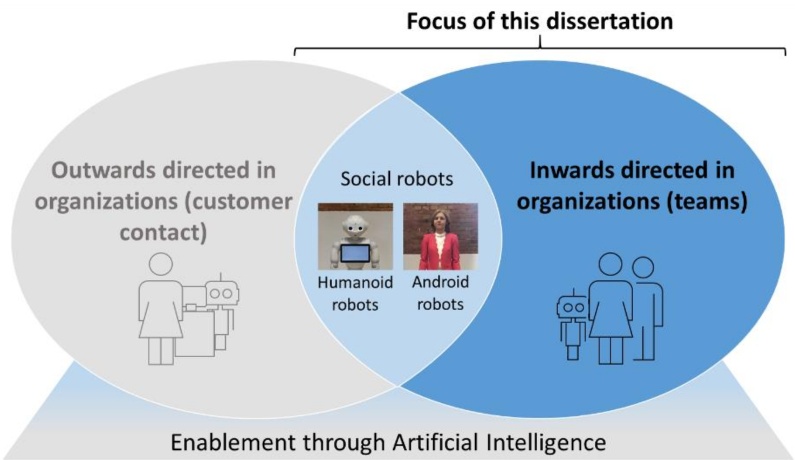


Figure 1-2. Focus Area of the Use of Social Robots in This Dissertation

Thus, the entire selection and decision-making process preceding the establishment of HRTs is largely neglected in research, although it plays an important role as a central prerequisite for the successful establishment of HRTs. This aspect also has a practical relevance, as employees need to be prepared and trained for the use of robots in their work teams analogous to the introduction of other new technologies, so that they are not overwhelmed (Kim, 2022).

This thesis aims to gain more insights into the decision for robots in two different team roles - team assistant and lower-level (team) manager - in order to contribute to a better understanding of important factors in the establishment of HRTs in organizations. The two roles were chosen because they represent different levels of team members, both of which are important to teams: Team assistants are a defined employee-level role in teams that, like other team members, have influence over a team's processes and outcomes (Gladstein, 1984; R.

Stock, 2004). Team managers have institutionalized authority over the members of a team and supervise them in achieving their common goals (Anzengruber et al., 2017). In doing so, they support team decisions, assign team tasks, and evaluate team and individual performance (Anzengruber et al., 2017; Simonet & Tett, 2013) Social robots are considered suitable for these roles due to their computational and behavioral capabilities (Breazeal et al., 2005; Feng et al., 2021; L. P. Robert et al., 2020). Thus, the second and third overarching research question of this dissertation are:

2. *What are underlying mechanisms of the decision for a robotic team assistant for a mixed HRT?*

3. *What are underlying mechanisms of the decision for a robotic lower-level (team) manager for a mixed HRT?*

To answer these research questions, both a conceptual approach (literature review; to answer RQ 1) and an empirical approach (empirical online research studies; to answer RQ 2 and RQ 3) were taken. The results are summarized in three research studies spanning the largely unexplored area of social robots' inwards directed use in organizational teams at both the employee and team manager levels (Figure 1-3). The studies are included in separate chapters in this thesis. The structure of the thesis is explained within the next section.

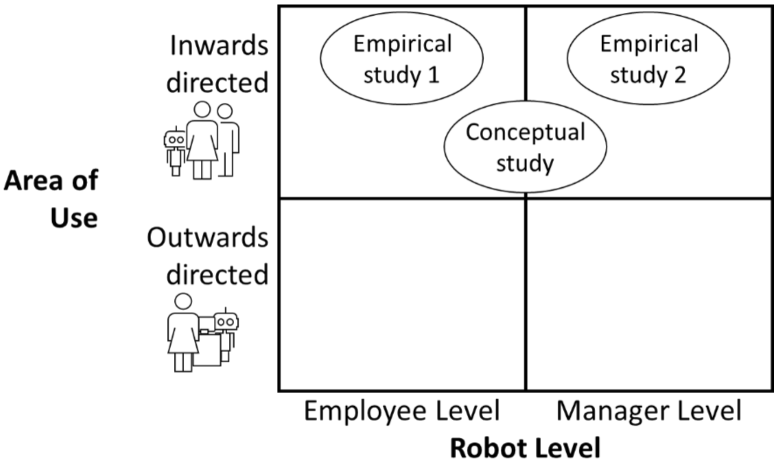


Figure 1-3. Classification of Research Studies Included in This Dissertation in the Research Landscape on Social Robots in Organizations

1.2 Thesis Structure and Synopsis

Guided by the three overarching research questions, this dissertation is divided into five chapters. Following the general motivation for the research in the introductory chapter, this thesis contains three research studies that aim to provide conceptual and empirical insights and findings about HRTs. Chapters two through four each consist of one study in the order shown in Table 1-1, which provides an overview of how the studies fit into the chapter structure. Chapter two (conceptual study) provides a literature review of existing research on HRTs, including a structured and universal definition of these teams. The third and fourth chapters each contain studies that address the underlying mechanisms of decisions for social robots in HRTs in offices that have different roles: the team assistant role (chapter three, empirical study 1) and the lower-level (team) manager role (chapter four, empirical study 2). Finally, chapter five concludes this thesis with a summary of contributions to research and practice, identification of limitations, and an outlook for future research.

The contents of each study are briefly summarized below:

Table 1-1. Overview Over Included Research Studies and Integration Into Chapter Structure

Chapter	**Research Study**
Chapter 2	***Conceptual study:*** Literature review on robots as team members
Chapter 3	***Empirical study 1:*** Decisions for robotic team assistants
Chapter 4	***Empirical study 2:*** Decisions for robotic lower-level (team) managers

Artificial intelligence and robotic technologies have evolved significantly in recent years and have become increasingly sophisticated and comprehensive. Accordingly, research on mixed human-robot teams (HRTs) consisting of both robots and humans has also expanded and attracted the attention of researchers from various disciplines such as organizational behavior, human-robot interaction, cognitive science, and robotics. The ***conceptual study*** (chapter two) provides a foundation for this dissertation and beyond as it features a comprehensive literature review of 194 studies on HRTs. In doing so, this study introduces a robot and team typology to derive a structured, universal definition of HRTs. It then structures previous research on HRTs using the input-process-output (IPO) model of teams (Gladstein, 1984) and provides insights into key study characteristics and findings. In addition, comprehensive avenues for future research on HRTs are proposed to help fill current research gaps.

Addressing one of the research gaps identified in the conceptual research study, ***empirical study 1*** (chapter three) considers an empirical online study on decisions for social robots in the role of team assistants as a natural first step before their integration into organizations. Based on the IPO model of teams (Gladstein, 1984) to structure the research and the expectation-disconfirmation paradigm (EDT; Oliver, 1980), this study focuses on humanoid robotic and android robotic team assistants. Using response surface analysis (RSA) following an approach by S. A. Brown et al. (2014), we find that for robotic team assistants, for teamwork (social skills and team orientation), positive disconfirmation and high levels of experiences lead to higher acceptance, and similar results emerge for a humanoid robot's taskwork (coordination skills and knowledge) skills. In contrast, for taskwork skills of android team assistants, high levels of positive disconfirmation lead to lower robot acceptance. The results of this study provides insights into considering diversely anthropomorphic robots and important aspects for implementing them in teams.

Finally, in the same vein as empirical study 1, ***empirical study 2*** (chapter four) takes a closer look at the mechanisms underlying decisions for robotic lower-level (team) manager candidates. By extending the TAM (Davis, 1989; Davis et al., 1989) and the expectation-disconfirmation paradigm (EDT; Oliver, 1980) to HRT settings, this investigation uses an empirical online study to compare the relationship between expected and experienced usefulness and attitude and the readiness to work with an android or humanoid robotic lower-level (team) manager. Results of a RSA (see S. A. Brown et al., 2014) show that there is a discrepancy between the evaluation of performance-related (usefulness) and relational (attitude) features of robotic lower-level managers. This study contributes to research on HRTs by providing insights into the implementation of social robots in the role of a lower-level (team) manager, thereby advancing the understanding of successful HRT implementation.

2 Conceptual Study: Literature Review on Robots as Team Members [1]

2.1 Introduction

Humans partner with robots in many current work settings to accomplish tasks in various fields. Many of these robots can be classified as social robots, interacting with humans in natural ways that include speech, gestures, and facial expressions (Breazeal, 2003). In contrast to industrial robots, they work like unique, contributing members of organizations and so-called human-robot teams (HRTs) (Hoffman & Breazeal, 2004).

Such teams are growing in presence and use, especially in light of the various restrictions imposed by the COVID-19 pandemic (Scassellati & Vázquez, 2020). Already in 2018, an estimated 82% of business leaders already believed that HRTs would be a daily reality within five years (Dell Technologies, 2018); when we recently surveyed 596 U.S. employees[2] (65% men, mean age = 36.92 years, SD = 10.85 years), we found that they could easily imagine working with a robot as teammate (39%), team assistant (50%), or even team leader (34%). Exemplary tasks of robots thereby include tracking of projects, performing real-time scheduling, and supporting complex organizational decision-making processes.

However, even as these uses and potential applications expand, research on HRTs remains limited by disciplinary silos. That is, the concept is interdisciplinary, but we lack syntheses of existing knowledge or common definitions used in relation to HRT across disciplines. Nor do we have a sense of what factors or characteristics of team members influence the functioning and outcomes of such HRTs. With this review, we attempt to systematically synchronize existing definitions and detail previous research on HRTs according to their theoretical perspectives, empirical designs, and major findings.

Our focus is on embodied robots, which we define as physical representations of AI in a physical world that can recognize and interact with their environment (Bradshaw et al., 2009; Fong et

[1] Based on Wolf and Stock-Homburg (2022) published in journal Group & Organization Management; updated to now include studies between 2020 and March 2023 to account for latest research in this field

[2] The survey participants were recruited via Amazon Mechanical Turk. We surveyed business leaders; they had an average of 6.99 (SD=6.431) years of leadership experience in various industries, including IT (23.2%), banking/ insurance (13.8%), and health care/social sectors (9.9%). They were responsible for teams (45.3%), departments (29.9%), business areas (11.1%), or the whole company (13.8%). The survey introduced social robots and their potential roles in organizations, and issued the prompt "I can imagine having a robot as an assistant/ colleague/supervisor," which participants answered on a 5-point Likert scale (1="not at all", 5="absolutely").

al., 2003; High-Level Expert Group on Artificial Intelligence, 2019).[3] For the review, we conducted online searches using Google Scholar and EBSCO but also reviewed journals and conference proceedings related to human–robot interactions. As detailed in supplementary material A[4] we searched 17 conferences and 40 journals. Most of them are from the fields of HRI, robotics, and computer science. We manually evaluated each study type, embodiment form, robot level, focus topic, and team size and applied various related exlusion criteria. Ultimately, we reviewed 194 relevant studies, published between 1990 and March 2023 (see Figure 2-1 and supplementary material A for more details on study selection). This review attempts to answer two questions:

1. How are human–robot teams defined in prior literature?
2. What intra-member characteristics, inter-member characteristics, and contingency factors influence input–process–output relationships in HRTs?

2.2 Proposed Typologies, Definitions, and Review Framework

2.2.1 Robot Typology

In recent efforts to categorize robots, a large number of robot typologies have been developed (for an overview, see Onnasch & Roesler, 2020). We propose a business-oriented robot typology (Figure 2-2) that depends on two main dimensions: social interaction intensity (Breazeal, 2003; Deng et al., 2019; Fong et al., 2003; Nass et al., 1994) and robot morphology (Onnasch & Roesler, 2020). In this context, we understand social interaction as the application of social models to interacting with a robot[5]. Across the two dimensions of our typology, we can identify four categories of robots that are particularly relevant to business contexts:

- *Machine-like robot with low social interaction*: Robots such as the Roomba vacuum cleaner (Forlizzi & DiSalvo, 2006) or the NIFTi ground vehicle (Kruijff, Kruijff-Korbayová, et al., 2014) are designed primarily with functionality in mind.

[3] Our focus explicitly is not on robot–robot teams, human–computer, or human–machine interactions. Disembodied agents limit communication channels, compared with embodied agents Deng et al. (2019), which in turn can limit the generalizability of findings. Furthermore, detailed considerations of the roles of agents in teams extend beyond the scope of this review.

[4] Supplementary materials A and B for this chapter are included in the Appendix section of this dissertation.

[5] In line with Breazeal (2003) and Fong et al. (2003) the low level of social interaction (see Figure 2-2) includes what Breazeal (2003, p. 169) calls “socially evocative” robots, which elicit social responses from humans without responding socially to them.

- *Human-like robot with low social interaction*: Robots such as Johnny 05 (SIM TU Darmstadt, n.d.), TIAGo (Pages et al., 2016), and Robonaut (Bluethmann et al., 2003) are humanoid robots with legs, arms, and heads. Despite this physical appearance, these robots are primarily designed to perform intended (work) tasks, not to engage in social interaction.
- *Machine-like robot with high social interaction*: Robots in this category, such as the Sociable Trash Box (Yamaji et al., 2011) and the Care-O-Bot (Kittmann et al., 2015), lack a human physical appearance but can elicit social responses (C. Schmitt et al., 2017).
- *Human-like robot with high social interaction*: Robots such as Elenoide (R. Stock et al., 2019) or Pepper (Pandey & Gelin, 2018) look very much like real humans and have strong social skills, including emotion recognition.

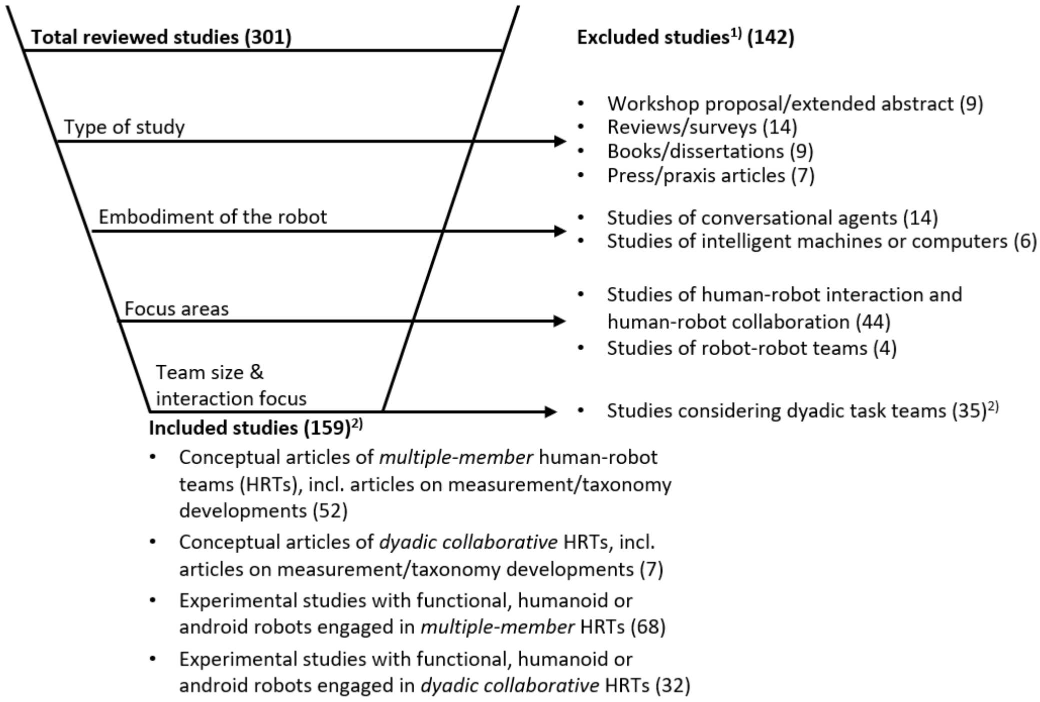


Figure 2-1. Overview of Reviewed, Included, and Excluded Studies
Note: 1) Please see supplementary material A for more details on the exclusion criteria. 2) In total we reviewed 194 studies in detail. Details on the 35 studies considering dyadic task teams can be found in supplementary material B.

2.2.2 Team Typology

2.2.2.1 All-Human Teams

Extant research provides a common agreement on the definition of human teams as collectives of three or more people (R. Stock, 2003), "who (a) exist to perform organizationally relevant tasks, (b) share one or more common goals, (c) interact socially, (d) exhibit task interdependencies …, (e) maintain and manage boundaries, and (f) are embedded in an organizational context" (Kozlowski & Bell, 2003, p. 334). Their dynamics span three main levels (de Wit & Greer, 2008; DeChurch et al., 2013): "tasks (i.e., goals, ideas, and performance strategies), … relationships (i.e., personality clashes, interpersonal styles)" (DeChurch et al., 2013, p. 560), and the processes used to manage or achieve teamwork (de Wit & Greer, 2008).

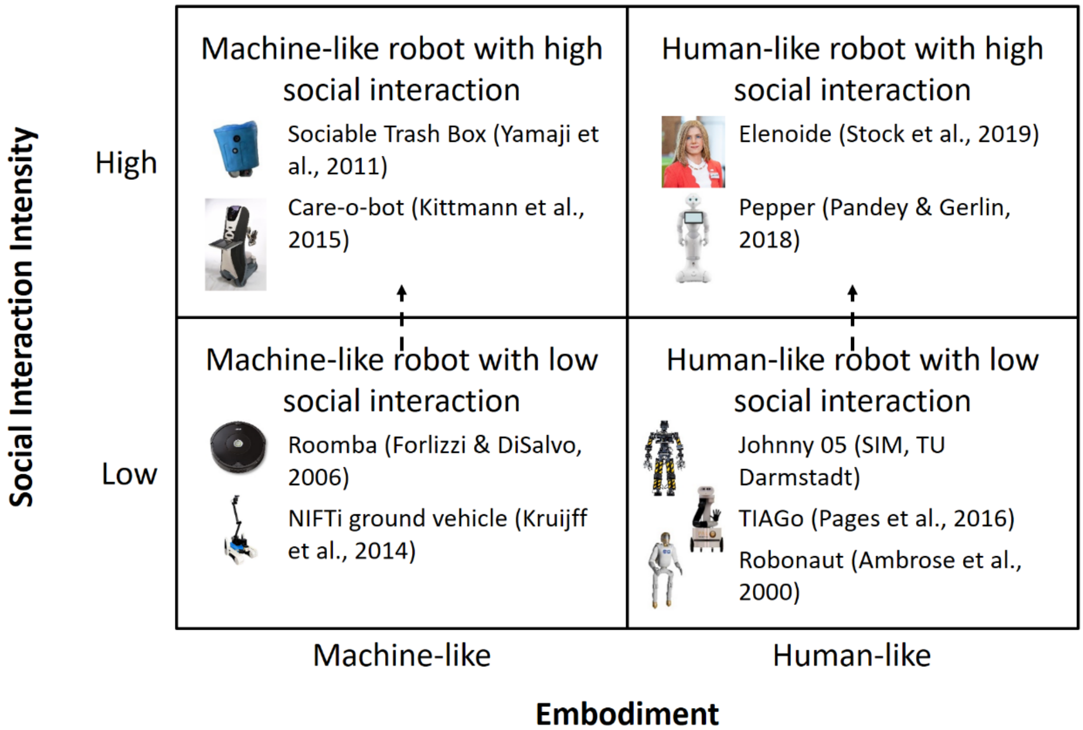


Figure 2-2. Robot Typology with Selected Examples from Literature

Note: Due to anthropomorphism, robots can be attributed more prominent human (social) characteristics than they originally were designed to include (see arrows).
Picture sources: Sociable Trash Box, Pepper, Johnny, TIAGo, Robonaut: all from ABOT database (http://abotdatabase.info//); Care-o-bot: Fraunhofer IPA (https://www.care-o-bot.de/de/care-o-bot-3/download/images.html); Roomba: iRobot (https://shop.irobot.de/roomba-staubsstaubsaugerroboter-roomba-606/R606040.html); NIFTi ground vehicle: Kruijff et al., 2014; Elenoide: leap in time GmbH Darmstadt

2.2.2.2 Technology Integration into Teams

Our literature review reveals various studies of technology in teams, published in journals such as *Journal of Strategic Information Systems*, *Journal of Management Information Systems*, and *Group & Organization Management*. In these studies, researchers investigate different levels of technology integration, from technology-intense (Thamhain, 2009) over technology-supported (Alnuaimi et al., 2010) to virtual (Townsend et al., 1998) teams, as we illustrate in Figure 2-3.

Technology-intense teams work in a technological environment, with technological products, as exemplified by teams that develop information systems (Thamhain, 2009). In investigating such teams, researchers address their compensation strategies and the influences on performance (Tremblay & Chênevert, 2008), determinants of project team success (Jetu & Riedl, 2012), and leadership issues (Thamhain, 2009).

In *technology-supported teams*, some parts of processes are supported by information and communication technologies that are used "for storing, transmitting, and processing digital data" (Shen et al., 2015, p. 492). For example, during Merck's regular "Internal Open Campaign," all employees are encouraged to submit their innovative ideas to a central online platform, form teams, and refine their ideas in support of rapid innovation (Merck KGaA, 2018). Information and communication technologies provide important support for team operations (Alnuaimi et al., 2010; Maruping & Agarwal, 2004), social processes (Maruping & Agarwal, 2004), and performance (McLeod, 1992). Motivation (Maruping & Magni, 2015) and leadership (D. M. Thomas & Bostrom, 2010) strategies to enable technology adaption or improve team performance (Kahai et al., 2004) also have been examined in this research area.

Virtual teams comprise "groups of geographically and/or organizationally dispersed coworkers" (Townsend et al., 1998, p. 18) that collaborate and accomplish work tasks by relying on information and communication technology. Researchers consider team performance (Maynard & Gilson, 2014) and leadership (B. S. Bell & Kozlowski, 2002; Eseryel et al., 2020), as well as social aspects such as familiarity (Maynard et al., 2019), trust (Jarvenpaa et al., 1998; Peters & Karren, 2009), and individual expectations (Bosch-Sijtsema, 2007). Due to globalization, virtual teams have been adopted by more and more organizations (Maynard et al., 2019).

A few management researchers also have gone a step further to examine *HRTs* (e.g., Gombolay, Gutierrez, et al., 2015; Gombolay, Huang, & Shah, 2015; Samani & Cheok, 2011), in which technology is more than a tool (Gervits et al., 2020). With artificial intelligence, robots can function as team members, in various roles, ranging from assistants or colleagues to team leaders (Ma et al., 2018). Finally, *remote HRTs* are geographically separated, with notable existing applications in USAR (Kruijff, Kruijff-Korbayová, et al., 2014) and space exploration (Fong et al., 2005) contexts. We know of no managerial research in this area.

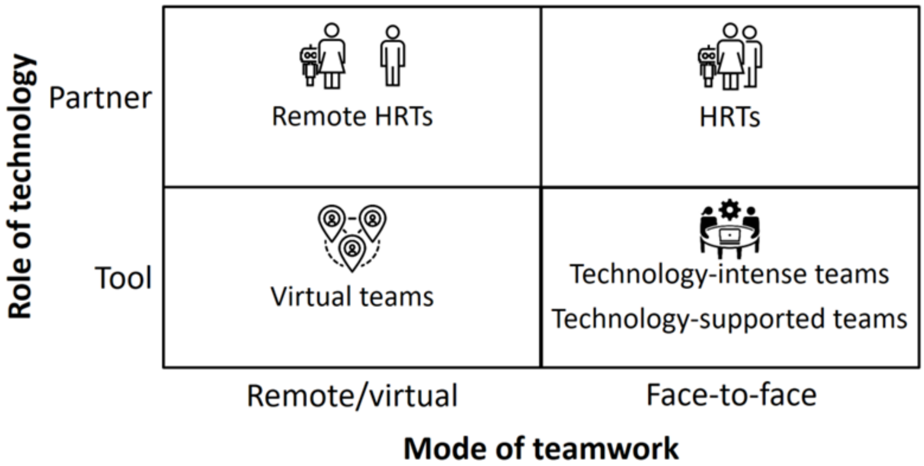


Figure 2-3. Different Modes of Technology Integration into Teams
Note: Sources for icons: top icons: own visualization; lower left icon: remote working by tulpahn; lower right icon: teamwork by Gerald Wildmoser, both from thenounproject.com

2.2.2.3 Human-Robot Teams

Although HRTs have been studies extensively—e.g., as “robot[s] as team member[s]” (HRI’07, 2007) and “robots in groups and teams” (Jung et al., 2017)—, there is no universal definition that reflects and is accepted by the wide range of disciplines that feature research on related topics (Figure 2-4). Therefore, our first reseach question attempts to provide an understanding of what is meant when referring to this concept in order to avoid meaning different things under the same name (see, e.g., Kelley, 1927; Marsh et al., 2019).

In particular, there is ongoing debate about whether the minimum required size of an HRT should be two or three members. Dyads with only two members represent very specific constellations and lack the dynamics that are of central interest for HRT research (Abrams & Rosenthal-von der Pütten, 2020). Nevertheless, we found many conceptual and empirical studies that claim to investigate HRTs by studying dyadic teams. Another dimension in which researchers differ is whether they focus on pure task interactions or on both task and social interactions within the team. Among the 121 reviewed studies that focus on multiple-member HRTs, we derive several elements related to the composition of HRTs; Table 2-1 (see appendix)[6] classifies the extant research on HRTs according to the team type and composition it considers, along with the definitions it offers. As it shows, many researchers investigate human-directed

[6] For better readability, the tables of this chapter are included in the appendix of the dissertation.

robot teams (especially for USAR tasks) or autonomous mixed teams without clearly assigned leadership. Relatively few empirical studies address human- or robot-directed mixed HRTs, and we find no studies of robot-directed human teams.

Four constellations of HRTs can be derived from these dimensions (Figure 2-4): (1) HRTs as *multiple-member collaborative teams*. That is, a *mixed human–robot team (HRT)* consists of at least three members (humans and robots) who perform common tasks interdependently and interact socially to achieve common goals. (2) *Multiple-member task teams* have more than two members who focus primarily on task interaction. These teams are found in space and USAR contexts, where robots work in teams with humans to increase efficiency and safety (Bluethmann et al., 2003). (3) *Dyadic collaborative teams* are human–robot dyads that interact interdependently, both socially and on a task level to achieve their common goals (Breazeal, Hoffman, & Lockerd, 2004). (4) *Dyadic task teams* engage only in task interaction to achieve their goals, e.g., in manufacturing a car (C. Liu & Tomizuka, 2014).

Two perspectives on HRTs can be distinguished: a broad and a narrow perspective. From a *broar perspective*, HRTs fall into three categories: multiple-member task teams, dyadic collaborative teams, and dyadic task teams. These broader perspectives, however, go beyond our narrow understanding of HRTs, but rather aim to capture the different perspectives in existing robotics research (in this review we do not consider the dyadic task teams in depth, instead see supplementary material B). From a *narrow perspective*, combining the insights gleaned from all-human team definitions (e.g., R. Stock, 2004) and robotics research, we define HRTs as multiple-member collaborative teams[7].

[7] Using our proposed definition, we can distinguish HRTs from related concepts, such as human–robot interaction (HRI) or human–robot collaboration (HRC). In particular, HRI is "the study of the humans, robots, and the ways they influence each other" Fong et al. (2001, p. 257), and HRC implies humans and robots "working jointly with others or together especially in an intellectual endeavor" S. A. Green et al. (2008, p. 1). Similar to HRTs, the involved parties (robots and humans) interact, such as by expressing or responding to emotions Kreijns et al. (2003). Yet HRC and HRTs are narrower than HRI, in that they pursue the achievement of joint goals (Bradshaw et al. (2009); Marge et al. (2009); You and Robert (2018c)). Uniquely in HRTs, team members work both interdependently and together (Bradshaw et al. (2009); Ma et al. (2018)).

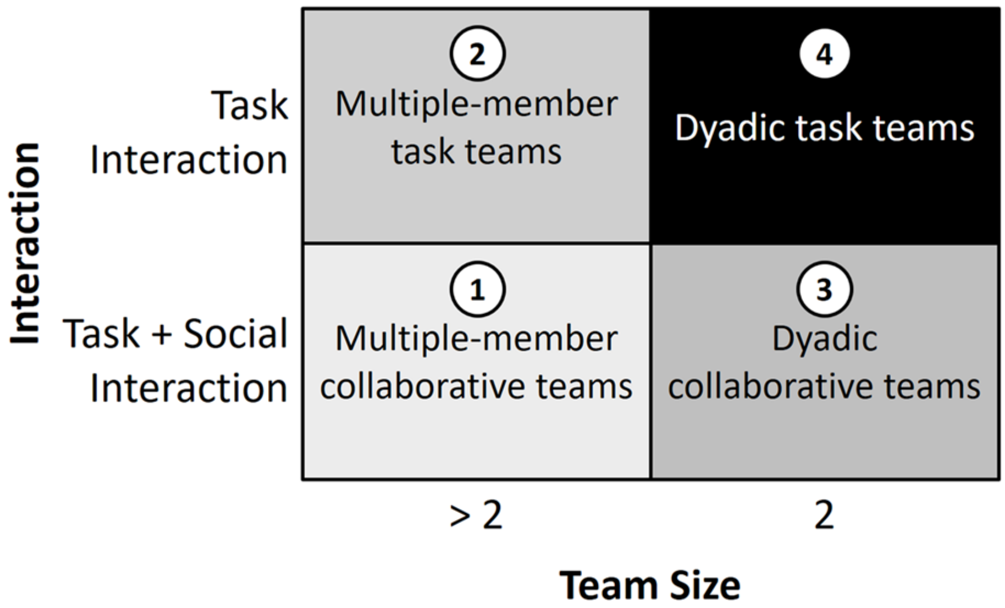


Figure 2-4. Overview of HRT-Definitions

Note: Definitions of HRTs include a narrow perspective of HRTs as multiple-member collaborative teams (1), and a broader perspective of HRTs as multiple-member task teams (2), dyadic collaborative teams (3), or dyadic task teams (4). The team types (1)-(3) are discussed in detail in this manuscript. Details on the dyadic task teams (4) can be found in supplementary material B.

2.2.3 Proposed Framework

In this overview, we rely on an input-process-output (IPO) model (Gladstein, 1984; You & Robert, 2018c; see Figure 2-5). Categories 1 and 2 focus on two important *input factors*: intra-member team characteristics, such as the (physical) robot design, robot behavior, or human preferences and behavior (Category 1), and inter-member team characteristics, including team composition, autonomy, and leadership (Category 2). Category 3 includes studies of *team processes* (Barrick et al., 1998; Gladstein, 1984) such as (physical) coordination, communication, collaboration, and trust. Studies in these categories affect *team outputs* (Barrick et al., 1998) as “psychological and business-related outcomes produced by teams” (R. Stock, 2004, p. 277). Studies in Category 4 examine moderating effects on input, process, and output. Finally, some studies depict causal chains (R. Stock, 2004) from the inputs through mediators to outputs (Category 5). The coding scheme used to classify studies is explained in detail in supplementary material A.

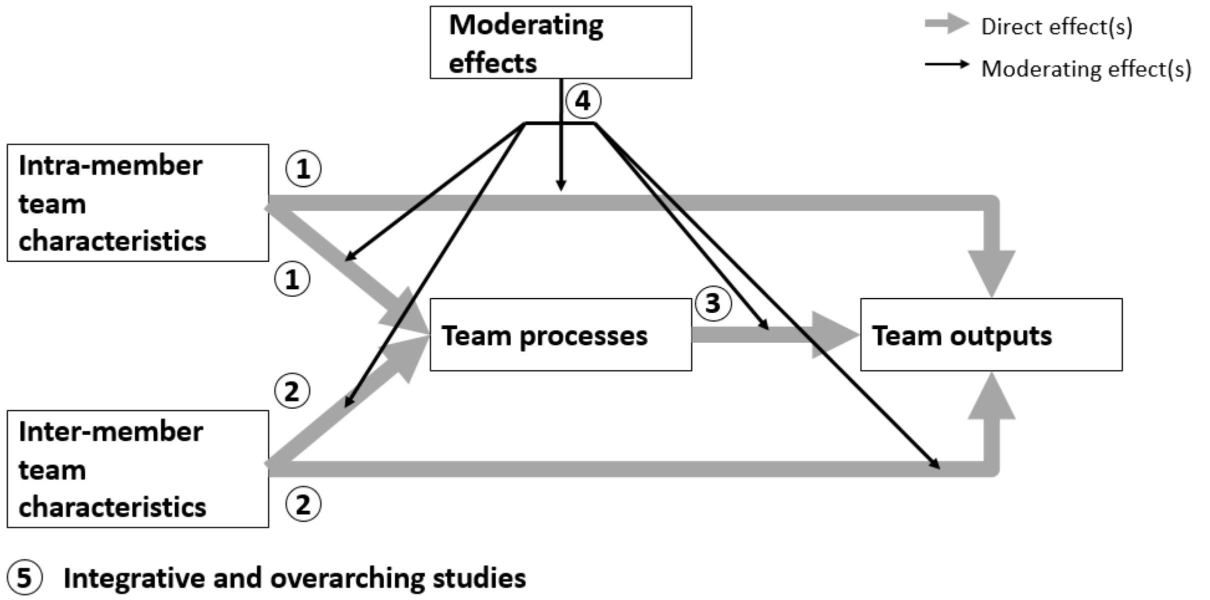


Figure 2-5. Proposed Framework (Adapted from Stock, 2004)

2.3 Conceptual and Empirical Findings Related to Human-Robot Teams

2.3.1 Category 1: Effects of Intra-Member Team Characteristics

2.3.1.1 Focus Areas and Key Findings

Table 2-2, Panels a-c (see appendix), summarizes the studies in this category in terms of the robot characteristics studied, the definition of HRT, samples, and key findings. Research on *(physical) robot design* for both dyadic HRTs and multiple-member HRTs tends to focus on robot hardware (e.g., degrees of freedom of components; Bluethmann et al., 2003), robot vitals for performance prediction (Ramesh et al., 2021), physical appearance in terms of anthropomorphism or robot size (Bartneck et al., 2006), or the use of gestures and facial expressions (Minato et al., 2004). The physical design of the robot is the explicit focus of conceptual and empirical studies of Robonaut, which was designed by NASA for use in space exploration HRTs (e.g., Bluethmann et al., 2003; Fong et al., 2005). These studies address the physical design features needed to perform its intended tasks (e.g., hands) and the requirements for controlling Robonaut in harsh conditions (Bluethmann et al., 2003).

The second dimension, *robot behavior*, appears in both conceptual and empirical research on dyadic and multiple-member HRTs. Conceptual studies tend to focus on "inefficient" robots that are not designed to increase the efficiency of a HRT, but rather to exhibit social behavior to facilitate their integration into teams and society at large (Kelly & Watts, 2017). Empirical studies of multiple-member HRTs relate to prosocial and positive behavior (Correia, Mascarenhas, et al., 2019; Rhim et al., 2019), fair resource allocation (Claure et al., 2020), social robot–robot and robot–human behavior (Fraune, Oisted, et al., 2020), vulnerable robot utterances (Traeger et al., 2020), and vulnerable robot behavior (Strohkorb Sebo et al., 2018). All of these features signal a robot's apparent personality, consistent with the Computers are Social Actors (CASA) paradigm and its prediction that humans treat robots as social entities (Nass et al., 1994). Such behaviors have positive effects on robot or team perceptions or processes. Specifically, prosocial robotic behaviors improve users' perceptions of and behaviors toward robots, lead to better social attribute ratings (Correia, Mascarenhas, et al., 2019), and result in increased human engagement (Strohkorb Sebo et al., 2018). Empirical studies of dyadic HRTs examining specific prosocial robot behaviors, such as explanations (Ezenyilimba et al., 2023; Hiatt et al., 2011; N. Wang et al., 2016a, 2016b; N. Wang et al., 2018) or, among others, apologies for errors (Natarajan & Gombolay, 2020), show positive effects of such behaviors on trust and team performance. Finally, robot touch appears to lead to better evaluations of a robot's social performance, skills, and fairness (Arnold & Scheutz, 2018). However, perceptions of robot touch need to be considered in the context of the interaction; for example, gender effects may emerge and have important influences.

The dimension of *human preferences and behaviors* has not been extensively studied in the context of HRT, possibly because is more often addressed in the context of HRI or HRC. We find one recent study of blame and credit attributions, using a multiple–member HRT (Lei & Rau, 2020), which shows that human team members "attributed more credit and less blame to the robot member than to themselves" (p.1). Experience and workplace culture were also found to have an effect on team behavior (Cunningham et al., 2013). Another study looks at membership preferences in HRTs (Correia, Petisca, et al., 2019) and shows that people who are more competitive prefer a performance-driven robot over a learning-driven one.

Finally, 4 studies of multiple–member or dyadic HRTs investigated the interplay among the three subcategories (Gombolay et al., 2017; Gombolay, Huang, & Shah, 2015; Law et al., 2021; Richert et al., 2016): Thus, different dimensions of intra-member team characteristics appear to be intertwined and important for understanding the role of robots in team contexts.

2.3.1.2 Disciplines, Study Characteristics, and Underlying Theories

We assign 27 studies to this category (18 of multiple–member HRTs, 9 of dyadic HRTs); most of them are based on cognitive science (8 studies), robotics (4), or space (3) foundations. Very little research in HRI or management includes teams with at least three team members; however, 4 studies from HRI and 1 reflecting a management-related perspective take dyadic perspectives. Only 1 study shows a longitudinal approach with three sessions in direct succession (Correia, Petisca, et al., 2019). 21 of the 22 empirical studies are conducted online or in laboratory settings, one study is a case study in a real hospital setting. They feature humanoid and functional robots. Several studies do not report the type of robot used. Studies of multiple–member HRTs mostly focus on collaborative teams. Teams include autonomous mixed teams (7 studies), a human-directed robot team (1), human/robot-directed mixed teams (4), as well as one robot-directed human team. Studies of dyadic collaborative HRTs also consider autonomous human–robot pairings (4), human-directed robots (3), or do not report the team setup. About one-third of the studies indicate their theoretical underpinnings. They draw on theories, such as fairness theory and equity models (Adams, 1963, 1966), the theory of mind (Hiatt & Trafton, 2010), emotional intelligence (Salovey & Mayer, 1990), social role theory (Hentschel et al., 2019), and situational awareness (Endsley, 1995). Further, some researchers base their work on the CASA paradigm (Nass et al., 1994).

2.3.1.3 Limitations

Most of the studies are based on student samples, with cross-sectional laboratory designs, which limits the generalizability of their findings (Levitt & List, 2005). None of the studies in this category feature real-world settings. They also ignore dynamic developments in teams over time (S. T. Bell & Marentette, 2011) and instead take static perspectives, suggesting the need for longitudinal studies. Furthermore, only one of these studies examines a robot-directed human/mixed team (see Table 2-1). Finally, some studies provide a sound theoretical basis for their research, but it is important to extend these efforts and perhaps apply other behavioral theories, such as social identity theory (Tajfel, 1974).

2.3.2 Category 2: Effects of Inter-Member Team Characteristics

2.3.2.1 Focus Areas and Key Findings

Table 2-3, Panels a-d (see appendix), provides an overview of the studies in this category. Conceptual studies of the *roles of humans and robots in HRTs* include discussions of the suitability of teams, robot integration, and task allocation, suggesting that robots should not replace humans but rather be treated as complements with individual strengths (Fusaro et al., 2021; Groom & Nass, 2007; Hari et al., 2020; Makarius et al., 2020). Conceptual research on dyadic HRTs discusses parallels between all-human teams and HRTs and the importance of shared mental models (M. Demir et al., 2020). Empirical research on multiple–member HRTs examines the ideal ratio of humans to robots (Burke & Murphy, 2004), how to include humans in HRTs (Strohkorb Sebo et al., 2020), the impact of the presence of robots on human decision making (Fuse & Tokumaru, 2020), the impact of robot reliability and positioning (Charisi et al., 2021), and the optimal organizational structure (Ranzato & Vertesi, 2017). Findings from these studies suggest, inter alia, that loosely coupled teams are the most successful (Ranzato & Vertesi, 2017) and that specialized interaction roles may hinder the inclusion of human team members in HRTs (Strohkorb Sebo et al., 2020). For dyadic HRTs, empirical studies examine robot-led versus human-led teams and find that the latter are preferred (Abendschein et al., 2021) and that intergroup bias also exists for such teams (Jong et al., 2021).

Investigations of *autonomy and control* in both dyadic and multiple–member HRTs take either a general view on the effects on teamwork (Bradshaw et al., 2012) or a more specific focus on adjustable autonomy (Sierhuis et al., 2003), in both conceptual and empirical efforts (e.g., Dias et al., 2008; Gombolay, Gutierrez, et al., 2015; Goodrich et al., 2007; Sellner et al., 2006). Results suggest that somewhat autonomous robots and shared control can facilitate the work of human team members and make HRTs more efficient (e.g., P.-J. Lee et al., 2010; Lewis et al., 2010; Sellner et al., 2006). Researchers have also proposed an algorithm for predicting team performance, based on the robot's performance in interaction with human team members or when it is autonomous (Crandall et al., 2003), as well as various control approaches for human-directed robot teams (Musić & Hirche, 2018; Musić et al., 2019), a control framework for USAR (Yazdani et al., 2016), an "HRT planning-execution framework" (Manikonda et al., 2007, p. 92), and a simulation framework taimed at supporting the development of command and control architectures (Dudenhoeffer et al., 2001).

Conceptual studies of *leadership* in HRTs cite potential stereotypes of robotic leaders (Gladden, 2014) or explore the emotions evoked by, benefits of, and possible forms of robotic leadership (Samani & Cheok, 2011). These studies present robotic leadership as a future phenomenon, in some cases arguing that it will emerge naturally (Gladden, 2014). Empirical studies also introduce a scalable, generalizable mathematical framework for modeling leader and follower behavior in multiple–member HRTs and show that this framework enables robots to influence human teams (Kwon et al., 2019; Li et al., 2021). They further explore robots in supervisory roles, highlighting their potential positive effects (Lopes et al., 2021) and areas, such as feedback, that require careful consideration (Yam et al., 2022).

Finally, *team perceptions* can take the form of shared mental models, which have been predicted (e.g., Nikolaidis & Shah, 2012) and examined for their influence on team performance (Gervits et al., 2020), which appears to be positive. In addition, a conceptual framework of in-group identification, cohesion, and entativity draws parallels to the dynamics of all-human teams (Abrams & Rosenthal-von der Pütten, 2020), and researchers have discussed the potential of a human-robot psychological contract (Bankins & Formosa, 2020). Several studies examine robots as in-group members of multiple–member or dyadic HRTs and find positive effects on robot acceptance and anthropomorphization (e.g., Eyssel & Kuchenbrandt, 2012; Fraune, 2020; Fraune et al., 2017; Fraune, Šabanović, & Smith, 2020). Conversely, some studies suggest that the introduction of robots into teams may also have negative effects on in-group identification (Savela, Kaakinen, et al., 2021; Savela, Oksanen, et al., 2021). Researchers have also investigated perceptions of fairness and its antecedents in HRTs, finding a number of influencing aspects (Chang et al., 2020; Chang et al., 2021). Another related topic concerns the parallels between HRTs and human–animal teams, such as USAR teams that include rescue dogs (e.g., E. Phillips et al., 2016). Arguably, human–animal teams could provide models for the development of HRTs.

2.3.2.2 Disciplines, Study Characteristics, and Underlying Theories

Most of the 50 studies (42 of multiple–member HRTs, 8 of dyadic HRTs) in this category are rooted in cognitive science (13 studies) and HRI (12), along withUSAR (8), , management (6), military (5), robotics (5), and space (1) research fields. Although some studies reflect a management perspective and many studies have a cognitive science or an HRI foundation, we note the considerable number of studies with an USAR or military background. The 30 empirical studies are all cross-sectional, online or laboratory experiments, though one field study pertains to USAR (Burke & Murphy, 2004). The team setups are mostly autonomous mixed teams (12 studies) or human-directed robot teams (9); two studies consider a human/robot-directed mixed team with a human and robotic co-lead and a human assistant (Gombolay, Gutierrez, et al., 2015) and a robot-directed human team (Yam et al., 2022)..

In terms of theoretical foundations, several researchers use in-group identification theories (e.g., social identity theory (Tajfel, 1974)). Quite a few studies use the theory of (shared) mental models (Rouse & Morris, 1986) and further consider situational awareness (Endsley, 1995). Finally, some researchers draw on sliding autonomy methodology (Sellner et al., 2006) for HRTs.

2.3.2.3 Limitations

Some empirical studies have relied on small sample sizes of fewer than 30 participants (e.g., Gombolay, Gutierrez, et al., 2015; Ranzato & Vertesi, 2017), and many feature quite young participants. The limitations of laboratory and cross-sectional studiesdescribed for Category 1 also apply to the studies in Category 2. We find slightly more variability in the team setups considered, but further research could expand the considered constellations. Most studies in this category, however, already make use of theoretical foundations.

2.3.3 Category 3: Effects of Team Processes

2.3.3.1 Focus Areas and Key Findings

Studies of team processes and their effects account for most of the extant research on HRTs (see Table 2-4, Panels a-d; see appendix), perhaps because unlike HRI or HRC, HRTs tend to be long-term in nature, requiring careful consideration of relevant processes that are at least partially unique to each team (Abrams & Rosenthal-von der Pütten, 2020). In addition, HRTs have long been popular, especially in military and USAR settings that require sophisticated coordination to accomplish their missions.

Researchers have identified several prerequisites for successful *(physical) coordination in HRTs* (Woods et al., 2004). In studying HRTs, researchers draw heavily on the concepts of coordination behavior in all-human dyads that seem promising (e.g., Bradshaw et al., 2009; T. Iqbal & Riek, 2017; Shah & Breazeal, 2010) or focus on indirect perceptions. Empirical studies on training (e.g., Nikolaidis et al., 2015; You & Robert, 2016), coordination strategies and frameworks (Aggravi et al., 2021; Aggravi et al., 2022; T. Iqbal et al., 2016; R. Liu et al., 2021; Shah et al., 2011; H. Wang et al., 2010), and automated cooperation (Gao et al., 2012; J. Wang et al., 2008) all find positive effects, such as on team fluency, perceived robot trustworthiness or team performance in HRTs.

Research on *communication in HRTs* for multiple–member HRTs identifies information flows supported by sensor networks (Kantor et al., 2006), the use of “Human-Robot Interaction Operating Systems” (Fong et al., 2006), back-channeling (Jung et al., 2013), real versus simulated video (Canning et al., 2014), and conflict moderation by robots (Jung et al., 2015). For dyadic and multiple–member HRTs, verbal versus non-verbal communication (e.g., Breazeal et al., 2005; Ciocirlan et al., 2019; Nikolaidis et al., 2018; Williams et al., 2015), based on partner knowledge and behavior (Lo et al., 2020) have been investigated. These studies mostly show positive effects of (extensive) communication in HRTs (Table 2-4). Another research path includes communication interfaces (Marge et al., 2009), communication models (e.g., Kruijff, Janíček, et al., 2014; Nakano & Goodrich, 2015), metrics for communication of proficiency (Norton et al., 2022), and the design/ implementation of HRTs for conversational HRI (Zheng et al., 2013).

Research on *collaboration in HRTs* refers to linkages explicitly established in an HRT context, which should not be confused with the broader topic of HRC. Conceptual studies range in focus, including the optimal composition of "hybrid teams" with robots, virtual agents, and humans as team members (Schwartz et al., 2016), collaboration challenges (Fiore et al., 2011), collaborative tools (Bruemmer & Walton, 2003), the development of collaborative robot teammates (Hayes & Scassellati, 2014), dynamic peer-to-peer teaming (Tang & Parker, 2006), task-oriented collaboration with semantic-based path planning (Yi & Goodrich, 2014), decision making (Stewart et al., 2012), and mutual initiatives (Bruemmer et al., 2002). Researchers also examined collaboration frameworks (e.g., Gervasi et al., 2020; Hoffman & Breazeal, 2004; Marble et al., 2003) for dyadic HRTs and a joint action perception framework (T. Iqbal et al., 2015) for multiple-member HRTs. Finally, for *trust*, four studies of dyadic HRTs discuss and examine the effects of appropriate trust (i.e., beneficial to team performance) (Ali et al., 2022; M. Chen et al., 2020; Ososky et al., 2013) and its measurement (Freedy et al., 2007).

2.3.3.2 Disciplines, Study Characteristics, and Underlying Theories

More than one-third of the 61 studies in this category (40 studies of multiple–member HRTs, 20 of dyadic HRTs) are rooted in HRI (18 studies), USAR (13), or cognitive science (12), followed by robotics (10), military (7), and space (1) research. Most of the 35 empirical studies are cross-sectional or do not specify the time frame for their experiments. However, the longitudinal study by Burke and Murphy's (2007) includes two runs over a two-day period. We find simulation studies (H. Wang et al., 2010), laboratory studies (You & Robert, 2016), and field experiments (Burke & Murphy, 2007). Studies of multiple–member HRTs mostly focus on task interactions, and the setups include human-directed robot teams (17) or autonomous mixed teams (9 studies) or else do not specify. For dyadic HRTs, researchers examine autonomous human-robot pairings (12), human-directed robots (4), or do not specify their setups (4).

In this category, almost half of the studies report theoretical considerations. These range from coordination theory (Malone & Crowston, 1990), to role theory (Braga, 1972), to social signaling and back-channeling (Dennis & Kinney, 1998). Again, several studies rely on shared mental models (Rouse & Morris, 1986). Another popular theory is situational awareness, which is the basis for various studies as detailed in Table 2-4, Panels a-d.

2.3.3.3 Limitations

Study samples tend to be small and young; many studies use laboratory settings to conduct cross-sectional experiments. Social robots are underrepresented, compared to functional robots, although they are specifically designed to interact with humans (Kirby et al., 2010), suggesting their particular suitability for HRTs. In terms of theoretical underpinnings, we see potential for studies to strengthen the theoretical soundness of the phenomena under investigation by integrating behavioral theories.

2.3.4 Category 4: Moderating Effects

2.3.4.1 Focus Areas and Key Findings

Moderator variables influence the strength of the relationships between independent and dependent variables (Baron & Kenny, 1986). These effects are often due to environmental or situational factors (Baron & Kenny, 1986), leading researchers to examine moderating effects for multiple-member HRTs that reflect human capabilities (Claure et al., 2020), robot appearance (Fraune, 2020), team composition (Fraune, Šabanović, & Smith, 2020), curiosity and control (You & Robert, 2016), task complexity (Jung et al., 2013), or number of sessions (Correia, Petisca, et al., 2019). For dyadic HRTs, researchers also examine the effects of number of sessions (Marble et al., 2004) and experience with the remote system (Marble et al., 2003). Most of these proposed moderators appear to exert positive effects on the relationships between the studied independent and dependent variables, as shown in Table 2-5, Panels a-b (see appendix). For example, curiosity positively moderates the effect between training and individual performance (You & Robert, 2016), task complexity positively influences the relationship between backchanneling and team functioning (Jung et al., 2013), and target detection increases with the number of sessions (Marble et al., 2004). For more details on these studies, see the descriptions in their respective main categories.

2.3.4.2 Disciplines, Study Characteristics, and Underlying Theories

The 9 studies (6 of multiple-member HRTs, 3 of dyadic HRTs) in this category come from cognitive science (4 studies), USAR (3), robotics (1), and management (1) research. Researchers use both functional and humanoid robots to conduct cross-sectional (4 studies) online or laboratory experiments. Two studies have longitudinal designs, with 3 or 4 sessions, respectively, but another study does not disclose its study setup. The teams represented by collaborative multiple-member HRTs are autonomous mixed teams (5 studies) or a human-led robot team (1 study). The dyadic HRTs involve human-directed robots engaged in both task and social interaction (2 studies). Five studies (Claure et al., 2020; Fraune, 2020; Fraune, Šabanović, & Smith, 2020; Jung et al., 2013; Marble et al., 2004) adopt theoretical foundations for their investigations, as described in the respective main categories.

2.3.4.3 Limitations

Relatively few studies in our sample consider moderating effects, and only two of them are longitudinal. It is unlikely that "one-size-fits-all" applies to HRTs (R. Stock, 2004), so moderators should be further investigated, especially in long-term studies of teams that include both humans and robots.

2.3.5 Category 5: Integrative and Overarching Studies

2.3.5.1 Focus Areas and Key Findings

In this final category, we include studies that propose overarching frameworks, metrics, and HRT designs; publications that address ethics in HRTs; and investigations of the inputs, processes, and outputs of HRTs, with an integrative perspective (Table 2-6, Panels a-c; see appendix). The *overarching frameworks, metrics, and HRT design* studies include proposals for new metrics and taxonomies that go beyond existing ones focused on HRI or HRC (Burke et al., 2008; Ma et al., 2022; Pina et al., 2008). They include components for assessing team performance (Pina et al., 2008; Visser et al., 2006). Ma et al. (2018) also consider general design concepts and Le et al. (2023) propose a framework for human-robot interdependence. As an emerging topic, *ethics in HRTs* appears in conceptual investigations of both dyadic and team interactions (Arnold & Scheutz, 2017; Smids et al., 2020; Tamburrini, 2009). Finally, *integrative studies* of mediated relationships in HRTs are relatively recent (e.g., Seeber et al., 2020; You & Robert, 2018c, 2019a; You & Robert, 2022a, 2022b; Table 2-6, Panels a-c). Two studies deserve special attention: Oleson et al. (2011) identify some antecedents of trust in HRTs (e.g., human, robot, and environmental characteristics). Then, with an input–mediator–output–input (IMOI) approach, an extension of the established IPO framework for teams, You and Robert (2018c) offer a dynamic perspective on HRTs that could inform studies of long-term HRTs.

2.3.5.2 Disciplines, Study Characteristics, and Underlying Theories

The 22 studies in this category (20 of multiple-member HRTs, 2 of dyadic HRTs) are rooted in cognitive science (9 studies), HRI (7), management (3), ethics (2), and military (1) research. All 12 empirical studies are cross-sectional, but they include both laboratory and field experiments. Teams are complex, however, so the comparatively small number of studies that take an integrative perspective is surprising. These studies include both functional and humanoid robots, such as those adapted from Lego® Mindstorms® sets (You & Robert, 2018c, 2019a, 2019b), but not any social robots. Multiple-member HRTs all reflect human-directed robot teams that are, in most cases, collaborative. Studies of dyadic HRTs also mostly consider dyadic collaborative teams and include human-directed robots or an autonomous human–robot pairing.

Approximately half of the studies in this category specify their theoretical underpinnings, building on, for example, motivational theories of individual and team motivation (Kanfer et al., 2008). Other theories include media synchronicity (Dennis et al., 2008); the technology acceptance model (Davis, 1986) and the unified model of technology acceptance and use of technology (Venkatesh et al., 2003); social identity theory; the IPO model; notions of trust related to teamwork (Zaheer et al., 1998), technology (McKnight et al., 2011), and robots (Yagoda & Gillan, 2012); and social categorization and attraction theories (Hogg & Turner, 1985).

2.3.5.3 Limitations

We note several limitations pertaining to integrative, overarching studies of HRTs, beginning with the lack of consideration of social robots, which are particularly relevant to HRTs and integrative investigations of them. Another important consideration is the time frame; many team processes evolve over time and should be studied with a dynamic approach to gain more insights. Finally, HRT designs other than human-directed robot teams need to be studied from an integrative perspective.

2.4 Discussion

2.4.1 Summary of Findings of Existing Research

Despite widely varying definitions of HRTs and different research foci, researchers from a variety of disciplines are all seeking insights into their aspects and related processes. In Figure 2-6 we summarize the major categories and subcategories related to the IPO model of teams. Because so few studies examine moderating effects, we cannot identify additional subcategories. In addition, we find that the existing research has a dominant focus on HRT inputs and processes, so we do not further elaborate on the subcategories of team outputs.

Intra-member team characteristics are considered less frequently than other topics and primarily in the context of team setups and processes, likely due to their interdependencies with HRI and HRC. Nevertheless, research on robot behavior is rooted in the HRT context and shows that positive robot behavior and transparency have positive effects on team processes and outcomes. Studies that examine both the physical and behavioral characteristics of robots also provide important hints for research directions, particularly in terms of holistic robot design. Human preferences and behaviors are also interesting topics to include in efforts to fully understand HRTs.

Inter-member team characteristics have been studied more extensively, with autonomy, control, and leadership included in many studies. Vastly different definitions of HRTs, across a variety of team setups (e.g., leadership), confirm the logic of this central focus. However, we also note that all empirical studies on (sliding) autonomy and control in HRTs indicate that (partially) autonomous robots and shared control can facilitate the work of human team members and make HRTs more efficient.

Compared to individual team members and team characteristics, *team processes* in HRTs and their effects have been studied very intensively. While physical coordination has been a topic for a long time, mainly with a focus on robotic aspects and the development of coordination concepts, but collaboration in HRTs has only recently attracted the attention of researchers. Interesting parallels are being drawn between HRTs and all-human teams in terms of the benefits of coordination or communication mechanisms. In general, studies indicate that well-choreographed coordination and communication efforts are key success factors for HRTs.

The presence of *moderating effects* in HRTs is coming more into focus, and it remains an important consideration, because moderator variables exert effects on the relationships among team inputs, processes, and outputs. There is no one size that fits all HRTs, so further research should seek insights into relevant moderators and their effects.

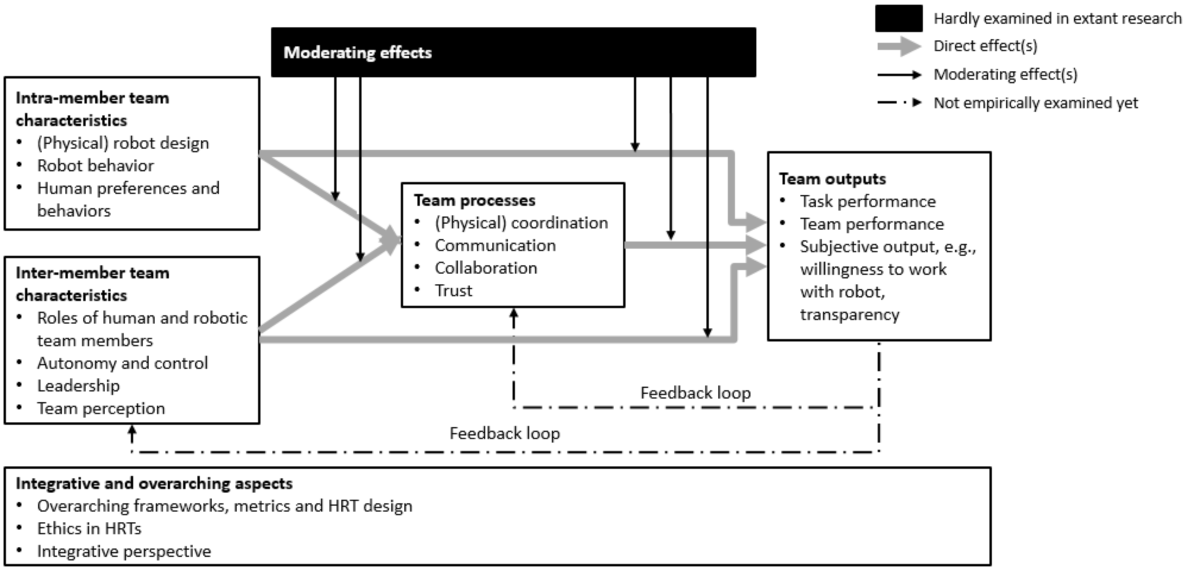


Figure 2-6. Overview of Main Categories and Subcategories Examined in the IPO Model of Teams

Finally, *integrative and overarching studies* are lacking, despite their importance for gaining a holistic, in-depth understanding of the mechanisms at work in HRTs. In this regard, it should be noted that HRTs are complex systems that require intensive research, and the use of insights from all-human team research could help to clarify them, especially in real-world settings. For example, You and Robert (2018c) discuss a loop in the IPO model that may be conceptually plausible for HRTs.

2.4.2 Summary of Limitations of Existing Research

Overall, HRTs have received a great deal of research attention, but there is still a long way to go in this area to determine what constitutes successful and sustainable HRTs for society and business. Therefore, along with the key findings, we identify three overarching limitations of existing research on HRTs. First, the field of cognitive sciences is emerging, but most of the research still comes from USAR, space exploration, or robotics efforts, mainly involving functional robots. This one-sided view of HRTs needs to be broadened to include managerial and cognitive perspectives too. Second, shared mental models and social identity theory provide good starting points, but the opportunities for applying behavioral theories, as addressed by research on all-human teams, are vast. Third, because it often involves student samples, small samples, laboratory studies, and cross-sectional investigations, existing HRT research leaves some considerable gaps that suggest a research agenda, as we discuss in the next section.

2.4.3 Limitations of this Review

This literature review has a number of limitations. First, there may be relevant publications that were not included in this review despite a thorough literature search and efforts to avoid selection bias. In addition, we focused on English-language publications for inclusion in our review. In this review, we focus on robots as team members, but we openly acknowledge the other forms of human–technology teams, beyond HRTs, such as teams with virtual assistants. These interactions may also be useful for HRTs. To the best of our knowledge, no studies have addressed teams with non-robotic but artificial team members in a business context. Therefore, another review could provide an overview of non-robotic artificial team members (e.g., virtual assistants) and compare the insights with our findings related to research on robotic team members. We also acknowledge the common risk of a publication bias for our study (Jager et al., 2020). Publication bias largely occurs before and during the scientific review process, limiting our ability to fully overcome it (see supplementary material A for information on our efforts to address potential biases).

2.4.4 Future Research Agenda

Beyond these considerations related to our review, we note some unexplored areas, both conceptual and empirical, that highlight the vast opportunities for learning more about the design, theoretical concepts, and practical implications of HRTs. We group those opportunities into two broad categories: *How* and *when* can robots can be team members?

How can robots be team members? It would greatly advance the field if research could *explain the mechanisms underlying interaction in HRTs based on behavioral theories*. Currently, there is no general theory for HRTs, which leads to an unstable theoretical foundation. In addition, most studies do not provide a solid theoretical rationale for their predictions (see, e.g. summary of limitations). An approach already being used by some researchers relies on studies of all-human teams a basis for HRT research, which ensures a more theory-driven effort (Krämer et al., 2012). In addition to social identity theory (Tajfel, 1974), shared mental models, and gender studies, leader–member exchange theory as applied to all-human teams (van Breukelen et al., 2006) might be an appropriate theoretical foundation for research on HRTs with social robots in particular. Another valuable effort might be to seek insights into *how individuals, companies, and society can prepare for HRTs*. Since all studies we found during our review are focusing on existing HRTs (see Tables 2-2 through 2-6), many open questions remain about how to prepare for HRTs. Researchers have a broader responsibility than core HRT topics; in particular, they should address the transition to HRTs and how individuals, companies, and society can engage in it beneficially.

When can robots be team members? To address this broad question, we recommend research that makes two main comparisons and two examinations. First, we urge researchers to compare *different types of HRTs in organizations*. Traditional team research distinguishes between permanent and project-based teams, top management and work teams, and so on (for an overview, see Hollenbeck et al., 2012). Interaction modes, processes, and outcomes are likely to differ across these teams (Hollenbeck et al., 2012; LePine et al., 2008). However, according to our review, different types of HRTs tend to be studied in isolation (see Table 2-1), rather than compared for similarities and differences. Such insights could improve the management of HRTs in organizations and support human team members. Second, research comparisons could address *different application scenarios of HRTs in organizations*. Most HRT research addresses specific application scenarios, such as rescue robots in USAR (Kruijff-Korbayová et al., 2015) or robots working on the International Space Station (Fong et al., 2005). Insights on HRTs in organizations in an office environment are still scarce (see disciplines of studies in different categories). Through an online survey, we learned that acceptance of robots in work-related HRTs has increased, especially during the COVID-19 pandemic. The results suggest four potential roles for robots in teams, differentiated according to their hierarchical level and task focus (Figure 2-7): (1) Robotic *team assistant* to support administrative and coordination work, (2) robotic *knowledge expert* to provide expertise in a specific field, (3) robotic *scrum master* (Scrum Alliance, n.d.) to work with the team and ensuring that the team adheres to agile values and principles, such as through coaching, (4) robotic *team leader/manager* with institutionalized authority over other team members. Third, researchers should study *HRTs in real-life settings*. The studies we reviewed are overwhelmingly conceptual or cross-sectional laboratory studies (see study characteristics in different categories), with limited ability to transfer the findings to real-life settings (Levitt & List, 2005). Particulary given current developments in the global economy and the increasing relevance of robots in everyday contexts, further research should examine HRTs in real-life settings. Fourth, we hope that more studies will examine the *long-term effects of HRTs*. Cross-sectional studies (see study characteristics in different categories) cannot accurately portray longer-term relationships among team members, so further studies should seek to capture all consequences of implementation efforts for HRTs. To this end, appropriate methods for the long-term study of HRTs should be developed.

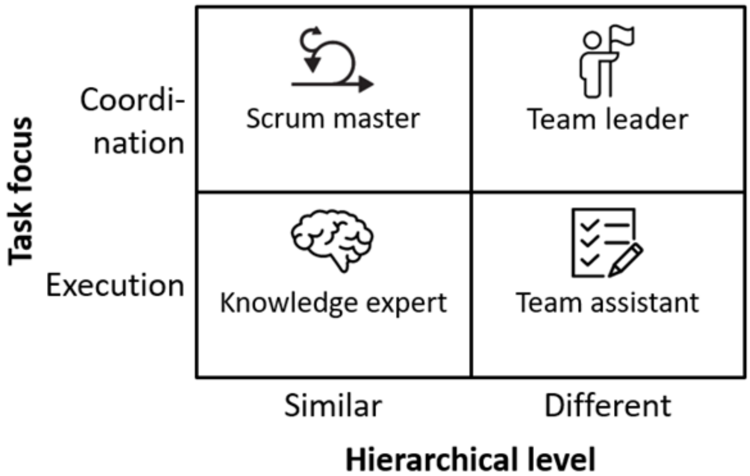


Figure 2-7. Potential Roles of Robots in HRTs

2.5 Conclusion

Human–robot teams are an emerging phenomenon and part of the future of work and society. However, existing research lacks some important insights. With this review, we identify some unexplored areas of research, many of which relate to real-life, long-term considerations of HRT deployment. We offer six suggestions for further research, reflecting the strong relevance of the topic and taking into account current developments in the global economy. We hope that this review provides inspiration for ongoing HRT studies.

3 Empirical Study 1: Decisions for Robotic Team Assistants[8]

3.1 Introduction

Developments in robotics and artificial intelligence (AI)-based technologies are skyrocketing. For example, the launch of ChatGPT, an AI-based program by developer OpenAI that generates text based on prompts, has received much attention worldwide. ChatGPT is likely to be a game-changer for many fields, such as education or science (Thorp, 2023; van Dis et al., 2023). Based on sophisticated technologies, tools like ChatGPT can also support workers in office environments, for example in assistive roles that perform tasks such as sorting and extracting documents, summarizing texts or meetings, and optimizing communication (Chui et al., 2022). But this is not the end of the story: The OpenAI Startup Fund recently invested $23.5 million in the Norwegian robotics company 1X (1X, 2023; Meyer, 2023). Tesla is working on its humanoid Tesla Bot and unveiled a new prototype of its Optimus robot at its Investor Day in March 2023 (Blain, 2023). And Figure, founded with the goal of extending human capabilities through advanced AI, plans to build a “feature-complete electromechanical humanoid” (FigureAI, 2023, Conclusion section) to be integrated into the workforce to help alleviate the severe labor shortages that currently exist (Ferguson, 2023). Consequently, integration of AI into robots can be considered the next step in this evolution.

Robots, as physical representations of AI (Glikson & Woolley, 2020), are characterized by the peculiarity of an automated social presence in that humans feel as if they are interacting with a real social entity while interacting with them (Čaić et al., 2020). This means that in addition to a more task-related competence, they can have a strong relational effect on the humans they interact with (You & Robert, 2018a). In particular, social robots that interact with humans naturally and based on social cues, such as gestures or facial expressions (Breazeal, 2003), seem promising in this regard. In collaboration with humans, these robots form mixed human-robot teams (HRTs) characterized by joint task completion and social interaction to achieve work-related goals (Wolf & Stock-Homburg, 2022).

With developments in AI enabling the performance of office tasks and advances in social robotics, the potential applications of robots in teams of knowledge workers are vast. Social

[8] Based on the conceptual framework published by Heitlinger et al. (2022) (presented at HRI 2022, online), this study incorporates empirical data from a completely revised manuscript currently under review at the *Journal of Service Research*. Compared to the previous conference publication and version of this dissertation, this chapter contains an updated study based on reviewer comments (e.g., regarding sample size) to ensure high quality of research data and results.

robots are particularly suited to the role of team assistants, supporting their (human) colleagues in day-to-day administrative tasks (Horsley, 2021), for the following three reasons: First, in office environments, the strength of robots lies in tasks such as project monitoring, scheduling, and decision support. Given their technical capabilities, robots can outperform and surpass humans (Young & Cormier, 2014). Thus, robots help to stabilize high quality levels and increase work efficiency (Gombolay, Gutierrez, et al., 2015; You & Robert, 2019b). In doing so, they not only improve processes, but can also increase employee satisfaction (Snyder, 2019). By performing repetitive tasks, robotic team assistants help free up the time of their human teammates.

Second, robots have the advantage of physical presence and are thus able to interact directly with the team members in their environment. Research has shown that co-location between robots and their human partners generally enhances the interaction (Bainbridge et al., 2011) and physical presence further increases trust perception (Y. Pan & Steed, 2016). In teams, co-location of members fosters team communication and information sharing, supports the establishment of relationships at work (Lalani & Marshall, 2022), and can increase team effectiveness (Paoli & Ropo, 2015).

Third, the physical embodiment of robots gives scope for the composition of design features that shape human-robot interactions. Personalization 0f (social) cues benefits social interactions (Chevalier et al., 2017) and helps to resemble face-to-face encounters (Tanaka et al., 2014). This enables social robots to transform from automated devices to highly autonomous social partners. This is particularly relevant as the majority of employees work on-site in their organizations—for example, in August-September 2022, more than 70% of private sector organizations in the United States had primarily or exclusively on-site work (Sahadi, 2023). Thus, their unique skill set and physical presence allows social robots to contribute to teams not only on a task-related level, but also on a social-emotional level, making them appropriate and regular team members. To account for this duality, we draw on the well-established distinction between taskwork and teamwork in team-based processes (Crawford & LePine, 2013; Mathieu et al., 2008).

Currently, little is known about how employees respond to highly-skilled robotic teammates. Previous research has shown that expectations play an important role in the acceptance of social robots (C. Edwards et al., 2016; Horstmann & Krämer, 2020; Lambert et al., 2020). From research on human-human interaction, we know that the fulfillment and overfulfillment of expectations by another party (e.g., leader, service provider) leads to high confidence with this party (R. M. Stock, 2011; R. M. Stock & Özbek-Potthoff, 2014). But robots may be different:

Opinions about AI-based technologies vary widely, with most people tending to be either positive or negative (Schepman & Rodway, 2020). While proponents of robots argue that they will revolutionize our work and greatly relieve human workers, especially in times of skilled labor shortages, opponents of robotic teammates fear that robots will steal people's jobs (Harvard Business Review, 2021; Snyder, 2019; Stylianou et al., 2015). Therefore, considering linear effects of robot characteristics on employee acceptance may fall short, as "the more the better" may not hold here.

Accordingly, this work goes beyond linear effects regarding the interplay between expectations and experiences toward taskwork and teamwork skills of robotic team assistants. In other words, we examine how (dis)confirmation of skill expectations and actual experiences affect robot acceptance. In line with research in information systems (cf. S. A. Brown et al., 2014; Venkatesh & Goyal, 2010) and research on all-human teams (Yang, 2014), we follow the expectation-disconfirmation approach to create a holistic picture of both teamwork and taskwork robot skill evaluations and their effects on robot acceptance. Thus, we establish an expectation-experience-based model for HRTs. In this model, we consider trust as a "cornerstone of sustainable relationships" (Ullman & Malle, 2018, p. 263), especially in work teams (Costa et al., 2018), and the intention to work with the robot following Venkatesh and Goyal . Consequently, we address taskwork and teamwork robotic team assistant skills in research question 1 (RQ1): *How does the interplay between expected and experienced taskwork and teamwork robot skills affect trust and the intention to work with the robot?* Skill evaluations may differ not only for different types of work performed in teams, but also for different types of robots. Varying levels of anthropomorphism and thus human-likeness of social robots can elicit individual responses from interaction partners (Hegel et al., 2008). Establishing when anthropomorphism is going too far is an important factor (Duffy, 2003). Our second research question (RQ2) addresses this issue: *Do employee responses to taskwork and teamwork robot skills vary for different types of robot assistants?*

With our research, we take a closer look at the actual implementation of robots in business environments, more specifically in work teams, and add to research in this area in several ways. First, we take into account recent developments in AI-based technologies that make the integration of such tools in offices a realistic scenario (e.g., Chui et al., 2022). Here, we address the need for a holistic understanding of human-robot collaboration in work contexts (K. A. Demir et al., 2019). Second, we explore the capabilities of taskwork and teamwork to provide insights into these two important components in team settings (cf. Mathieu et al., 2008). Third, by establishing an expectation-experience-based model for HRTs, we also contribute to recent research on a theoretical and methodological level. This approach allows for a more nuanced understanding of the topics studied (see also J. R. Edwards, 2002). Fourth, we also consider different types of human-like robots to assess different effects of anthropomorphism. For practitioners, we provide detailed and structured guidance on how to integrate social robots into HRTs. In particular, we show how employee acceptance evolves for different types of tasks and social robots. This helps organizations determine the potential impact of the interplay of expectations and experiences that shape human-robot collaboration.

3.2 Literature Review

With developments in robotics and AI, HRTs have gained a lot of traction in recent years. There are many papers on HRTs, conceptual (e.g., Abrams & Rosenthal-von der Pütten, 2020; Groom & Nass, 2007) and empirical (e.g., Gombolay, Huang, & Shah, 2015; You & Robert, 2022b) in nature (see, e.g., Sebo et al., 2020; Wolf & Stock-Homburg, 2022). A basic notion of conceptual papers on HRTs is that such teams are gaining importance in different domains, including the workplace, and humans will not be substituted but rather complemented by robots (Groom & Nass, 2007).

In such HRTs, robots can take on different roles ranging from follower to peer to leader (Tsai et al., 2022). Focusing on robots in follower roles (e.g., team assistants) in HRTs, the literature can be structured between two ends of a scale for the type of assistance: *taskwork assistance* on one end and *teamwork assistance* on the other end. Taskwork assistance refers to intellectual or physical support for completion of team-specific tasks, e.g., support for knowledge or service work like task allocation or support for carrying heavy loads (cf. Crawford & LePine, 2013). Teamwork assistance, in contrast, refers to social aspects of assistance, e.g., social-emotional support or integration into the team (cf. Mathieu et al., 2008). Specifically, coordination skills and knowledge are elements of intellectual taskwork assistance. Coordination skills involve the ability to efficiently plan, organize, and manage tasks, processes and resources to achieve specific goals within a team (Marks et al., 2001). These skills are task-centered and focus on the mechanics of task performance. Kowledge associated with taskwork skills refers to the specialized expertise, information and competencies required to successfully perform specific tasks or fucntions relevant to the team's goals (Cannon-Bowers & Salas, 1998; Dunham & Burt, 2014). These skills and knowledge are considered taskwork skills because they are primarily focused on the successful completion of the actual work or tasks for which the team is responsible.

Teamwork assistance, in contrast, includes social skills and team orientation. Social skills encompass a range of interpersonal skills, including effective communication, active listening, conflict resolution, empathy, and relationship building (Klein et al., 2006). These skills facilitate harmonious interactions and communication among team members. Team orientation reflects an individual's commitment to collective goals and willingness to collaborate within a team, prioritizing shared goals over personal interests (Coyle-Shapiro). Social skills and team orientation are categorized as teamwork skills because they are essential for building strong interpersonal relationships within the team and fostering a positive team environment.

Traditionally, research on robotic assistance in HRTs focuses on (physical) *taskwork assistance* outside an office environment, especially in production or urban search and rescue (Wolf & Stock-Homburg, 2022). In such contexts robotic assistants support physical delivery (You & Robert, 2018a; You & Robert, 2022a, 2022b), production tasks ("place-and-drill task", Nikolaidis & Shah, 2013), or help to find and retrieve victims (Burke & Murphy, 2004). In these constellations, team identification was found to lead to higher emotional attachment and better team performance (You & Robert, 2018a; You & Robert, 2022b). Human-robot cross training also was found to improve team performance (Nikolaidis & Shah, 2013). One study by Gombolay et al. (2017) found that increased robotic autonomy led to decreased situational awareness of human team members and that the consideration of human preferences led to a higher preference to work with the robotic assistant (Gombolay et al., 2017). Finally, one study by Abendschein and colleagues studied robotic teaching assistants in mixed human-robot teaching teams and found that human-led teams with a robotic assistant were preferred over robot-led teams (Abendschein et al., 2021).

Despite the importance of social interaction in teams, *teamwork assistance* by robots is an emerging phenomenon in the context of HRTs and therefore less studied. Among the few studies focusing on teamwork assistance in HRTs, Kelly and Watts (2017) argue that robots should not only be efficient, but also "slow but likeable" (Kelly & Watts, 2017, p. 1, p. 1) in order to be accepted as full team members. In empirical investigations, Strohkorb Sebo et al. (2018) and Traeger et al. (2020) found that robots' social behavior in the form of vulnerable statements helps to improve not only human-robot, but also human-human interaction in HRTs, thus playing an important role in shaping interactions in these teams. Taken together, this shows that while the taskwork aspect of robotic assistance has been extensively researched, a focus on office environments is still lacking. Similarly, teamwork assistance is currently an understudied phenomenon, despite promising results from initial studies.

Another aspect of interest are expectations, experiences, and expectation-disconfirmation that have been in the focus of a number of investigations in the context of human-robot interaction. For example, Paepcke and Takayama (2010) examined expectation-setting tactics for robot capabilities and found that initial beliefs about a robot's capabilities are influenced by these tactics. Specifically, setting lower expectations led to less disappointment and more positive evaluations of the robot's competence. Horstmann and Krämer (2020) found that people's expectations about a social robot's future role, as either a competitor or assistant, influence perceptions of its sociability. Their research underscores that the robot's behavior has more impact on evaluations during real interactions than initial expectations or individual backgrounds. Similarly, in two studies C. Edwards et al. (2016) and A. Edwards et al. (2019) found that initial expectations and impressions about the conversational partner may influence subsequent interactions with social robots. Finally, E. Phillips et al. (2017) explored how robot appearances evoke expectations in human-robot interactions and categorized these expectations.

Overall, as technological developments increasingly enable robots to take on social roles in teams and the furthe rintegration of social robots is anticipated, we see potential for further research to better understand team constellations in which different robotic assistants provide not only taskwork but also teamwork assistance for their teams. With our work, we want to step into this research gap in order to learn more about this promising field of application.

3.3 Conceptual Background

3.3.1 Input-Process-Output Model and Expectation-Disconfirmation Theory

Our research framework (Figure 3-1) is inspired by the Input-Process-Output (IPO) Model which has been established in team research (e.g., Gladstein, 1984; Mathieu et al., 2008; McClough & Rogelberg, 2003). It also has attracted considerable attention in information systems research (e.g., Powell et al., 2004; Subiyakto & Ahlan, 2014). The IPO Model differentiates between team inputs, processes, and outputs. *Inputs* are comprised of team level or organizational/contextual factors (Driskell et al., 2018); they are considered antecedents for team member collaboration (Gladstein, 1984; Mathieu et al., 2008). Characteristics of individual team members are among these input factors (Driskell et al., 2018), for instance in the form of competencies (Mathieu et al., 2008). Team interaction *processes* are directed toward task completion as an overarching goal of work teams. They describe how inputs are transformed into outputs (Driskell et al., 2018; Mathieu et al., 2008). These *outputs* include performance and affective reactions (Mathieu et al., 2008). IPO Models have been used before in HRT research (e.g., Esterwood & Robert, 2020; Wolf & Stock-Homburg, 2022).

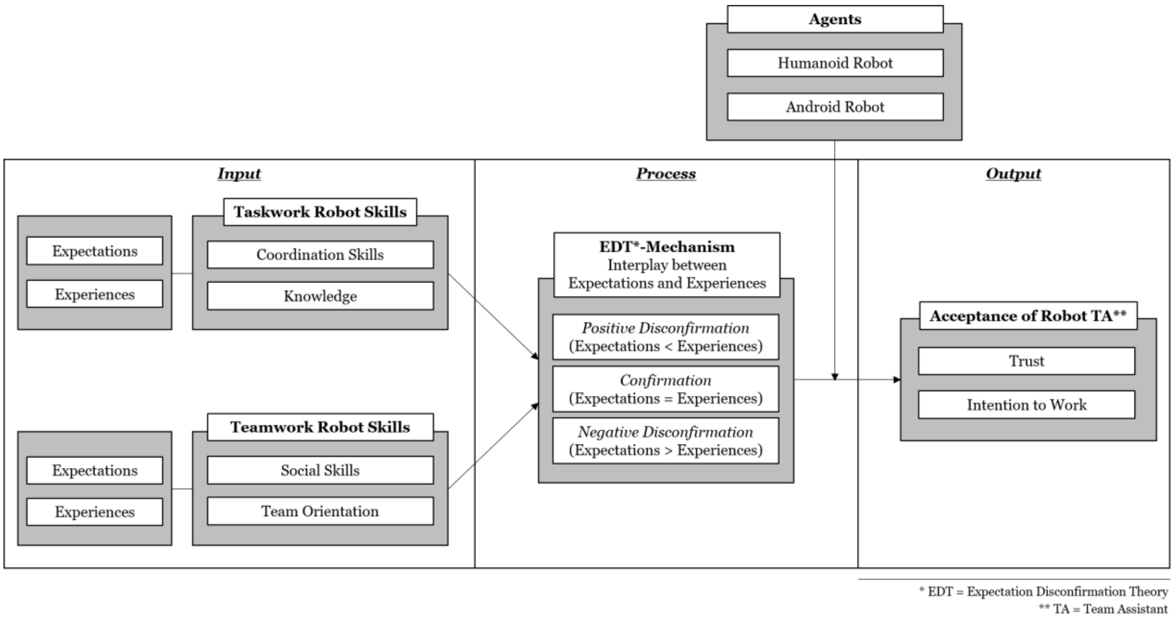


Figure 3-1. Research Framework

Expectation Disconfirmation Theory (EDT) proposes a framework to study outcome evaluations not only based on actual experiences of a product or service, but also in relation to prior expectations. These expectations create a frame of reference that build the basis for later judgements. If experiences do not meet expectations, a discrepancy is created: Experiences can either be worse than expected (negative disconfirmation) or better than expected (positive disconfirmation) (Oliver, 1980; Venkatesh & Goyal, 2010). In information systems research, EDT has been applied as a theoretical lens to study user acceptance (Venkatesh & Goyal, 2010) or trust in technology (N. K. Lankton et al., 2016). EDT in this context is primarily studied in combination with polynomial modeling and response surface analysis. With this method, the interplay between expectations and experiences is illustrated by means of models with varying complexity. S. A. Brown et al. (2014) for instance investigate linear (first-order), quadratic (second-order), and cubic (third-order) polynomial models in their work.

Building on the IPO model (Mathieu et al., 2008) and EDT (Venkatesh & Goyal, 2010), we establish an expectation-experience-based model for HRTs. We first take team *input* variables into consideration and focus on team member characteristics (cf. Driskell et al., 2018) to answer

RQ1. *Taskwork* in this regard is aimed at the accomplishment of team-specific tasks (Crawford & LePine, 2013), for instance through coordination activities (Fisher, 2014). *Teamwork* specifically focuses on team member interactions (Mathieu et al., 2008) and interpersonal processes (Fisher, 2014). In our research framework we follow this notion by investigating both robotic taskwork and teamwork skills. Taskwork team assistant skills are represented by coordination skills and knowledge. Teamwork team assistant skills, in contrast are comprised of social skills and team orientation. This allows for a nuanced investigation of robotic team assistant skills in office environments. Regarding the team *process*, we investigate expectation disconfirmation and focus on the relationships between taskwork and teamwork expectations and experiences. For team *outputs*, our dependent variables are also characterized by a duality in that we consider trust as soft factor of robot acceptance and the intention to work with the team assistant as hard factor in line with prior considerations on the IPO Model (cf. Mathieu et al., 2008).

3.3.2 Hypotheses Development

Team assistants can be considered facilitating agents that provide services to teams in order to improve team effectiveness (Beavers & Hexmoor, 2002). In traditional service contexts, the relationship between services and (customer) outcomes can be characterized by an inverted S-shaped curve (R. M. Stock, 2011). Similar patterns have been observed in organizational contexts, for instance in subordinates' identification with their leaders (R. M. Stock & Özbek-Potthoff, 2014).

Transferring this to our context, we propose that an inverted S-shaped curve is also observable in relationships between expectation and experiences of robotic team assistant skills in their role as team service providers. This would imply that the center of the surface is relatively flat, as we can find a zone of tolerance (Johnston, 1995) for small gaps between expectations and experiences. This is based on cognitive dissonance theory (Festinger, 1957) that postulates that individuals try to minimize the difference between their expectations and experiences to reach consonance, hence biasing their experiences towards their expectations. Thus, there should only be small effects on employees' robot acceptance of the team assistants.

Moving to the left part of the surface, a negative disconfirmation of expectations (i.e., underfulfilment) would cause the surface to increasingly "go down". This implies lower levels of robot acceptance, due to cognitive dissonance (Festinger, 1957). Specifically, the relationship between negative disconfirmation and employees' robot acceptance should show a concave pattern. This expectation is consistent with disappointment theory (Loomes & Sugden, 1986). According to this theory, disappointment emerges in situations where the outcome of a decision falls short of initial expectations, while elation emerges when the outcome exceeds initial expectations (Homburg et al., 2004). In particular, "the intensity of disappointment and elation both increase at the margin" (Loomes & Sugden, 1986, p. 272), resulting in a concave trend towards negative disconfirmation.

Conversely, on the right part of the surface, the opposite case of positive disconfirmation (i.e., overfulfilment of expectations) would, accordingto disappointment theory, result in a rising surface, i.e., higher robot acceptance. This right part of the surface would be characterized by a convex shape.

Extant literature suggests that the above mentioned human theories can be applied to human-computer and human-robot interaction (M. Demir et al., 2020; Krämer et al., 2012; Visser et al., 2018; Visser et al., 2020). Accordingly, we propose the following hypotheses:

H1: There is an inverted S-shaped relationship between (a) android and (b) humanoid robot *taskwork* team assistant skills and robot acceptance by the employee.

H2: There is an inverted S-shaped relationship between (a) android and (b) humanoid robot *teamwork* team assistant skills and robot acceptance by the employee.

With our hypotheses, we also consider different agent types (RQ2): humanoid and android robotic team assistants. Humanoid and android robots are characterized by differing levels of human-likeness and evoke varying user responses. Humanoid robots "resemble people in form or behavior to some degree" (Fox & Gambino, 2021; p. 295) and are able to socially interact with humans (S. Zhao, 2006). Still, they are quite mechanical-looking (MacDorman & Ishiguro, 2006). In contrast to this, android robots are designed to mimic human beings closely (MacDorman & Ishiguro, 2006). Due to their automated social presence (van Doorn et al., 2017), both android and humanoid social robots make humans feel like being faced with a real social entity (Čaić et al., 2020). We therefore expect analogous relationships between expected and experienced taskwork and teamwork robot skills and employees' acceptance of the robots. We evaluate individual trajectories for each agent for both taskwork and teamwork skills to gain a refined understanding of each robot type.

3.4 Method

3.4.1 Online Experiment

3.4.1.1 Experimental Design

We conducted the experiment as an online study. Workers from the platform Amazon Mechanical Turk (MTurkers) were recruited as participants. For data quality purposes, we only admitted MTurkers with an acceptance rate of more than 95% to participate in the experiment. Upon successful completion of the experiment participants received financial compensation. Online studies are a common and proven research method also in HRI research (Bryant et al., 2020; Feil-Seifer et al., 2021; Horstmann & Krämer, 2019; Leiner, 2019; Preusse et al., 2021; Reich-Stiebert et al., 2019), including the investigation of anthropomorphic robots (Knof et al., 2022; Lohse et al., 2007; Ye et al., 2020). They have a number of advantages, including reduced experimenter influence, access to larger samples, and increased generalizability (Aguinis et al., 2021; Reips, 2002).

We conducted the experiment in the form of a virtual selection scenario as part of a corporate project. To assess individual ratings and differences between the humanoid and android robots, participants viewed each agent in random order in a within-subjects design. During the online experiment, the scenario was presented to the participants in the form of a vignette. Such a vignette-based approach is used to present contextual and explanatory facets (Atzmüller & Steiner, 2010) and has been used previously in robotics research (e.g., Lutz & Tamò-Larrieux, 2021). Previous research has shown that vignettes are an appropriate method for studying teams, including their task-related and social-emotional levels(Dennis et al., 2012). In this study, the use of the vignette in particular allows for accurate creation of participants' understanding of the selection scenario. In the vignette, participants were asked to assume the role of an employee who wanted to join a new project team. There were different teams to choose from. The only difference between the teams was the team assistant. Typical tasks of a team assistant (e.g., communicating with team members and coordinating appointments) were given as examples.

3.4.1.2 Experimental Procedure and Manipulation

As a first step in the experiment, we asked for demographic information about the participants. We also assessed previous experience with robots. In a next step, we assessed expectation disconfirmation for each team assistant separately: Participants were first asked to indicate their expectations for each agent before watching a video of the agent in a team-based project scenario. This video was the basis for the evaluation of the agents and the selection results. During the video, the team assistant interacted with a project team with three additional members. The team assistants performed tasks that were part of that specific role within the team, so that the participants could get an idea of the skills and capabilities of the agent directly in the team setting. Specifically, the team assistants showed their taskwork and teamwork skills by communicating with team members, showing an overview over the meeting agenda, and coordinating an appointment. The videos used in the online experiment were produced at the conducting department. The android robot in the role as team assistant is pictured in Figure 3-2b, the humanoid robotic team assistant in Figure 3-2a. As part of the setup, we mimicked a realistic project meeting environment in the videos, including a conference table and typical devices in the work environment. As the manipulation in our study, the team assistant changed for each video; all other aspects remained the same across the videos. After watching the video, participants were asked to indicate their experience with each agent. We also assessed intention to work with each agent and trust in the agents as indicators of agent acceptance. For the humanoid robot candidate (Figure 3-2a), we used a Pepper robot developed by SoftBanks Robotics. This type of robot has been used in a variety of contexts in human-robot interaction (Pandey & Gelin, 2018). For the android robot candidate (Figure 3-2b), we used a custom-built female android robot with an IBM Watson chatbot that closely mimics human appearance.


a. Humanoid Robot


b. Android Robot

Figure 3-2. Robotic Agents in the Role as Team Assistants

3.4.2 Sample Characteristics

The sample of our online experiment originally consisted of 1,284 MTurk participants. Several participants were excluded due to the following criteria: 63 participants did not meet our employment requirements (employed or independent workers or company owners) and 19 were not from the United States. We further excluded 86 participants that failed more than two out of three attention checks. 12 participants were excluded due to speeding (Leiner, 2019). Moreover, 21 participants indicated video and audio issues and were thus excluded. Our final sample consisted of 1,083 MTurkers. The participants had a mean age of 35.65 years (SD_{age} = 11.12). 48.7% of the participants identified as male, 51.2% as female and 0.1% as diverse. Regarding their professional status, 86.1% of the sample were employed workers, 10.1% independent workers and 3.8% company owners. Participants rated their project work experience high with a mean of 8.16 ($SD_{project}$ = 1.84) on a scale from 1 (*I have no experience at all*) to 10 (*I have very much experience*). To gain a better understanding of our sample, we asked participants to indicate their experiences with robots. These ratings were on moderately high levels: M_{exp} = 7.07 (SD = 2.51) again on a scale from 1 (*I have no experience at all*) to 10 (*I have very much experience*). 64.0% of participants experienced robots at work, while 39.5% had experiences with robots in their free time, 26.9% in a store, 20.5% in media, 16.3% in a hotel, and 14.7% in a museum; 4.0% of the sample chose other. We were also interested in the nature of their experiences: 67.0% of participants saw robots in films or online, 58.2% in real life, 37.7% had an actual interaction with a robot, 17.2% programmed robots, 12.7% worked together with robots, 7.9% owned a robot, and 1.3% chose other. Participants could select multiple options.

3.4.3 Measures and Statistical Analyses

With regards to our EDT-mechanism, we assessed the input variables before (expectations) and after the video-based interaction (experiences). For *taskwork* team assistant skills, we measured coordination skills and knowledge. The items for coordination skills were based on Song et al. (2019), a sample item for expected coordination skills is: “I expect this [agent] to ensure that within the team, related tasks are well coordinated”. For knowledge, we adapted our items from Dunham and Burt (2014), a sample item for expected knowledge is: “I expect this [agent] to have mastered the required tasks of his/her job”. *Teamwork* skills were comprised of social skills and team orientation. The social skills scale was adapted from Silvera et al. (2001). A sample item is: “I expect this [agent] to fit in easily in social situations”. For team orientation (Kilcullen et al., 2022) the following item illustrates the construct: “I expect this [agent] to be willing to put himself/herself out to help the work group”. To gather experiences, the corresponding parts of the items were adapted. As outcome variables, we relied on trust and the intention to work with the agent as indicators of robot acceptance. The items for trust were adapted from

McKnight et al. (2002). A sample item is: “The [agent] acts in my best interest”. For intention to work with the team assistant, we relied on Venkatesh and Goyal (2010), a sample item is: “I would intend to work with the [agent]”. As control variables for our analyses, we relied on affinity for technology interaction (Lezhnina & Kismihók, 2020) and prior experiences with robots as introduced in the sample characteristics. If not specified otherwise, all scales featured 7-point Likert-type scales (1: *totally/strongly disagree* to 7: *totally/strongly agree*).

Reliability analysis using Cronbach's α (Cronbach, 1951) shows that the measures exceed 0.7. Average variance extract values are also above the threshold of 0.5 and the Fornell-Larcker criterion (Fornell & Larcker, 1981) is overall fulfilled.

For the statistical analyses, we relied on approaches by S. A. Brown et al. (2014) and Shanock et al. (2010, 2014) based on J. R. Edwards and Parry (1993) and Cohen et al. (2003) to conduct polynomial modeling and run tests of surface values as part of response surface analysis. Results of a hierarchical polynomial regression analysis up to third order were used to determine the best order of the used models based on significant increase of R^2. For example, a third-order regression equation can be written as $Z = b_0 + b_1X + b_2Y + b_3X^2 + b_4XY + b_5Y^2 + b_6X^3 + b_7X^2Y + b_8XY^2 + b_9Y^3$, where Z = dependent variable, X = experiences, Y = expectations, and regression coefficients $b_0, b_1, \dots, b_9$ used as input for the response surface. We then relied on significance tests of various surface values calculated using the regression coefficients for the best order to evaluate characteristics of resulting response surfaces. For example, the regression analysis showed that a third-order model was the best fit. We then examined the response surface spanned by the associated regression coefficients in more detail and performed the tests of surface values mentioned above. These tests are partially based on previous literature (S. A. Brown et al., 2014; Shanock et al., 2010, 2014), we further developed additional tests following the approach by Cohen et al. (2003).

3.5 Results

With t-tests, we confirm that the manipulation worked as intended: As a t-test against the midpoint of the scale showed, participants could clearly identify the two agents as robots ($M_{humanoid} = 6.03, SD = 1.11, t(1082) = 60.39, p < 0.01$; $M_{android} = 5.86, SD = 1.19, t(1082) = 51.30, p < 0.01$). Another t-test comparing the evaluations of machine-likeness (1) vs. human-likeness (7) of the two robots confirmed that the humanoid robot was perceived ($M_{humanoid} = 4.47, SD = 2.09$) as significantly ($t(2155.54) = 4.40, p < 0.01$) less humanlike than the android robot ($M_{android} = 4.86, SD = 1.96$). Participants further perceived both robots similarly as teammates ($M_{android} = 4.92, SD = 1.92; M_{humanoid} = 4.82, SD = 1.95$; t-test against midpoint of the scale from tool (1) to teammate (7), n.s. differences between robots). Tests against the midpoint of the scale showed that participants perceived the scenario as realistic for both agents ($M_{humanoid} = 5.47, SD = 1.38, t(1082) = 34.91, p < 0.01$; $M_{android} = 5.47, SD = 1.37, t(1083) = 35.33, p < 0.01$).

Results of hierarchical regression up to third order showed that for the *humanoid* robot, third-order models are the best fit for outcome assessments of robot acceptance related to evaluations of *taskwork* robotic team assistant skills. Thus, the corresponding response surfaces also follow third-order models. Subsequent response surface analyses showed that the surfaces follow an inverted S-shape with highest values for the greatest values of positive disconfirmation (right corner of the surface, see Figure 3-3a). Corresponding tests of the response surface (Table 3-1) specifically showed that the cubic slope along the line of perfect disconfirmation $a_{y,0}^3$ is positive and significant and the corresponding surface value for the linear slope of the surface on its far right corner with the highest positive disconfirmation, $a_{y,3}$, is positive and significant, supporting the wave-shape of the surface. The linear slope of the surface from its center along the line of perfect disconfirmation ($a_{y,0}$) is not significantly different from zero in most cases, indicating the zone of tolerance in the middle of the surface. Higher absolute values of confirmation are associated with increasing outcome assessments, as indicated by $a_{x,0}$ being positive and significant.

In contrast, for outcome assessments related to evaluations of *taskwork* robotic team assistant skills for the *android* robot mostly second-order models are most suitable. The response surfaces follow an inverted U-shaped surface (see Figure 3-3b) that is slightly skewed to the area of positive disconfirmation and has the highest values for high absolute values of confirmation. This shape was confirmed by surface value tests (Table 3-2): The linear slopes in the center of the surface along the line of perfect confirmation and the line of perfect disconfirmation, $a_{x,0}$ and $a_{y,0}$, are positive and significant indicating the increase of outcome evaluations for higher absolute values of confirmation and slight positive disconfirmation. The quadratic slope of the surface along the line of perfect disconfirmation in its center ($a_{y,0}^2$) is negative and mostly significant and the slope of the surface on its far right corner ($a_{y,3}$) is significantly negative, indicating the inverted U-shape.

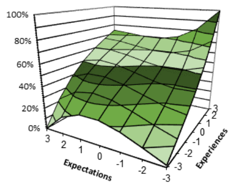
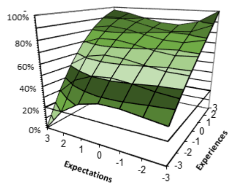
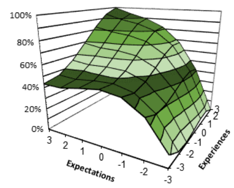
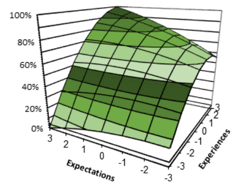
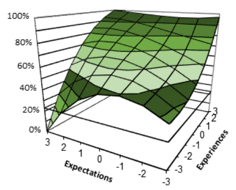
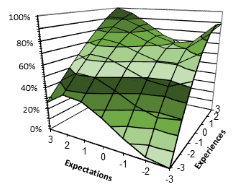
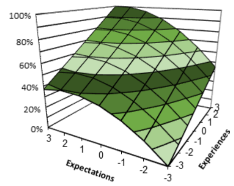
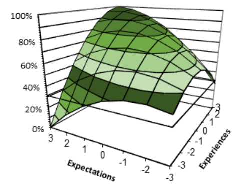
DV \ IV	a. Humanoid Robotic Team Assistant		b. Android Robotic Team Assistant	
	Coordination Skills	Knowledge	Coordination Skills	Knowledge
Trust	 $T = 4.186 + 0.486C_1 + 0.428C_2 - 0.006C_1^2 - 0.055C_1C_2 - 0.019C_2^2 + 0.016C_1^3 - 0.039\,C_1^2C_2 + 0.059C_1C_2^2 - 0.029C_2^3$	 $T = 4.050 + 0.584K_1 + 0.270K_2 - 0.098K_1^2 + 0.062K_1K_2 - 0.033K_2^2 + 0.007K_1^3 - 0.026K_1^2K_2 + 0.047K_1K_2^2 - 0.029K_2^3$	 $T = 4.148 + 0.616C_1 + \ 0.293\ C_2 + 0.017C_1^2 + 0.113C_1C_2 - 0.180C_2^2 - 0.031 * C_1^3 + 0.000C_1^2C_2 - 0.012C_1C_2^2 + 0.041C_2^3$	 $T = 4.016 + 0.721K_1 + 0.150K_2 - 0.150K_1^2 + 0.102K_1K_2 - 0.030K_2^2$
	$R^2 = .648$, adjusted $R^2 = .644$ $F(11{,}1071) = 179.090, p < 0.01$	$R^2 = .631$, adjusted $R^2 = .627$ $F(11{,}1071) = 166.428, p < 0.01$	$R^2 = .718$, adjusted $R^2 = .715$ $F(11{,}1071) = 247.897, p < 0.01$	$R^2 = .646$, adjusted $R^2 = .644$ $F(7{,}1075) = 280.534, p < 0.01$
Intention	 $I = 4.090 + 0.568C_1 + 0.382C_2 - 0.009C_1^2 + 0.091C_1C_2 - 0.120\,C_2^2 + 0.012C_1^3 - 0.063C_1^2C_2 + 0.048C_1C_2^3 - 0.006C_2^3$	 $I = 4.034 + 0.463K_1 + 0 - 370K_2 - 0.099K_1^2 - 0.022K_1K_2 + 0.025K_2^2 - 0.004K_1^3 + 0.022K_1^2K_2 + 0.033k_1K_2^2 - 0.045K_2^3$	 $I = 3.996 + 0.499C_1 + 0.424C_2 + 0.001C_1^2 + 0.027C_1C_2 - 0.098C_2^2$	 $I = \ 4.059 + 0.575K_1 + 0.214K_2 - 0.200K_1^2 + 0.251K_1K_2 - 0.155K_2^2$
	$R^2 = .577$, adjusted $R^2 = .573$ $F(11{,}1071) = 132.920, p < 0.01$	$R^2 = .460$, adjusted $R^2 = .455$ $F(11{,}1071) = 83.054, p < 0.01$	$R^2 = .530$, adjusted $R^2 = .527$ $F(7{,}1075) = 173.014, p < 0.01$	$R^2 = .448$, adjusted $R^2 = .444$ $F(7{,}1075) = 124.582, p < 0.01$

Figure 3-3. Response Surfaces for Outcome Assessments of Taskwork Robotic Team Assistant Skills for the Humanoid and Android Robotic Team Assistant

Note: C_1, K_1, refer to perceived coordination skills / knowledge, C_2, K_2, refer to expected coordination skills / knowledge, T refers to trust, I refers to Intention

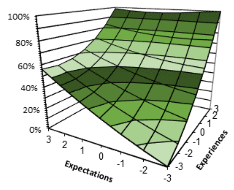
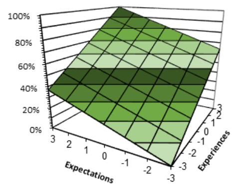
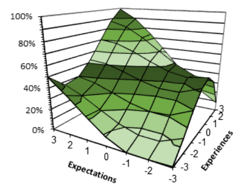
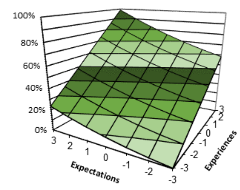
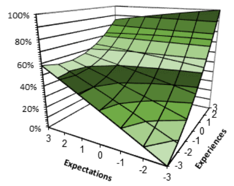
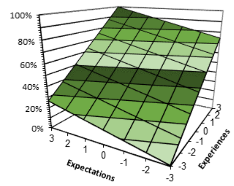
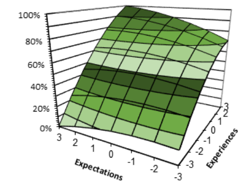
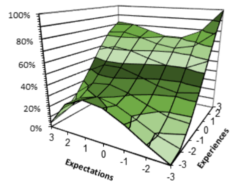
	a. Humanoid Robotic Team Assistant		b. Android Robotic Team Assistant	
DV \ IV	Social Skills	Team Orientation	Social Skills	Team Orientation
Trust	 $T = 4.373 + 0.466S_1 + 0.173\,S_2 + 0.065 - 0.063S_1S_2 + 0.016S_2^2$	 $T = 4.534 + 0.376O_1 + 0.215O_2$	 $T = 4.269 + 0.542S_1 + 0.196S_2 - 0.030\,S_1^2 + 0.040S_1S_2 + 0.029\,S_2^2 - 0.030\,S_1^3 + 0.038S_1^2S_2 - 0.012S_1S_2^2 - 0.015S_2^3$	 $T = 4.405 + 0.402O_1 + 0.192O_2 + 0.000O_1^2 + 0.018O_1O_2 + 0.012O_2^2$
	$R^2 = .597$, adjusted $R^2 = .595$ $F(7, 1075) = 227.730, p < 0.01$	$R^2 = .563$, adjusted $R^2 = .561$ $F(4, 1078) = 346.906, p < 0.01$	$R^2 = .648$, adjusted $R^2 = .644$ $F(11, 1071) = 179.141, p < 0.01$	$R^2 = .631$, adjusted $R^2 = .628$ $F(7, 1075) = 262.169, p < 0.01$
Intention	 $I = 4.291 + 0.581S_1 + 0.198S_2 + 0.088S_1^2 - 0.112S_1S_2 - 0.005S_2^2$	 $I = 4.413 + 0.540O_1 + 0.187O_2$	 $I = 4.235 + 0.670S_1 + 0.070S_2 - 0.072S_1^2 + 0.058S_1S_2 - 0.027S_2^2$	 $I = 4.133 + 0.629O_1 + 0.322O_2 + 0.053O_1^2 - 0.030\,O_1O_2 - 0.027O_2^2 - 0.033O_1^3 - 0.009O_1^2O_2 + 0.047O_1O_2^2 - 0.033O_2^3$
	$R^2 = .577$, adjusted $R^2 = .574$ $F(7, 1075) = 209.326, p < 0.01$	$R^2 = .597$, adjusted $R^2 = .596$ $F(4, 1078) = 400.056, p < 0.01$	$R^2 = .563$, adjusted $R^2 = .560$ $F(7, 1075) = 197.910, p < 0.01$	$R^2 = .596$, adjusted $R^2 = .592$ $F(11, 1071) = 143.601\ p < 0.01$

Figure 3-4. Response Surfaces for Outcome Assessments of Teamwork Robotic Team Assistant Skills for the Humanoid and Android Robotic Team

Note: S_1, O_1, refer to perceived social skills / team orientation, S_2, O_2, refer to expected social skills / team orientation, T refers to trust, I refers to Intention

Turning to outcome assessments of robot acceptance related to evaluations of *teamwork* robotic team assistant skills (social skills and team orientation), the regressions for the *humanoid* robot showed best fits for simple (first- and second-order) models. The corresponsing response surfaces follow shapes with highest outcome assessments for high absolute values of experiences (see Figure 3-4a). The test for the linear slope of the surface on its far right corner, $a_{y,3}$, showed that it is positive and significant. Further, the linear slopes of the surfaces in its center along the line of perfect confirmation ($a_{x,0}$) and along the line of perfect disconfirmation ($a_{y,0}$) are positive and significant (Table 3-3).

Table 3-1. Results of Tests of Surface values for Taskwork Robotic Team Assistant Skills of the Humanoid Robot

	Tests	Coordination Skills	Knowledge
Trust	$\|b_6\|, \|b_7\|, \|b_8\|, or\ \|b_9\| > 0$	Supported	Supported
	$a_{y,3} > 0$	Supported	Supported
	$a_{y,0}^3 > 0$	Supported	Supported
	$a_{x,0} > 0$	Supported	Supported
	$a_{y,0} = 0$	Supported	Not supported
Intention	$\|b_6\|, \|b_7\|, \|b_8\|, or\ \|b_9\| > 0$	Supported	Supported
	$a_{y,3} > 0$	Supported	Tends to be supported
	$a_{y,0}^3 > 0$	Supported	Tends to be supported
	$a_{x,0} > 0$	Supported	Supported
	$a_{y,0} = 0$	Supported	Supported

Note: Surface values indexed with x refer to the line of perfect confirmation (i.e., experiences = expectations), surface values indexed with y refer to the line of perfect disconfirmation (i.e., experiences =- expectations)

Table 3-2. Results of Tests of Surface values for Taskwork Robotic Team Assistant Skills of the Android Robot

	Test	Coordination Skills	Knowledge
Trust	$\|b_3\|, \|b_4\|,\ or\ \|b_5\| > 0$	Supported	Supported
	$a_{y,3} < 0$	Supported	Supported
	$a_{y,0}^2 < 0$	Supported	Supported
	$a_{x,0} > 0$	Supported	Supported
	$a_{y,0} > 0$	Supported	Supported
Intention	$\|b_3\|, \|b_4\|,\ or\ \|b_5\| > 0$	Supported	Supported
	$a_{y,3} < 0$	Tends to be supported	Supported
	$a_{y,0}^2 < 0$	Tends to be supported	Supported
	$a_{x,0} > 0$	Supported	Supported
	$a_{y,0} > 0$	Tends to be supported	Supported

Note: Surface values indexed with x refer to the line of perfect confirmation (i.e., experiences = expectations), surface values indexed with y refer to the line of perfect disconfirmation (i.e., experiences =- expectations)

Table 3-3. Results of Tests of Surface Values for Teamwork Robotic Team Assistant Skills of the Humanoid Robot

	Test	Social Skills	Team Orientation
Trust	$a_{y,3} > 0$	Supported	Supported
	$a_{x,0} > 0$	Supported	Supported
	$a_{y,0} > 0$	Supported	Supported
Intention	$a_{y,3} > 0$	Supported	Supported
	$a_{x,0} > 0$	Supported	Supported
	$a_{y,0} > 0$	Supported	Supported

Note: Surface values indexed with x refer to the line of perfect confirmation (i.e., experiences = expectations), surface values indexed with y refer to the line of perfect disconfirmation (i.e., experiences =- expectations)

Table 3-4. Results of Tests of Surface Values for Teamwork Robotic Team Assistant Skills of the Android Robot

	Test	Social Skills	Team Orientation
Trust	$a_{y,3} = 0$	Supported	Supported
	$a_{x,0} > 0$	Supported	Supported
	$a_{y,0} > 0$	Supported	Supported
	$a^2_{y,0} = 0$	Supported	Supported
Intention	$a_{y,3} = 0$	Supported	Not supported
	$a_{x,0} > 0$	Supported	Supported
	$a_{y,0} > 0$	Supported	Supported
	$a^2_{y,0} = 0$	Not supported	Supported

Note: Surface values indexed with x refer to the line of perfect confirmation (i.e., experiences = expectations), surface values indexed with y refer to the line of perfect disconfirmation (i.e., experiences =- expectations)

For the *teamwork* robotic skills, overall, the outcome assessments for the *android* robot paint a mixed picture of second- and third-order regression models and corresponding response surfaces (Figure 3-4b). These surfaces mostly follow shapes with highest outcome assessments for high absolute values of confirmation. The response surface for team orientation and intention deviates from this in that highest outcome assessments are associated with highly positive disconfirmation. The linear slopes along the lines of interest in the center of the surface, $a_{x,0}$ and $a_{y,0}$, are positive and significant for all surfaces. The quadratic slope of the surface along the line of perfect disconfirmation in its center ($a^2_{y,0}$) is mostly not significant from zero, indicating no U- or inverted U-shape. The slope of the surface on its far right corner, $a_{y,3}$, is not statistically significant from zero for all combinations of independent and dependent variables except team orientation and intention, for which it is positive and significant (Table 3-4).

3.5.1 Supplementary Analyses

To supplement our response surface analysis, we looked at preference indications for the robotic agents. This information was considered important to understand whether the robot acceptance based on the expectation-experience interplay matches the general preference to work with the robot. We included the following item in our questionnaire that allowed for a pairwise comparison: "Please indicate who you prefer as a team assistant." Participants could choose between the humanoid and the android robot on a scale from 1 to 7. 1 would indicate an absolute preference for the humanoid and 7 absolute preference for the android robot. We tested the preferences with a t-test against the midpoint of the scale. With a mean of 4.46 and a standard deviation of 2.14, participants significantly preferred the android robot to the humanoid robot ($t(1082) = 7.03, p < 0.01$). The high standard deviation indicates that preferences varied greatly within the sample.

Interestingly, 61.00% preferred the android robot as team assistant by choosing the values 5, 6 or 7 on the scale. 35.40% indicated preferences for the humanoid robotic team assistant (values 1, 2 or 3). Only 3.60% chose the midpoint of the scale. This means that participants in an employee role clearly preferred the android robot. However, considering our response surface analysis, high perceived taskwork skills of the android robot in combination with low expectations (positive disconfirmation) lead to rejection in terms of low robot acceptance.

3.6 Discussion

The departure point of this paper was the question of how to successfully integrate social robots as AI-based technologies into work teams. Especially a role as team assistant is considered appropriate in corresponding literature for the setup of HRTs (see for instance Wolf & Stock-Homburg, 2022). In our research, we focus on taskwork and teamwork robotic assistant skills following this distinction in extant work (cf. Crawford & LePine, 2013). Our research is rooted in EDT (Oliver, 1980; Venkatesh & Goyal, 2010) which has a long-standing tradition in information systems research. We transfer this nuanced concept to HRTs in the form of an expectation-experience-based model that investigates interplays between taskwork skills, teamwork skills and robot acceptance in a comprehensive way.

3.6.1 Research Implications

Teamwork robotic team assistant skills refer to social aspects of team member interactions (Mathieu et al., 2008). The results of the response surface analysis show that for the humanoid robot the highest levels of robot acceptance are reached for high levels of experiences. In order words, experiencing the robot as proficient in teamwork skills is the decisive factor for outcome evaluations. For the android robotic team assistant, the surfaces paint a mixed picture. Generally speaking, high levels of experiences (and additionally confirmation) also lead to high robot acceptance for most investigated relations. This result is similar to the implications drawn for the humanoid robot. However, the relationship between expected and experienced social skills and trust does not fit this picture for the android robot: high levels of positive disconfirmation lead to low trust while high levels of negative disconfirmation (i.e., expectations fall below experiences) also increase trust in the robot. Overall, the proposed inverted S-shaped relationship between teamwork robotic team assistant skills and robot acceptance was not confirmed.

For *taskwork* robotic team assistant skills focusing on task accomplishment (Crawford & LePine, 2013), the surfaces for the humanoid robotic assistant follow the proposed inverted S-shaped surfaces: robot acceptance is highest with the highest level of positive disconfirmation. Of interest for this shape is also the zone of tolerance (Johnston, 1995), showing that not only for perfect confirmation but also for small deviations of expectations and experiences robot acceptance remains relatively stable. This indicates that a small mismatch between skill expectations and experiences is tolerated by potential teammates. As such technologies are currently only emerging (Chui et al., 2022), employees seem to be rather open about them and overlook small imperfections. For the android robotic team assistant, we did not find the proposed inverted S-shaped curves, but rather inverted U-shaped surfaces: The highest levels of robot acceptance are mainly observable for a match between expectations and experiences and slight positive disconfirmation, i.e., experiences exceed expectations only to a small extent. For high levels of positive disconfirmation, where experiences considerably exceed prior expectations of the robotic assistant's taskwork skills, the curve "drops". This decline is associated with relatively low levels of robot acceptance despite high perceived skill levels, i.e., trust in and intention to work with the android robot significantly decrease.

We consider this unexpected result a threat effect posed by high taskwork skills of the android robotic team assistant in the office context. Current media portrayals of job loss due to machines and automation emphasize a potential negative impact on employment. This may lead to job insecurity and concerns across many industries (Alcover et al., 2021; Bhargava et al., 2021). Research shows that in the working world, the „human touch“ and soft skills are not perceived to be affected by the integration of technology (e.g., robots) to the same extent as routine office tasks (Bhargava et al., 2021; Chui et al., 2015). A likely response to a potential threat is reactance (Miron & Brehm, 2006; Taylor, 1983). Psychological reactance theory (Brehm, 1966) acts as a framework to explain why individuals express rejecting behaviors and may show a negative attitude in the face of a potential threat (Quick & Stephenson, 2008). A common reaction in this regard is the derogation of the threating source (Miller et al., 2007; Miron & Brehm, 2006; Worchel & Brehm, 1970) – which in our case is the high taskwork skill level of the android robotic team assistant.

The concept of psychological reactance has been observed in human-agent (S. Liu et al., 2008) and human-robot interaction before (Aimi S. Ghazali et al., 2018; Aimi Shazwani Ghazali et al., 2020). Interestingly, research has found that the stronger the social agency of the robot, the more pronounced are the effects of reactance, such as negative cognitions (Roubroeks et al., 2011). Social agency is operationalized as the „degree to which a social agent is perceived as being capable of social behavior that resembles human-human interaction“ (Roubroeks et al., 2011, p.157). This notion is supported by works from Aimi S. Ghazali et al. (2018) that demonstrate that social robots with rather minimal social cues evoke lower levels of reactance compared to agents with high levels of social cues. Android robots are characterized by a very high level of anthropomorphism in contrast to more mechanical-looking humanoid robots (MacDorman & Ishiguro, 2006). Additionally, android robots are seemingly more “perfect” by human standards (Duffy, 2003; Matsui et al., 2005) and thus may evoke fear and a sense of threat, especially in combination with high skill levels where humans can be outperformed. This difference between the robot types may explain why reactance only occurred for the android robot and not for the humanoid. After all, anthropomorphism can go too far (Duffy, 2003).

Furthermore, the authors have been part of a research project investigating longitudinal developments in several HRTs. In this project, it became clear that the majority of the 12 participants that worked with the robots during a period of eight weeks preferred to work with the android robot (also in the role of team assistant) and not with the humanoid robot. They also ascribed a higher level of social agency and social cues to the android robotic team assistant. However, when the android robot had too much knowledge it was perceived as too powerful and evoked feelings of scariness. Our supplementary analysis regarding team assistant preferences also shows that participants would choose the android robot to be part of their team. To sum up our findings, participants clearly prefer the android robot for the role as team assistant, but do not go the full way by derogating extremely high levels of positive disconfirmation, i.e., experiences greatly exceeding expectations. This relation may be described with the following phrase: *Wash me, but don't make me wet!* – participants want the android robotic team assistant and it should perform and support them in their work but it should not have any negative implications for them. In light of this finding, it is especially relevant to overcome the negative evaluations for high android robotic taskwork skills and foster robot acceptance.

This study establishes an expectation-experience-based model for HRTs, building upon the IPO model and EDT. This contributes to ongoing research both on a theoretical and methodological level. The utilized methodological approach using regression and response surface analysis allows for a nuanced understanding of the topics under investigation (see also J. R. Edwards, 2002). By extending the central aspects of teamwork and taskwork from all-human teams to human-robot teams, we emphasize the relevance of social (human) psychology theories as a promising start in exploring the role of social robots in office work environments.

3.6.2 Managerial Implications

Our work supports practitioners in integrating sophisticated AI-based technologies into organizations. With our differentiation of taskwork and teamwork we create a holistic and realistic picture of aspects that need to be considered when implementing social robots into teams. The assessment of our expectation-experience-based models show that mostly, it is important to focus on optimal experiences of the robotic team assistant. Especially good levels of robot acceptance are achieved in the case of positive disconfirmation where the gap between (low) expectations and (high) experiences is highest. A potential strategy in this regard may be to undersell the robot's capabilities to employees in order to create low expectations that may be exceeded later on. To best ensure this, this underselling should be coupled with efforts of stable programming and operation of the robotic team assistants. According to our investigations, this method would apply to teamwork skills for both robotic agents and to taskwork skills for the humanoid robotic team assistant. In contrast to this, for the highly anthropomorphic android, such a strategy would backfire as high levels of positive disconfirmation regarding taskwork leads to a threat effect resulting in downgrading of the agent. Here, a match between expectations and experiences would be preferable.

We could further show that our participants prefer the android robot in direct comparison to the humanoid robot. When combining this finding with our response surface analysis, for high taskwork skill levels, robot acceptance steeply declined. As described before, we consider this a threat effect resulting in reactance towards the android robotic team assistant. We observe such a threat effect not only in the light of robots that exhibit high levels of task-related skills in our experiment, but also towards other AI-based technologies. ChatGPT for instance—a tool that is noted for its high levels of human-like language and considered a potential threat for jobs—has been banned in Italy (McCallum, 2023), with Germany maybe following in their footsteps (Cuthbertson, 2023). Additionally, evaluations of AI-based systems appear to be rather extreme in either a very positive or negative direction (Park & Woo, 2022). A recent study by Schepman and Rodway (2020) that validated a scale capturing attitudes towards AI suggests that people hold mixed views of AI and tend to gravitate towards the extreme points of the scale. Our own data on preferences towards the robotic team assistants confirms this in that most participants expressed clear preferences with only a very small amount of responses ranging in the middle of the scale. Our experiment and corresponding research (e.g., Aimi S. Ghazali et al., 2018; Aimi Shazwani Ghazali et al., 2020) suggest, that the amount of social cues and the level of anthropomorphism may shape acceptance and reactions towards such technologies: Designing technologies with less social cues may be a strategy to counteract threat and reactance effects with regard to high taskwork skill levels. Strategies to increase acceptance of android robots may also be beneficial: Following de Graaf et al. (2016), equipping robot users with skills to effectively utilize the robot or directly addressing potential user concerns may increase acceptance of android robots. This is especially relevant when integrating the preferred android robotic team assistants with high skill levels in work teams.

Taken together, organizations and practicioners should carefully consider the specific teamwork or taskwork focus of team assistance and weigh the pros and cons of different social robots and technologies. This assessment and decision should be coupled with initiatives to manage employee expectations and experiences, including trainings and informative communication for employees, as well as stable robot programming and operation.

3.6.3 Limitations and Future Work

Team-based contexts are generally characterized by high levels of complexity (Hagemann & Kluge, 2017). In our work, we focused on taskwork and teamwork robotic team assistant skills to create a comprehensive picture of team-based contexts. Specifically, we investigated the interplay between expectations and experiences in an expectation-experience-based model of HRTs. Future research could take into consideration other potentially relevant variables that are influenced by the establishment of HRTs such as team effectiveness (cf. M. Demir et al., 2020). A similar approach can be used for this purpose. As AI-based agents for the role of team assistants, we looked at android and humanoid robots to consider different levels of anthropomorphism (cf. Duffy, 2003). As we found differences in evaluation patterns between the office robots, future work can look at other types of intelligent agents that may be implemented in office contexts, such as avatars (Konecki et al., 2015).

3.6.4 Conclusion

With our research, we establish an expectation-experience-based model for the integration of social robots into HRTs. Specifically, we show that both taskwork and teamwork robotic team assistant skills shape robot acceptance in terms of trust and intention to work with the robot. For teamwork, our results point toward the conclusion that a positive disconfirmation (expectations exceed experiences) and high levels of experiences positively affect acceptance for humanoid and android robots. This relation also holds for taskwork team assistant skills for the humanoid robot. For the android robotic team assistant, a positive disconfirmation leads to less robot acceptance. We consider this downgrading effect in the face of high taskwork robotic skill levels as reactance response toward a threat. A potential mechanism that explains the differences between the two robotic agents are varying levels of anthropomorphism: the android robot expresses more social cues and human-likeness in comparison to the humanoid robotic team assistant.

4 Empirical Study 2: Decisions for Robotic Team Managers[9]

4.1 Introduction

An aging workforce and shortages of skilled workers are challenging many Western economies (McGrath, 2021). In the United States as of May 2023, organizations with 9.8 million job openings were competing to attract only 5.5 million job seekers (U.S. Bureau of Labor Statistics, 2022, 2023). Certain sectors, such as professional and business services – including business management –, have particularly large surpluses of job openings relative to the number of unemployed. These trends, coupled with breakthrough developments in AI, have spurred the introduction of smart technologies, such as social robots, in various work environments (Bezrukova et al., 2023). Social robots are robots that interact with humans in natural ways, using speech, gestures, and facial expressions (Breazeal, 2003). In turn, they can work side-by-side on complex tasks, like inventory management (Bogue, 2019), and support complex decision-making (Agostini et al., 2017). Accordingly, social robots can be "placed in [lower-level] management-like positions" (Young & Cormier, 2014, para. 2).

But when a social robot takes a lower-level management position in a human-only team: How do human team members respond? A team works interdependently on tasks and interacts socially to achieve common goals (Kozlowski & Bell, 2003). A lower-level manager has institutionalized authority over the members of a team and supervises them in achieving their common goals (Anzengruber et al., 2017) by supporting team decisions, assigning tasks, and evaluating team and individual performance (Simonet & Tett, 2013)10.

In this paper, we argue that such tasks can be effectively performed by social robots, for several reasons. First, even at lower organizational levels, managers often have to make complex decisions, spontaneously and under time pressure (J. Thomas & Mengel, 2008). Social robots can facilitate organizational decision-making by handling multiple tasks simultaneously, monitoring different decision criteria and options, and making complex decisions within seconds (Samani & Cheok, 2011).

[9] Based on the conceptual framework published by Wolf and Stock-Homburg (2021) (presented at ICIS 2021, Austin, TX), this study incorporates empirical data from a completely revised manuscript currently under review at the journal *Group and Organization Management*. Compared to the previous conference publication and version of this dissertation, this chapter contains an updated study based on reviewer comments (e.g., regarding sample size) to ensure high quality of research data and results.

[10] In contrast to managers, leaders are focused on motivating, inspiring and developing their followers (Kniffin et al. (2020)). While there is an overlap between management and leadership and they complement each other (Kotter (1990)), they should still be considered separately (Kniffin et al. (2020); Northouse (2015)).

Second, managers need to make fair and effective decisions, even in the face of extreme uncertainty or stress (Finn et al., 2020). Social robots have been shown to make fairer and more effective decisions than humans (L. P. Robert et al., 2020), using their AI capabilities to take human preferences into account (Gombolay, Gutierrez, et al., 2015).

Third, managers need to assess individual and team performance in order to oversee the achievement of goals (Simonet & Tett, 2013). Thanks to their connectedness with human team members (Breazeal, 2003) or organizational structures and systems (Dell Technologies, 2018), social robots can consider comprehensive input as basis for their assessment. Further, social robots have only artificial emotions (Stock-Homburg, 2022) and their observations and decisions are assumed to be unaffected by moods (Chamorro-Premuzic & Ahmetoglu, 2016). Through purposeful programming, robotic managers can evaluate team and individual performance more predictably and transparently and thus more objectively than human managers (N. Wang et al., 2016b). Fourth, recent studies indicate increasing acceptance of robots as lower-level managers. Oracle (2019) found that 64% of 8,370 managers and employees surveyed would trust a robot more than their manager, about half would turn to a robot for advice, and 82% even believe robots can do things better than human managers.

We recognize that many of these aspects still represent untapped potential and that it will be some time before they become an everyday reality. Surprisingly, despite growing importance of robots in work contexts and general agreement on the potential of robotic lower-level managers (Bankins & Formosa, 2020; Griep, 2022), little research has been conducted on the use of robots as managers (Sebo et al., 2020, see Literature Review). However, extant studies suggest that it is not far-fetched to see social robots take on this role.

Current HRI research often takes a “the more the better” view of robot characteristics (Gombolay, Gutierrez, et al., 2015). This is a rather simplistic approach that overlooks the dual nature of advances in AI and robotics, bringing both opportunities and ethical challenges. An example of such a challenge is the potential for unwanted heteronomy. This highlights the risk of over-reliance on automated AI and robotic systems, which could undermine human autonomy and decision-making in critical scenarios (Dietvorst et al., 2018; R. Parasuraman et al., 2000). Human safety is another concern (Arkes et al., 2007). In a collaborative environment, ensur-ing that AI and robotic systems have fail-safes and are designed with safety-first principles is vital to protect team members from physical or psychological harm. Finally, the issue of potential unfairness raises questions about the impartiality of AI and robotic decision-making (Bankins et al., 2022; B. Green & Chen, 2019; M. K. Lee, 2018). In a team context, this could lead to biased task allocation, performance evaluation, and career progression opportunities.

Although our research does not directly address the ethical implications for lower-level managers, it aims to take an initial step towards understanding human responses to robotic lower-level management. This understanding is crucial for facilitating the responsible integration of social robots within organizational structures.

In our approach, we explicitly focus on embodied robots as physical representation of AI (Wolf & Stock-Homburg, 2022) for a number of reasons. First, the embodiment of robots allows to use multiple communication channels and enhance engagement with them (Deng et al., 2019; Groom et al., 2010). Second, robots' physical presence and ability to move within the physical workspace allows for a more tangible and immersive collaboration (You & Robert, 2022a). Third, in contrast to computers or conversational agents, robots' human-like appearance generates a so-called "social presence", which in turn in-creases human acceptance of robotic managers (K. M. Lee et al., 2006). Our first research question is: What mechanisms underlie employees' readiness to work with a robotic lower-level manager?

Research on organizational teams in general (Brummelhuis et al., 2012)and human-robot teams (HRTs) in particular (Hoffman & Breazeal, 2004) recognizes that collaboration depends on performance-related and relational features. Performance-related features include overall contributions to team performance, such as the usefulness of a member's contribution (Sonnentag & Frese, 2002) and in general require more mechanical skills (M. K. Lee, 2018). Relational features instead refer to social aspects, such as employees' enjoyment of working together in a team (Gittell et al., 2006) and require "human" skills (M. K. Lee, 2018). Thus, our second question is: How do performance-related and relational features affect employees' readiness to work with a robotic lower-level manager?

We address these research questions through an experimental vignette online study in which participants were asked to put themselves in the role of an office worker and decide whether they wanted to work with robotic or a human manager in a project team based on videos. We examine whether and how nonlinear relationships emerge from the interplay between employees' expectations of a robotic manager and their actual experiences. In particular, we examine how this interplay affects employees' readiness to work with the robotic manager. We specifically investigate a human-only team in which a social humanoid or android robot takes a lower-level management role.11 A humanoid robot has “a human-like morphology such as a face, arms, and legs” (Mende et al., 2019, p. 535) but is clearly distinct from humans. In contrast, an android robot is designed to be “indistinguishable from humans in its external appearance and behavior” (MacDorman & Ishiguro, 2005, p. 289).

We extend existing research in several important ways. First, we examine the previously unexplored issue of employees’ readiness to work with robotic lower-level managers in an office environment. Shedding light on this topic is important because firms are suffering from a huge shortage of skilled workers not only at the subordinate, but also at the lower manage-ment level. The use of robots at the lower management level could be at least one (out of several) steps for companies to solve this problem. Additionally, we provide insights into how employees’ readiness differs for different types of robots. Second, from a theoretical perspective, we provide insights into the design of HRTs by extending expectation–disconfirmation theory in the context of HRI, examining performance-related and relational features, as indicated by the robot acceptance model (Heerink et al., 2010). In addition, we compare fictional employee-robotic manager interactions with employee-human manager interactions. Third, from a methodological perspective, we extend previous research, which often relies on difference scores, by using polynomial regression analysis and response surface analysis (J. R. Edwards & Parry, 1993). This is important because difference scores cannot fully capture the interplay between employees’ expectations and experiences regarding a robotic lower-level manager. We also provide a new set of test criteria for examining surface scores that can be applied to general IS research, supporting the understanding of employees’ responses to over- and underfulfillment of their expectations by a robotic lower-level manager. Fourth, our findings provide a starting point for robot developers and practitioners seeking to integrate robots into work teams. In particular, in light of the European Commission’s recently published proposal for an Artificial Intelligence Act (Proposal for Regulation 2021/0106, 2021), our research provides valuable insights into the actual application of robots and AI for work in the future.

4.2 Literature Review

Research on HRTs addresses the topic of management in these teams in a number of papers (see Sebo et al., 2020; Tsai et al., 2022 for reviews). However it typically does not focus on robots in the role of managers (Smith & Green, 2018) or considers perspectives other than those

[11] In this study we explicitely focus on robotic lower-level managers. The focus is therefore on processes and operations and less on strategic actions.

of employees (Shanks et al., 2021). In our review, we explicitly include only studies with a team-internal focus in which robots take on the role of manager or leader in a HRT[12] (see Appendix C for additional information). The reviewed literature is structured along two dimensions: management context and number of followers (Figure 4-1). For *management context*, we distinguish between studies set in a knowledge work context and those set in other contexts, such as USAR or manufacturing. Regarding the *number of followers*, we distinguish between studies of dyadic relationships, where the robot has a single follower, and studies of robotic managers interacting with multiple followers.

Conceptual studies tend to be set across contexts. Gladden (2014) describes different archetypes of robotic leaders. Samani and Cheok (2011) conceptually argue that effective robotic leadership involves multitasking abilities, learning, collaboration, and adaptability. In addition, Samani et al. (2012) speculate about areas (e.g., stock trading, transportation) in which robotic managers or leaders leaders might outperform humans. Overall, these studies consistently predict that robotic managers and leaders will evolve naturally in the future.

Studies set in USAR include a study by Kwon et al. (2019) in which the authors develop a mathematical framework to model the behavior of leaders and followers in HRTs. This was addressed and validated by (Li et al., 2021) showing that robots can successfully influence teams to achieve common goals.

Two studies consider dyadic HRTs in the manufacturing context. The results by Messeri et al. (2023) show that when a robot takes the lead in a tower-building task, the human is more productive but also experiences more physiological stress than when the human takes the lead. The study by Noormohammadi-Asl et al. (2022) examines a robot considering human following preferences in an object sorting task, which has been shown to improve team performance. The studies in these two categories show that robotic managers may be useful in various situations.

Three empirical laboratory studies examine management in HRTs at the interface of manufacturing and knowledge work. Castro et al. (2017) found that automated scheduling by a robot in a dyadic HRT enhances team efficiency without compromising human comfort. Gombolay, Gutierrez, et al. (2015) study a human-robot co-led team assembling a LEGO kit, and reveal that participants prefer to assign control authority to the robot leader in task allocation which supports team efficiency. Despite use of the term “leadership”, a closer examination of the study design reveals that the robot has more of a lower-level management

[12] In the literature, the term robotic manager and robotic executive are often used interchangeably. Therefore, we review literature on both robotic managers and robotic leaders.

role, due to its task focus. Another study by Lopes et al. (2021) investigates transactional and transformational leadership styles, finding both to be suitable for robots for collaborative tasks.

Finally, three studies are set in the knowledge work context. Yam et al. (2022) find that anthropomorphism can have negative effects for robots delivering negative feedback on a knowledge task. For creative tasks, Cichor et al. (2023) showed that transformational robotic leadership behaviors positively influence human perceptions and reactions. Lastly, Geiskkovitch et al. (2016) find that people tend to follow robotic orders to continue to work on repetitive tasks even when they may not desire to do so, underscoring the potential influence of robots in work contexts and raising important ethical considerations.

Overall, the literature review shows that robots in the role of managers are on the rise. Furthermore, the studies show that both performance and relational aspects are important in HRTs with robotic managers. The valuable insights about robotic managers and leaders during ongoing teamwork from extant literature are informative, but at the same time reveal gaps regarding employees' readiness to work with a robotic lower-level manager, which we address with our research.

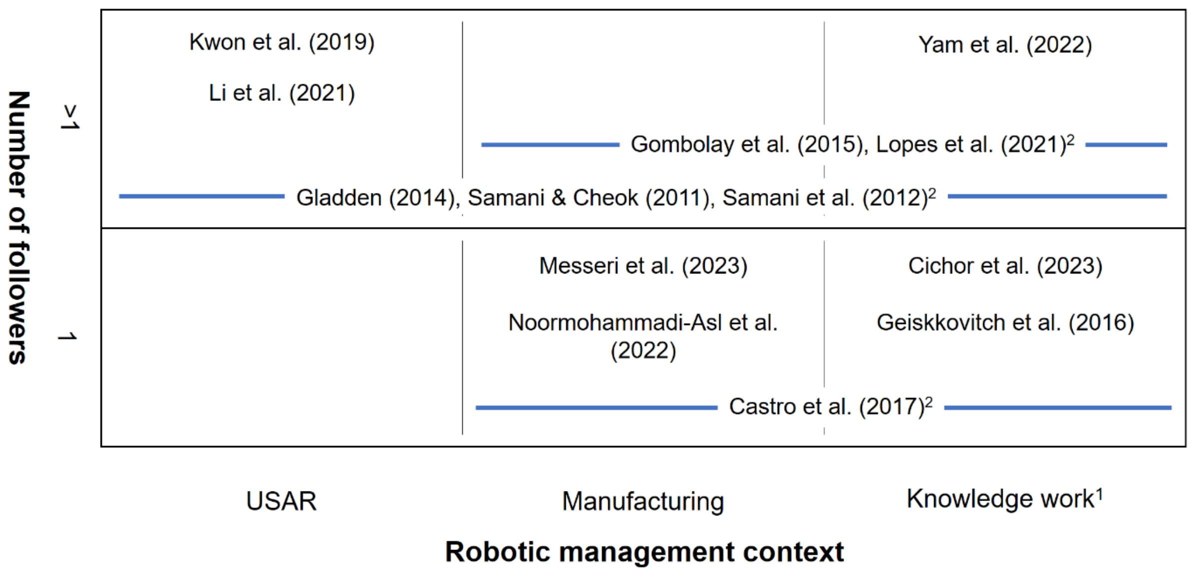


Figure 4-1. Categorization of Studies on Robotic Management Constellations

Notes: 1. Including data base management and sports decision making; 2. Cross-context examination

4.3 Conceptual Background, Study Framework, and Hypotheses

4.3.1 Expectation-Disconfirmation Theory

Expectation–disconfirmation theory (EDT) addresses the interplay between prior expectations and actual experiences (Oliver, 1980; Venkatesh & Goyal, 2010). Expectations are a "set of pre-exposure beliefs" (Venkatesh & Goyal, 2010, p. 283); experiences are actual perceptions and observations of an event (B. Schmitt & Zarantonello, 2013). Their interplay can lead to either confirmation, so that experiences match expectations, or disconfirmation, which reflects a "discrepancy between expectations and actual experiences" (Venkatesh & Goyal, 2010, p. 283).

Expectations, experiences, and their interplay have been addressed in many laboratory studies focusing on HRI (Horstmann & Krämer, 2020; Paepcke & Takayama, 2010). However, we note a tendency to address either expectations or perceptions; in studies investigating their interplay, the reliance on difference scores introduces some shortcomings, including ambiguity (because of dimension reduction by calculating the difference of two scores to produce one score) and reliability issues (J. R. Edwards, 2002). These shortcomings are problematic, in that they leave an unexplained gap in how users react when a robot exceeds or fails to meet their expectations. Researchers therefore suggest a more fine-grained approach to consider expectations and experience separately using polynomial regression and response surface analysis (J. R. Edwards & Parry, 1993). In this way, models with different levels of complexity can be investigated (see Method section).

4.3.2 Study Framework

Figure 4-2 depicts our study framework, which includes two paths of performance-related and relational evaluation. Following Venkatesh and Goyal (2010), we combine the Technology Acceptance Model (TAM; Davis, 1989; Davis et al., 1989) and EDT (Oliver, 1980). We rely on the TAM to extract relevant features of the robotic lower-level manager for employees' expectations and experiences, which we include as independent variables. The well-established TAM has been widely used (e.g., Hess et al., 2014), including in robotics research and as a basis for developing new HRI models (Heerink et al., 2010) or human–robot collaborations (Bröhl et al., 2019). Researchers also have empirically examined robot acceptance using the TAM as a theoretical foundation (e.g., You & Robert, 2018a). To evaluate the first independent variables of performance-related robotic features, we investigate employee expectations and experiences of the usefulness of robotic lower-level managers. Theoretically, our basic assumptions are rooted in met expectations hypothesis and equity theory (Adams, 1963; Porter & Steers, 1973; Path 1). Consistent with the TAM, we define the usefulness of a robotic lower-level manager as the extent to which employees believe that working with a robotic lower-level manager will improve their job performance (Davis et al., 1989). As our second independent variables, we examine the relational features of robotic managers. We conceptualize these features as social, not task-related aspects of teamwork, such as employees' enjoyment of working with the robot in a team (Gittell et al., 2006). Specifically, we focus on employees' expected and experienced attitudes toward robotic lower-level managers. Our conceptual basis is the theory of reasoned action (Fishbein & Ajzen, 1975; Path 2). Attitudes reflect employees' positive or negative feelings or enjoyment of working with a robotic lower-level manager (Venkatesh & Goyal, 2010).[13] The expectation–disconfirmation outcomes of the expectation-experience comparison should determine employees' readiness to work with a robotic lower-level manager. This readiness is our dependent variable for both pathways investigated (Figure 4-2). Readiness to work with a robotic lower-level manager refers to employees' willingness to work with a robotic lower-level manager to achieve work goals (A. Parasuraman, 2000). It reflects acceptance of the robotic lower-level manager. We also include the behavioral variable of robot selection to assess robot acceptance.

We expect some potential moderating effects that affect the relationship between the independent and dependent variables (Baron & Kenny, 1986). Thus, we examine two different types of robots in the lower-level management role: an android and a humanoid robot. We further control for human–human interactions by investigating a human lower-level manager and employees' prior experiences with robots and technology affinity

[13] We exclude the TAM dimension of *ease of use* because it is unlikely that employees expect to avoid effort when working for a manager. Instead, they are likely to seek to exert substantial effort in the pursuit of common goals (Northouse (2015)).

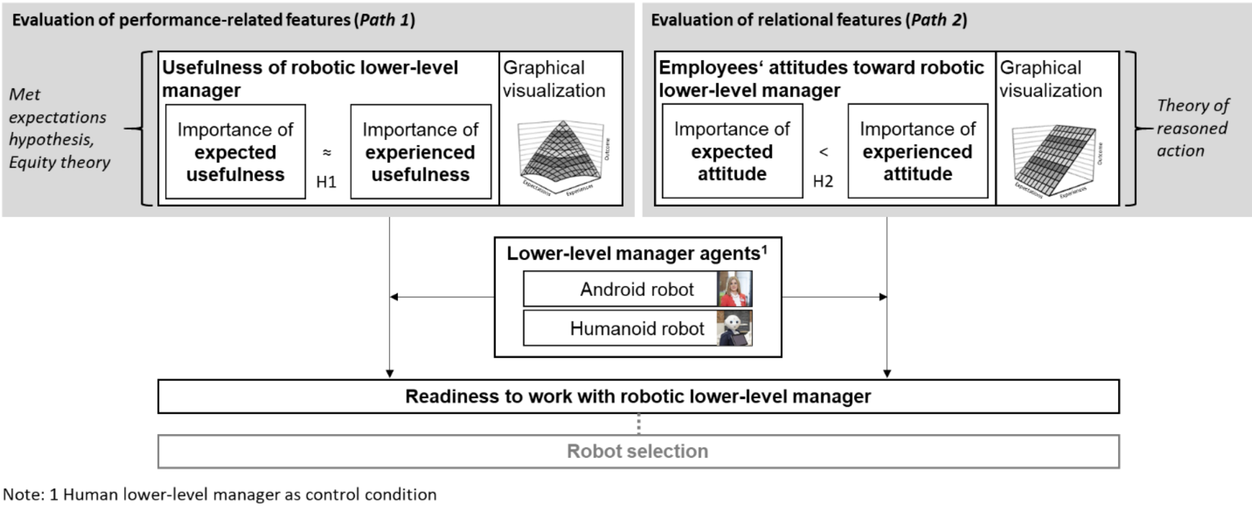


Figure 4-2. Study Framework

4.3.3 Hypotheses

The first hypothesis concerns the interplay between expectations and experiences of the performance-related feature usefulness. The effects of this interplay on employees' readiness to work with a robotic lower-level manager (path 1 of the study framework, see Figure 4-2) are predicted with a three-dimensional surface.

We predict an inverted U-shaped model in which confirmation (experiences meeting expectations) leads to the highest readiness to work with a robotic manager (see S. A. Brown et al., 2014). This is consistent with the notion of the met expectations hypothesis (Porter & Steers, 1973). Specifically, met expectations (i.e., *confirmation* between expectations and experiences) are associated with the highest readiness to work with a robotic manager. This confirmation represents the center of the predicted surface (see Figure 4-2).

At the center of the surface, readiness to work with a robotic manager increases with the level of confirmation, i.e., the absolute value of expectations and experiences, resulting in an ascending ridge. This is consistent with the social psychology literature, which predicts also the level of the independent variables is important (Humberg et al., 2020). In other words, when employees' expectations are met at a low level, they are associated with a lower readiness to work with the robotic manager than when they are met at a high level. When expectations are not met by experiences, *negative disconfirmation* occurs. Employees' readiness to work with a robotic manager is low. When expectations are exceeded by experiences, *positive* *disconfirmation* occurs. According to equity theory (Adams, 1963), positive disconfirmation decreases em-ployees' readiness to work with a robotic manager. This is because positive disconfirmation leads to psychological tension due to discrepancies between expectations and experiences.

This effect is also plausible given the current discussion about robots in our society. On the one hand, employees want to work with robots that meet certain performance standards (i.e., meet expectations). However, if a robot is "too good," employees may fear that the robot will not only excel at its own job, but also take their jobs. For example, prior literature shows that employees from different occupational backgrounds fear robots entering the workplace (Turja & Oksanen, 2019).

In summary, we expect an inverted U-shaped curvilinear surface with the highest readiness to work with a robotic manager at the peak in the middle of the surface. As negative disconfirmation increases, the "surface goes down" and employees' readiness to work with a robotic manager will decrease. Similarly, with positive disconfirmation the surface goes down again. Positive disconfirmation again leads to dissatisfaction, so employees' readiness to work with the robotic manager decreases. We therefore hypothesize

> *H1: For robotic lower-level managers, the relationship between expectations and experiences of the* ***performance-related feature usefulness*** *and employees' readiness to work with the manager follows a* ***curvilinear inverted U-shaped surface****.*

In contrast, for the relational feature of employee attitudes (path 2 of the study framework, see Figure 4-2), due to the different nature of the interactions, we expect a three-dimensional surface that is strongly focused on experiences. In other words, the better the experiences, the higher employees' readiness to work with a robotic manager.

We argue that for relational features, experiences are the dominant source of employees' readiness to work with a robotic manager for several reasons. First, relational features are more difficult to capture than performance-related features. Performance-related features focus on the handling and completion of a task, which is usually specified in advance. This allows for some "baseline" of expectations for these features. Relational features, in contrast, focus on feelings toward another entity with which an employee inter-acts. Social robots are not yet commonplace in organizations (World Economic Forum, 2020b) and robot presentations often focus on performance-related features. Therefore, expectations for relational features are less pronounced than expectations for performance-related features (Horstmann & Krämer, 2019).

Second, according to the theory of reasoned action (Fishbein & Ajzen, 1975), attitudes are determined by a person's salient beliefs, which are in turn determined by experiences. Prior literature also confirms that attitudes based on direct experience strongly affect subsequent evaluations and behavior (Fazio et al., 1978).

Third, given the current discussion about robots in our society, positive disconfirmation of relational features may lead to positive surprises in the form of unexpected "harmony", acceptance and rapport during the human-robot interactions (Cao et al., 2021; Oracle, 2019; Stafford et al., 2014).

Taken together, we expect that the interplay between employees' expectations and experiences of attitudes toward a robotic manager and the effects on employees' readiness to work with the manager will be experience-based. Specifically, increasing experience will be associated with greater readiness to work with the robotic manager. Thus, we hypothesize

> *H2: The relationship between employees' expectations and experiences of the* ***relational feature attitude*** *toward the robotic manager and employees' readiness to work with the robot follows a* ***linear experience-based surface****.*

Hereby, experience have a greater impact on employees' readiness to work with the robot than expectations. By testing these hypotheses, we aim to gain insight into the mechanisms underlying employees' acceptance of robotic lower-level manager (RQ1) and whether differences emerge between evaluations of performance-related versus relational features (RQ2).

4.4 Experimental Online Study

4.4.1 Experimental Vignette and Setup

Our online study, conducted using Amazon Mechanical Turk (MTurk), uses an experimental vignette methodology and questionnaire (Aguinis & Bradley, 2014; Atzmüller & Steiner, 2010; see Appendix D for the rationale). The vignette for our online study asked participants to imagine that they worked for an international company and had just finished their last work project. They were asked to imagine that they were looking for their next project to work on. They were also asked to chose between three project teams with either an android robot, a humanoid robot, or a human as team manager. The three teams were otherwise described in exactly the same way. The vignette provided basic information about the role and responsibilities of a team manager. These tasks include assigning of tasks to team members, evaluating performance, and sharing information. The vignette also explained that the decision should be based on observations of a team discussion involving one of the robots or a human manager. We developed the vignette using publicly available job descriptions for lower-level managers and practical and scientific literature (Anzengruber et al., 2017; Simonet & Tett, 2013) and pretested and discussed it with seven scientists for refinement.

In the study, the participants were first asked about their expectations of working with a robotic leader before they watched short videos (duration of 39 resp. 44 seconds) of a team with a robotic or human lower-level manager as a proxy for actual interactions. After this, participants rated their post-experience perceptions. The team discussions shown in the video center around current tasks and deadlines, and the need to schedule a new meeting. Their presentations depict a conventional corporate office meeting room (see Figure 4-3), with a large conference table, laptops, documents, pens, coffee cups, and a flipchart.

The android robot closely resembles a woman with light skin, blonde hair, and blue eyes; the humanoid robot is a Pepper model (SoftBank Robotics, 2020). Both were equipped with an AI-based chatbot and followed the same script exhibiting the same competences. In the control condition, the human wore business attire similar to the android robot. To ensure comparability of the results, we used a within-subject design, such that each participant watched videos of both the robots and the human (in randomized order) and answered questions related to all three.

a. Android Robot as lower-level manager

b. Humanoid robot as lower-level manager

Figure 4-3. Video Setups in the Online Study

4.4.2 Measures

Measurement scales for our main constructs were drawn from extant literature whenever possible. We measure expected and experienced usefulness (S. A. Brown et al., 2014) and employees' expected and experienced attitudes (Venkatesh & Goyal, 2010). The usefulness scale includes items related to improving the quality of work or making it easier to do one's job. Items in the attitude scale include, for example, whether it is fun to work with the manager agent or whether the agent makes work more interesting. To measure employees' readiness to work with a robotic lower-level manager, we developed a new single-item scale. We meas-ured participants' choice of the lower-level manager in two ways using pairwise comparisons and an absolute ranking. The measure for social categorization of the three agents to gain additional insights into their impressions is adapted from Homburg et al. (2009). Scales and items are listed in Table 4-1.

A reliability analysis, using Cronbach's alpha (Cronbach, 1951) shows that the measures exceed the threshold of 0.7. The average variance extracted values also attain the threshold value of 0.5 and the Fornell-Larcker criterion (Fornell & Larcker, 1981) is met. A power analysis of the increase in the explained variance (R^2) as one of the main decision factors to determine the regression model used for the RSA using G*Power 3.1 (Faul et al., 2009) showed adequate power (Cohen, 1988).

4.4.3 Sample

We conducted the study in fall 2022 over a time period of $\sim$ 4 weeks. The study invitation was sent to people currently working on Amazon MTurk who had achieved an approval rate of more than 95% (Peer et al., 2014) and were located in the United States. They received monetary compensation for their participation to compensate them for their time. Informed consent was obtained before beginning the study and study participation was volun-tary. A total of 8,764 U.S. participants participated and completed the questionnaire. After exclusion of unfit participants, 7,061 valid participants remained (see Appendix E). Their average age was 35.62 years (SD = 11.31) and 49.9% were male (49.8% female, 0.3% diverse). We collected information about the participants' previous experience with robots, which indicated an average experience of 7.21 (SD = 2.52) on a 10-point scale. Participants' technology affinity, as their propensity to actively engage in intensive interactions with technology (Lezhnina & Kismihók, 2020) was rated an average 5.36 (SD = 1.04) on a 7-point scale.

Using analysis of variance (ANOVA), with a least significant difference (LSD) post hoc analysis and t-tests, we confirm that the manipulation control worked as intended. Participants could clearly identify ($p < 0.05$) which agents were robotic lower-level managers ($M_{AR\ (android)} = 5.85, SD = 1.21$; $M_{HR\ (humanoid)} = 5.93, SD = 1.17$; $M_{Hu\ (human)} = 4.12, SD = 2.23$). T-tests relative to the midpoint of the scale also confirm that participants recognized that the agents had management responsibility ($M_{AR} = 5.65, SD = 1.19, \Delta M = 1.65,\ t(7060) = 116.188, p < 0.01$; $M_{HR} = 5.64,\ SD = 1.22,\ \Delta M = 1.64,\ t(7060) = 113.134, p < 0.01$; $M_{Hu} = 5.83, SD = 1.12, \Delta M = 1.83,\ t(7060) = 136.605, p < 0.01$). Participants further perceived the scenario as realistic for all agents ($M_{AR} = 5.29, SD = 1.61, \Delta M = 1.29, t(7060) = 67.169, p < 0.01$; $M_{HR} = 5.23,\ SD = 1.65, \Delta M = 1.23, t(7060) = 62.545, p < 0.01$; $M_{Hu} = 5.89, SD = 1.13, \Delta M = 1.89,$ $t(7060) = 140.444, p < 0.01$), as confirmed by t-tests relative to the midpoint of the scale..

Table 4-1. Scales

Manipulation Check and Control Variables	
Manipulation check for the type of the lower-level manager and its role (newly developed)	*In the video above, the <agent> at hand…* • *…is a robot.* • *…has management responsibility.*
Manipulation check for realism of the scenario (newly developed)	*Above scenario is… ((1) "…not realistic at all" to (7) "…as realistic as possible")*
Control variable "previous experience with robots" (newly developed)	*Experience with robots ((1) "I have no experience at all" to (10) "I have very much experience")*
Control variable "technology affinity" (adapted from Lezhnina and Kismihók (2020)), anchored by (1) "absolutely not" and (7) "absolutely"	• *I like to occupy myself in greater detail with technical systems.* • *I like testing the functions of new technical systems.* • *When I have a new technical system in front of me, I try it out intensively.* • *I enjoy spending time becoming acquainted with a new technical system.* • *I try to understand how a technical system exactly works.*

	• *I try to make full use of the capabilities of a technical system.*
Independent Variables	
Usefulness expectations (adapted from Brown et al. (2014))	*I expect that <agent> will …* • *… enable me to accomplish tasks more quickly.* • *… improve the quality of the work I do.* • *… make it easier to do my job.* • *… enhance my effectiveness on the job.* • *… give me greater control over my job.* • *… improve my productivity.*
Attitude expectations (adapted from Venkatesh and Goyal (2010))	• *Using <agent> will be a good idea.* • *<Agent> will make work more interesting.* • *Working with <agent> will be fun.* • *I expect that I like working with <agent>.*
The experiences items parallel the expectations items but have been slightly reworded to reflect the past-oriented nature (after the video-based interaction) of these items.	
Dependent Variable	
Readiness to work with the robotic lower-level manager (newly developed)	*Readiness to work with <agent> ((0) "not at all" to (100) "absolutely sure")*
Supplemental Analyses	
Pairwise comparison (newly developed)	*Please indicate who you prefer as a team manager for each pairing by dragging the slider to the respective robot/human that you prefer for each pairing below. (each pairwise comparison anchored by (1) <agent shown on left> to (7) <agent shown on right>)*
Absolute ranking (newly developed)	*Drag and drop the most preferred robot/human for the position of the team manager to the top, and the least*

	preferred robot/human for the position of the team manager to the bottom. (ranking positions (1) "most preferred" to (3) "least preferred")
Social categorization (adapted from Homburg et al. (2009))	• *This <agent> is part of my social group.* • *I strongly identify with this <agent>.* • *I feel good to be working with this <agent>.* • *I would like to tell that I am working with this <agent>.* • *This <agent> fits well to me.* • *I feel attached to this <agent>.*

Note: All items were measured using a 7-point Likert scale, anchored by (1) "totally disagree" and (7) "totally agree", unless noted otherwise.

4.5 Data Analysis and Results

4.5.1 Method and Data Preparation

To test our hypotheses regarding the effects of (dis-)confirmed expectations about the performance-related robotic feature of usefulness and the relational robotic features of employees' attitudes on readiness to work with robotic lower-level managers, we employ a polynomial regression analysis and response surface analysis (RSA), as described by J. R. Edwards and Parry (1993) and adapted by S. A. Brown et al. (2014). This approach is superior to difference scores (J. R. Edwards, 2002) in several important ways (see Appendix F).

To reduce multicollinearity, we center the independent variables, expected and experienced usefulness of the robotic lower-level manager and employees' expected and experienced attitudes toward the robotic lower-level manager, around their scale center (J. R. Edwards, 1994; J. R. Edwards & Parry, 1993). The results of the Durbin-Watson test (Durbin & Watson, 1951) indicate that our data do not suffer from autocorrelation problems.

We performed hierarchical regression analyses up to the third order to identify the best order for the regression model based on the central criterion that the next highest evaluated order does not provide a significant increase in explained variance (R2). After determining the best order, we analyzed the regression results of this order in more detail and performed an RSA of the surface defined by the regression results. A detailed description of the methodological background can be found in Appendix F.

4.5.2 Usefulness

For the android robotic lower-level manager, we determine that a third-order regression model is most suitable ($R^2 = .483$, adjusted $R^2 = .483$, $\Delta R^2 = .002$, $p < 0.01$; $F(11,7049) = 599.476$, $p < 0.01$). This model is represented by

$$Z = 55.923 + 13.874\, U_1 + 1.317\, U_2 - 0.953\, U_1^2 + 0.212\, U_1 U_2 - 0.141\, U_2^2 - 0.420\, U_1^3 + 0.114\, U_1^2 U_2 - 0.128\, U_1 U_2^2 + 0.081\, U_2^3, \quad (1)$$

with Z = readiness to work with the robotic lower-level manager, U_1 = experienced usefulness, and U_2 = expected usefulness. We find a high goodness-of-fit (Cohen, 1988).

To test for the hypothesized curvilinear inverted U-shape of the surface, we performed the tests for the generalized-negativity model proposed by S. A. Brown et al. (2014), which follows a perfect and symmetrical inverted U-shape. The results of these tests, together with the examination of the response surface indicate that the tests are partially satisfied and the response surface follows a shifted, S-shaped curve (see Figure 4-4a and Table F2 in Appendix F): The highest local outcome values are not along the line of perfect confirmation (where $U_1 = U_2$), but shifted to the right into the area of positive disconfirmation (where $U_1 > U_2$).

To allow the further investigation of the response surface, we define a new set of test criteria for the S-shaped curve (see Table 4-2 and details in Table F3 in Appendix F). These tests show that experience has a greater influence on the outcome than expectations ($13.874 = b_1 > b_2 = 1.317, p < 0.01$) and that at least one cubic coefficient is significantly different from zero ($|b_6| = 0.420$, $p < 0.05$). The surface has a positive linear slope along the line of perfect confirmation for $U_1 = 0$ ($a_{x,0} = 15.191, p < 0.01$), which is consistent with other models. The corresponding quadratic slope is significantly negative ($a_{x,0}^2 = -0.882, p < 0.01$). Along the line of perfect disconfirmation, the response surface has a positive slope for $U_1 = 0$ ($a_{y,0} = 12.556$, $p < 0.01$) and a (though statistically not significant) negative slope for $U_1 = 3$ ($a_{y,3} = -15.361, n.s.$). The surface also has a negative quadratic ($a_{y,0}^2 = -1.306, p < 0.05$) and cubic ($a_{y,0}^3 = -0.744, p < 0.05$) slope along the line of perfect disconfirmation in $U_1 = 0$ and the absolute value of the slope for negative disconfirmation ($|a_{y,\text{neg. disc.}}| = 9.778$) is greater ($p < 0.05$) than the absolute value of the slope for positive disconfirmation ($|a_{y,\text{pos. disc.}}| = 1.945$), defining its characteristic S-shape.

For the humanoid robotic lower-level manager, analogous to the android robotic manager, a third-order regression model with expected and experienced usefulness as independent variables is most appropriate ($R^2 = .488$, adjusted $R^2 = .487$, $\Delta R^2 = .003$, $p < 0.01$; $F(11{,}7049) = 611.013$, $p < 0.01$). The model is

$$Z = 55.366 + 13.589\,U_1 + 2.350\,U_2 - 1.127\,U_1^2 + 1.461\,U_1U_2 - 1.163\,U_2^2 - 0.398\,U_1^3 + 0.013\,U_1^2U_2 - 0.162\,U_1U_2^2 + 0.109\,U_2^3, \tag{2}$$

with variables defined as in equation (1).

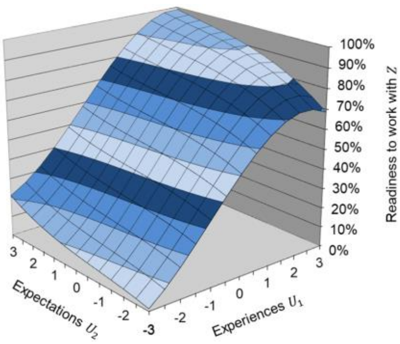
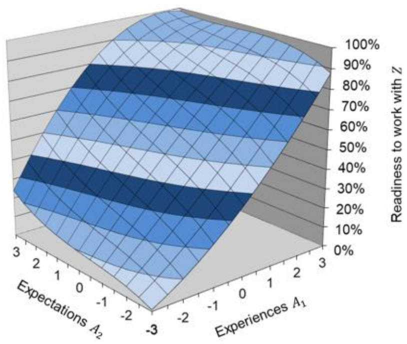
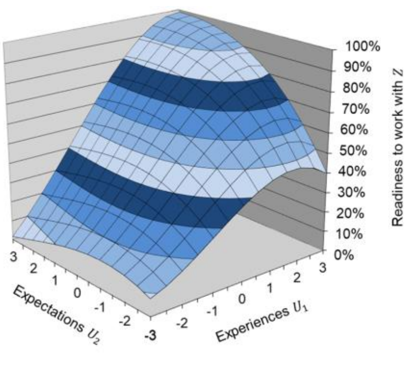
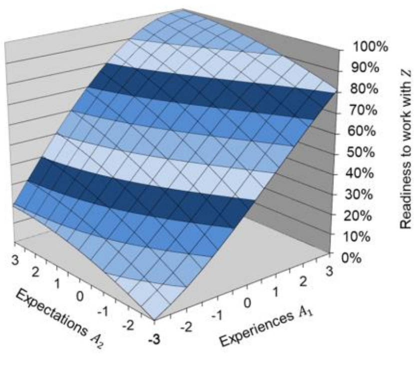
<table>
<tr><th></th><th>Performance-related robotic feature (usefulness)</th><th>Relational robotic feature (attitude)</th></tr>
<tr><td>Android robotic lower-level manager</td><td>a.

</td><td>b.

</td></tr>
<tr><td>Humanoid robotic lower-level manager</td><td>c.

</td><td>d.

</td></tr>
</table>

Figure 4-4. Three-Dimensional Response Surfaces for Different Robotic Agents as Lower-Level Managers

The tests of the proposed inverted U-shaped model and the investigation of the response surface again show that the tests of the generalized-negativity model are partially satisfied and the results follow a shifted, S-shaped surface with highest result values for positive disconfirmation (see Figure 4-4c and Table F2 in Appendix F). Using the test criteria for the S-shaped curve (see

Table 4-2 and in detail Table F3 in Appendix F), we can see that at least one cubic coefficient is significantly different from zero ($|b_6| = 0.398$, $p < 0.01$). Experience has a greater influence on the outcome than expectations ($13.589 = b_1 > b_2 = 2.350, p < 0.01$) and the surface has a positive linear slope along the line of perfect confirmation for $U_1 = 0$ ($a_{x,0} = 15.940, p < 0.01$). The corresponding quadratic slope is significantly negative ($a_{x,0}^2 = -0.828, p < 0.01$). The response surface has a positive slope for $U_1 = 0$ ($a_{y,0} = 11.239$, $p < 0.01$) and a negative slope for $U_1 = 3$ ($a_{y,3} = -29.666$, $p < 0.01$) along the line of perfect disconfirmation. The surface has a negative quadratic ($a_{y,0}^2 = -3.751, p < 0.01$) and cubic ($a_{y,0}^3 = -0.681, p < 0.05$) slope along the line of perfect disconfirmation in $U_1 = 0$ and the absolute value of the slope for negative disconfirmation ($|\mathrm{a}_{\mathrm{y,neg.\,disc.}}| = 16.360$) is greater ($p < 0.05$) than the absolute value of the slope for positive disconfirmation ($|\mathrm{a}_{\mathrm{y,pos.\,disc.}}| = 6.147$).

Table 4-2. Results of Test Criteria for S-curve

Test criteria	**Results for android robot**	**Results for humanoid robot**
1) $b_1 > b_2$	Supported	Supported
2) $a_{x,0} > 0, a_{y,0} > 0$	Supported	Supported
3) $|b_6|$, $|b_7|$, $|b_8|$, $or\ |b_9| > 0$	Supported	Supported
4) $a_{y,0}^3 < 0$	Supported	Supported
5) $a_{x,0}^2 < 0$	Supported	Supported
6) $a_{y,0}^2 < 0$	Supported	Supported
7) $|\mathrm{a}_{\mathrm{y,neg.\,disc.}}| > |\mathrm{a}_{\mathrm{y,pos.\,disc.}}|$	Supported	Supported
8) $a_{y,3} < 0$	Tends to be supported	Supported

4.5.3 Attitude

For the android robotic lower-level manager, the results of the regression analysis indicate that a third-order model is best suited for employees' expected and experienced attitudes as independent variables ($R^2 = .537$, adjusted $R^2 = .536$, $\Delta R^2 = .003$, $p < 0.01$; $F(11, 7049) = 743.591$, $p < 0.01$). For this model,

$$Z = 56.300 + 11.606\, A_1 + 4.836\, A_2 - 0.622\, A_1^2 - 0.273 A_1 A_2 - 0.061\, A_2^2 - 0.023\, A_1^3 - 0.462\, A_1^2 A_2 - 0.101\, A_1 A_2^2 + 0.168\, A_2^3, \quad (3)$$

with Z = readiness to work with the robotic lower-level manager, A_1 = employees' experienced attitude, and A_2 = employees' expected attitude, we find high goodness-of-fit (Cohen, 1988).

In tests of the proposed linear surface focused on experience, consistent with the experiences-only model proposed by (S. A. Brown et al., 2014), we find that the response surface only partially supports this hypothesized model and does not follow a linear shape (see Figure 4-4b and Table F4 in Appendix F). Instead, while the outcome is dominated by experiences, we find that the surface follows a curvilinear shape with degressive outcome values for increasing expectations and experiences.

Thus, we define a new set of test criteria for examining the degressive response surface (see Table 4-3 and, for details, Table F5 in Appendix F). At least one cubic coefficient is significantly different from zero ($|b_7| = 0.462$, $p < 0.01$). The linear slopes along both lines of interest are positive ($a_{x,0} = 16.443, p < 0.01$; $a_{y,0} = 6.770\ , p < 0.01$) and the slope along the line of perfect confirmation is greater than the slope along the line of perfect disconfirmation ($p < 0.01$). The surface also has a negative quadratic slope at $U_1 = 0$ along the line of perfect confirmation ($a_{x,0}^2 = -0.956, p < 0.01$) and (although not statistically significant) along the line of perfect disconfirmation ($a_{y,0}^2 = -0.409, n.s.$). The cubic slope along the line of perfect disconfirmation at $U_1 = 0$ is not statistically significant ($a_{y,0}^3 = 0.170, n.s.$). Finally, the slope for both maximum confirmation ($a_{x,3} = -0.562, n.s.$) and maximum disconfirmation ($a_{y,3} = 8.893, n.s.$) along the respective line of interest are not significantly different from zero, defining the degressive shape of the surface.

In terms of employees' expected and experienced attitudes toward the humanoid robotic manager, a third-order model is most appropriate ($R^2 = .537$, adjusted $R^2 = .536$, $\Delta R^2 = .003$, $p < 0.01$; $F(11, 7049) = 742.044$, $p < 0.01$). This model is represented by

$$\mathrm{Z} = 55.759 + 11.349\, \mathrm{A}_1 + 5.206\, \mathrm{A}_2 - 0.587\, A_1^2 - 0.017\, A_1 A_2 - 0.338\, A_2^2 - 0.127\, A_1^3 - 0.310\, A_1^2 A_2 + 0.017\, A_1 A_2^2 - 0.008\, A_2^3, \quad (4)$$

and variables defined as in equation (3). It provides high goodness-of-fit (Cohen, 1988).

The corresponding response surface partially supports the test criteria of the hypothesized experience-only model. While it is dominated by experience, it follows a curvilinear shape that has degressive outcome values for increasing expectations and experience (see Figure 4-4d and Table F4 in Appendix F).

Table 4-3. Results of Test Criteria for Degressive Curve

Test criteria	Results for android robot	Results for humanoid robot
1) $a_{x,0} > a_{y,0}$	Supported	Supported
2) $a_{x,0} > 0, a_{y,0} > 0$	Supported	Supported
3) $\|b_6\|, \|b_7\|, \|b_8\|, or \|b_9\| > 0$	Supported	Supported
4) $a^3_{y,0} = 0$	Supported	Supported
5) $a^2_{x,0} < 0$	Supported	Supported
6) $a^2_{y,0} < 0$	Tends to be supported	Supported
7) $a_{x,3} = 0$	Supported	Supported
8) $a_{y,3} = 0$	Supported	Supported

The test criteria for the degressive curve model (see Table 4-3 and, for details, Table F5 in Appendix F) again show that a cubic coefficient is significantly different from zero ($|b_7| = 0.310$, $p < 0.05$). The linear slopes along both lines of interest are positive ($a_{x,0} = 16.555, p < 0.01$; $a_{y,0} = 6.143\ , p < 0.01$). The slope along the line of perfect confirmation is greater than the slope along the line of perfect disconfirmation ($p < 0.01$). The surface has a negative quadratic slope in $U_1 = 0$ along the line of perfect confirmation ($a^2_{x,0} = -0.942, p < 0.01$) and along the line of perfect disconfirmation ($a^2_{y,0} = -0.909, p < 0.05$). The cubic slope in $U_1 = 0$ is not statistically significant along the line of perfect disconfirmation ($a^3_{y,0} = 0.208, n.s.$). Finally, the slope for both maximum confirmation ($a_{x,3} = -0.648, n.s.$) and maximum disconfirmation ($a_{y,3} = 6.310, n.s.$) along the respective line of interest are not significantly different from zero.

4.5.4 Exploratory Supplemental Analyses: Overall Acceptance of Robotic Manager

Complementing our main analyses, results for the human lower-level manager can be found in Appendix G. We further analyzed potential gender differences in participants' readi-ness to work with robotic lower-level managers. Results showed that response surfaces for male and female participants follow the shapes of the response surfaces for the whole sample. A qualitative difference is observable for the performance-related feature of usefulness for the android robot. For this, the response surface for the female participants showed a less pronounced decline for increasing positive disconfirmation as compared to the response surface for the male participants (see Appendix H for additional details).

We further look into the social categorization of the different agents. An ANOVA with a LSD post hoc analysis shows that the android robotic lower-level manager ($M_{android\ robot} = 4.76$, $SD = 1.64$) and the humanoid robotic lower-level manager ($M_{humanoid\ robot} = 4.75, SD = 1.63$) score the same ($\Delta M_{android\ robot,humanoid\ robot} = 0.01, n.s.$) when it comes to their social categorization. Compared with both robotic managers, the human lower-level manager ($M_{human} = 5.46, SD = 1.05$) scores significantly ($\Delta M_{human,android\ robot} = 0.69, p < 0.01, \Delta M_{human,humanoid\ robot} = 0.71, p < 0.01$) higher in terms of social categorization.

We consider several different proxies for the acceptance of a robotic lower-level manager, relative to a human lower-level manager. A correlation analysis (see Figure 4-3) indicates a weak, positive correlation between employees' readiness to work with the android or the humanoid robotic manager and their absolute ranking of the selection of this robot ($r_{android\ robot} = .29, p < 0.01$; $r_{humanoid\ robot} = .17, p < 0.01$). For the human manager, we find a weaker significant positive correlation ($r_{human} = .09, p < 0.01$).

In a pairwise comparison, t-tests relative to the midpoint of the scale show that participants prefer the human lower-level manager over both robotic lower-level manager. Specifically, in the comparison between the humanoid robot (1) and the human (7), they provide a score of $M = 5.33, SD = 1.89$ ($\Delta M = 1.33, t(7060) = 59.368, p < 0.01$), and for the comparison between the android robot (1) and human (7), $M = 5.32, SD = 1.89$ ($\Delta M = 1.32, t(7060) = 58.871, p < 0.01$). Participants also prefer the android robotic manager over the humanoid robotic manager, $M = 4.66, SD = 2.06$ ($\Delta M = 0.466, t(7060) = 27.036, p < 0.01$). Thus, we identify a descending order of preference: human lower-level manager, then android robotic lower-level manager, and finally humanoid robotic lower-level manager.

In the absolute ranking of the lower-level managers, participants ranked them in three positions, from (1) most preferred to (3) least preferred; we inverted the rankings so that a higher value corresponds to a better rank. Consistent with the pairwise comparison, an ANOVA with a LSD post hoc analysis shows that the human manager ($M_{human} = 2.40, SD = 0.83$) is preferred over the android robotic manager ($M_{android\ robot} = 1.86, SD = 0.70, \Delta M_{human,android\ robot} = 0.54, p < 0.01$) and the humanoid robotic manager ($M_{humanoid\ robot} = 1.75,\ SD = 0.76, \Delta M_{human,humanoid\ robot} = 0.65, p < 0.01$); furthermore, the android robotic manager is preferred over the humanoid one

$(\Delta M_{android\ robot,humanoid\ robot} = 0.11, p < 0.01)$. Thus, we get the same descending order of preference with the absolute ranking.

4.6 Discussion

4.6.1 Research Implications

Starting point for this study was the question of the potential for robots to contribute to solving the shortage of skilled workers and lower-level managers in companies. Extant studies on human acceptance of robotic team assistants (for a review, see Wolf & Stock-Homburg, 2022) hint that people seem willing to integrate robots as assistants in their office environments. Moreover, the acceptance of robots has increased over time (Savela et al., 2018; Turja & Oksanen, 2019). However, to move beyond an initial understanding of human responses to robotic team assistants (Heerink et al., 2010), we advance to the next level of robotic integration: robots in supervisory roles, as lower-level managers who can assign tasks, facilitate organizational decisions, and so on (Simonet & Tett, 2013). By exploring the theoretically and practically relevant question of whether employees will accept social robots as lower-level managers, our study contributes to existing research in several ways.

4.6.2 Research into Robots as Lower-level Managers

To our knowledge, our study is among the first to examine robots as lower-level managers in an office environment. Our online experiment includes two types of robots, an android and a humanoid robot. We distinguish between the performance-related feature of employees' expected and experienced usefulness of a robotic manager and the relational feature of expected and experienced attitudes toward a robotic manager.

In terms of the *performance-related feature* of usefulness, the acceptance of the android and humanoid robotic lower-level manager follows an S-shaped pattern. We distinguish three parts of the surface to reflect differences in employees' expectations and experiences with a robotic lower-level manager. Starting on the left side of the surface in the area of negative disconfirmation, where employees' expectations are not met by their experiences, we find an increase in readiness to work with the manager as expectations and experiences increase. This increase continues through the middle of the surface, where experiences meet expectations, into positive disconfirmation, where experiences exceed employees' expectations. Up to this point, employees' readiness to work with the robotic manager increases steadily with decreasing margins. The second part of the resulting response surface is a ridge in the area of positive disconfirmation. Beyond this ridge, however, in the third part of the surface, we observe a decrease in employees' readiness to work with the robotic manager. These findings can be explained through prospect theory (Kahneman & Tversky, 1979) and the too-much-of-a-good-thing effect (Pierce & Aguinis, 2013). Prospect theory postulates that negative effects of losses (in this study: negative disconfirmation) are stronger than positive effects of gains (in this study: positive disconfirmation). This explains the shape of the surface in its left part up to the ridge in the area of positive disconfirmation - for slightly exceeded expectations of the robot's usefulness, there is still an increasing readiness to work with the robot. According to the too-much-of-a-good-thing effect, an initially positive relationship can turn negative if the underlying antecedent "is taken too far, such that the overall relation becomes nonmonotonic" (Busse et al., 2016, p. 131). In our study, this explains the shape of the right part of the surface. If expectations of the robot's usefulness are exceeded too much by experiences, readiness to work with the robot decreases. Thus, a slight positive disconfirmation is desirable, with respect to employees' expectations and experiences of the usefulness of both an android and humanoid robotic manager. The robustness of these results was confirmed by stability tests conducted on a subset of the original sample.

For the *relational feature* of employees' attitudes toward the manager, employees' readiness to work with the android and humanoid robotic lower-level manager follows a degressive curve-shaped pattern. Starting from the left side of the surface, we find that although expectations play a significant role in employees' readiness to work with the manager, experiences clearly dominate the relationship. Overall, outcome values are comparatively low on the left side of the surface, where experiences do not match prior expectations. The surface continues to rise through the middle, where experiences match expectations. It shows decreasing margins on the right side for high values of confirmation and positive disconfirmation.

The dominance of experiences might be because of the fact that employees' expectations are mainly based on observations of android and humanoid robots in the media, outside of real-world interactions or a work context (Horstmann & Krämer, 2019). Such expectations may not be particularly strong, so they can easily be dominated by experiences, due to recency effects. This is the tendency to base judgments on more recent information; Baddeley & Hitch, 1993). Attitudes based on experience then in turn influence subsequent evaluations and behavior (Petty et al., 1997). This is also consistent with the theory of reasoned action (Fishbein & Ajzen, 1975). Similar patterns of experience dominance also appear in studies of information systems

(S. A. Brown et al., 2008) and human resource management (Hom et al., 1999). Again, stability tests confirm the robustness of the findings.

Accordingly, answering our second research question (*RQ2*), one size does not fit all; we find differences in how performance-related (usefulness) and relational (employee attitude) features affect employ-ees' readiness to work with a robotic lower-level manager. We further found that android robots are overall preferred over humanoid robots in the role of lower-level managers. The results of our research suggest that robots as lower-level managers in the workplace are a possible future scenario. At the same time, we found that overly positive experiences of performance-related features can lead employees to feel threatened and fear for their jobs. These implications affirm research on ethical concerns regarding the use of this technology (B. Green & Chen, 2019) and suggest its potential transfer to human-robot team settings.

Our study extends the TAM (Davis, 1989; Davis et al., 1989) to include EDT notions (Oliver, 1980; Venkatesh & Goyal, 2010) in a human-robot interaction research setting. By combining these concepts, we extend the theory-driven consideration of expectations and experiences of the performance-related feature usefulness and the relational feature attitudes from the TAM to the specific setting of choosing a robotic lower-level manager. Previous research has applied TAM and EDT separately to robot-related interactions or team settings (e.g., Bröhl et al., 2019; Horstmann & Krämer, 2020; Turja & Oksanen, 2019), but we are not aware of any applications of expectations and experiences to robot-managed team settings.

We further extend the application of EDT, as well as prospect theory, the too-much-of-a-good-thing-effect, and the theory of reasoned action to settings with social robots in office work environments. These theories help to define the mechanisms that determine employees' readiness to work with robotic lower-level managers. Thus, in reply to our first research question (RQ1), we affirm that theories from social (human) psychology can be a good starting point for investigating social robots in office work environments.

We apply polynomial regression and RSA to investigate the underlying mechanisms by which performance-related and relational features affect readiness to work with robotic lower-level managers. Following a methodological approach proposed by J. R. Edwards and Parry (1993), we conduct a detailed investigation of the expectation-experience relationship, which provides fine-grained results regarding to the patterns that this relationship may take. In addition, we overcome the shortcomings of difference scores (J. R. Edwards, 2002). By examining different combinations of expectations and experiences of performance-related and relational features, we gain a better understanding of the underlying mechanisms. To our knowledge, this study is the first to examine readiness to work with a robotic lower-level manager in a concrete application context with behavioral variables, which represents an important step in the field.

In addition, we contribute to general information systems research by providing a new set of test criteria for studying surface values as key features of response surfaces. These criteria can be applied not only to the human-robot team setting of this study, but also to other HRI settings, more general information systems research settings, such as human-computer interaction studies, and management research.

4.6.3 Limitations and Areas for Further Research

Our study has several limitations. First, we sought to determine whether social robots would be accepted as lower-level managers, but because social robots are not yet a reality in most organizations, we had to rely on an online study with a vignette and short videos as proxies for actual interactions (Aguinis & Bradley, 2014). While research has shown that results from online studies are comparable to results from laboratory studies (Babel et al., 2022), further research should include in-person experiments in laboratory or field settings to validate our findings and to examine readiness to work with robotic lower-level managers in different contexts, including real teams in organizations. In this regard, next steps could include investigating different robot types as co-leaders alongside with human co-leaders in teams as an important intermediate step (Gombolay, Gutierrez, et al., 2015), as well as studying robotic middle-level managers and leaders responsible for larger and/or multiple teams (DeChurch et al., 2010). Another area for future research could be the examination of virtual agents as lower-level managers to compare outcomes with those of robots and to link this research to broader human-computer interaction.

Second, a longitudinal study might include repeated exposures to robot lower-level managers to determine whether the outcomes might change over time (Leite et al., 2013). Longitudinal efforts are currently lacking in HRI and HRT research (Baraka et al., 2020; Diederich et al., 2022). These efforts could turn to literature in the broader information science context that identifies differences between short- and long-term effects (Bhattacherjee & Premkumar G., 2004; Vance et al., 2018; Venkatesh & Morris, 2000).

Third, we focus on a rather specific area in investigating the interplay between expectations and experiences with robotic lower-level management. Further research could expand this view to include contextual factors and other aspects. For example, researchers could investigate the antecedents of expectations of social robots, from both performance-related and relational perspectives, to learn how expectations of different types of social ro-bots are formed (MacDorman, 2019; MacDorman & Ishiguro, 2006). In addition, future research could continue to shed light on the broader implications of robots in organizations to address ethical concerns (B. Green & Chen, 2019) about the use of automated decision-making systems in the workplace.

Fourth, the diversity of the robots and humans in the human-robot teams shown in our study is limited. Future research should therefore pay closer attention to this to get insights into potential biases (e.g., gender bias) arising from the choice of robot or team set-up and to support generalizability of findings. This includes the explicit consideration of different robot types and their implied personality (Esterwood et al., 2022), gender and ethnicity as well as the diversity of human team members. Such considerations are important design features for robots. Expanding the focus on robot leadership, aligning expectations of ideal leadership with explicit leader behaviors by manipulating the leadership style of robotic (lower-level) team leaders may be a promising approach.

Fourth, we use employees' readiness to work with a robotic lower-level manager as the dependent variable. In this way, we gain insight into participants' behavioral intentions. Further research could use other proxies, such as the social integration of a robot, especially in real-world research settings in organizations.

4.6.4 Managerial Implications

Social robots offer a promising answer to the skilled worker shortage and aging workforce in many Western economies. Moreover, social robots are on the verge of becoming a regular part of our daily lives. The practical implications of our research thus should therefore be relevant with regard to various aspects.

First, our research shows that while the android and humanoid robotic lower-level manager are associated with high levels of acceptance, the human manager is preferred overall. Robots should therefore continue to be used as a fallback solution to address labor shortages and an aging workforce. At the same time, managers and executives should not ignore these developments and should start preparing today for the inevitable changes and challenges of the future of work. When making strategic decisions about adopting robotic managers, managers and executives should favor android robots because they have higher acceptance than humanoid robots.

Second, we note the relevance of both performance-related and relational features. Performance-related features include the robotic manager improving the quality of work or making it easier for employees to do their jobs. Relational features include that it is fun to work with a robotic manager, or that a robotic manager makes work more interesting. Although conventional views emphasize the performance-related, reliability, cost-effectiveness, or programming stability benefits of robots, we also emphasize the importance of relational features like fun to work with a robotic manager. Companies should not exclusively focus solely on performance-related features when introducing robots. Instead, they should also consider how people will interact with the robots on a relational level.

Third, in line with current ethics discussions about robots in our society, our results show that for performance-related features, overly positive experiences can lead employees to feel threatened and fear for their jobs. In contrast, for relational features, positive experiences with these features increase employees' readiness to work with a robotic manager. Organizations should actively address these findings to ensure the best possible implementation and acceptance of robots. For performance-related features, they should engage employees and reduce anxiety. Two specific tactics could be expectation management, which involves clearly communicating robotic capabilities, and employee training, which helps clarify the limits of robot use and supports employee-robot interactions. Relational features should leverage investments in positive experiences to make interactions as enjoyable as possible.

4.7 Conclusion

This study represents an important first step in filling some gaps in extant research on the acceptance of robotic lower-level managers in human-only teams (HRTs). As a result of the shortage of skilled workers and managers robots are becoming increasingly important. By investigating the mechanisms that determine employees' readiness to work with android and humanoid robotic lower-level managers, we extend the understanding of HRT settings. By presenting a series of research and managerial implications, we hope this study serves as a starting point for ongoing investigations into the implementation and successful evolution of HRTs with robotic managers.

5 Thesis Conclusion and Contributions

The starting point of this disseration was the ambition to advance knowledge about HRTs and provide insights into the path to these teams of the future. Since previous research on HRTs lacks a consistent understanding of HRTs and their important characteristics and influencing factors, and since the establishment of HRTs is not yet explored in research, this dissertation aims to answer three overarching research questions (see chapter 1.1):

1. *How are human-robot teams (HRTs) defined and what are important characteristics and influencing factors?*
2. *What are underlying mechanisms of the decision for a robotic team assistant for a mixed HRT?*
3. *What are underlying mechanisms of the decision for a robotic lower-level (team) manager for a mixed HRT?*

In line with these research questions, one conceptual and two empirical research studies provide a range of insights and findings about HRTs. The following sections present the major overarching research contributions and practical implications of this dissertation. I conclude with a discussion of limitations and opportunities for future research.

5.1 Research Contributions

In addition to the research contributions already outlined in the research studies, the main overarching *content-related*, *theoretical*, and *methodological contributions* of this dissertation are highlighted below.

In terms of *content-related contributions*, the main contribution of the literature review (chapter 2), which aims to answer overarching RQ 1, is the provision of a structured and universal definition of HRTs and the identification of an agenda for HRT research based on the characterization of extant research and its gaps. The developed definition of HRTs brings together different views of these teams and integrates them in terms of interaction types as well as number of interaction partners, drawing on all-human team research. This approach reflects a holistic view of HRTs in organizations. To guide future research, study structures extant research in a literature review of 194 studies and identifies success factors and research gaps. The study suggests avenues for future research in two areas: *How can robots be team members,* and *when?* The resulting research agenda helps researchers structure their efforts to gain a holistic and comprehensive understanding of HRTs and address existing research gaps.

Building on the foundations of the literature review in the conceptual study, empirical studies 1 (chapter 3) and 2 (chapter 4) address two of the identified research gaps (see Figure 5-1). Their main content-related contribution lies in the consideration of the social robot selection that precedes the establishment of HRTs.

In doing so, empirical study 1 provides detailed insights into the differences between humanoid robotic and android robotic team assistants, showing that for social robots in this role, for teamwork (social skills and team orientation), positive disconfirmation and high levels of experiences lead to higher acceptance, and similar results emerge for a humanoid robot's taskwork (coordination skills and knowledge) skills. In contrast, for taskwork skills of android team assistants, high levels of positive disconfirmation lead to lower robot acceptance. Furthermore, the results show that android robotic team assistants are preferred over humanoid robotic team assistants.

For robotic and human lower-level (team) managers, empirical study 2 finds that there is a discrepancy between the consideration of performance-related (usefulness) and relational (attitude toward the robot) features of robotic lower-leve (team) managers: The relationship between expectations and experiences of usefulness and the readiness to work with the robotic manager follows an S-shaped pattern. Thus, a slight overfulfillment of expectations is associated with the highest levels of readiness. In contrast, with respect to attitude toward the robot, the results instead follow a degressive curve for which actual experiences dominate the outcome. Increasing positive experiences are associated with decreasing positive evaluations of readiness.

Taken together, the results of empirical studies 1 and 2 suggest that "one size does not fit all" when it comes to the different roles (team assistant, lower-level (team) manager) and features (taskwork-/performance-related, teamwork-related/relational) for robots for HRTs in an organizational context (see Table 5-1). Overall, the content of this thesis contributes to providing new insights into the foundations and initial steps of the establishment of HRTs. In addition, this dissertation points to avenues for future research in this area.

Table 5-1. Comparison of Findings Related to Integration Decisions for Social Robots in Empirical Studies 1 and 2

	Empirical Study 1	**Empirical Study 2**
Team role	Robotic team assistant	Robotic lower-level (team) manager
Role of expectations and experiences	Both expectations and experiences of usefulness and attitude play a role in decisions.	Both expectations and experiences of usefulness and attitude play a role in decisions.
Differences between evaluations of taskwork-/performance-related and teamwork-related/relational features	Differences can be observed: For taskwork-related features of android team assistants, high levels of positive disconfirmation lead to lower robot acceptance. In contrast, for a humanoid robot's taskwork-related features positive disconfirmation and high levels of experiences lead to higher acceptance. Similar results emerge for teamwork-related features of humanoid and android robots.	Differences can be observed: performance-related features, employees' readiness to work with robot managers follows an S-shaped pattern. A slight overfulfillment of expectations is associated with the highest levels of readiness. For relational features, the results instead follow a degressive curve. Increasing positive experiences are associated with decreasing positive evaluations of readiness.
Differences to humans	Not in the focus of this study.	Decision models for performance-related features are more complex for robotic managers than human managers. Decision models for relational features are similar for human and robotic managers

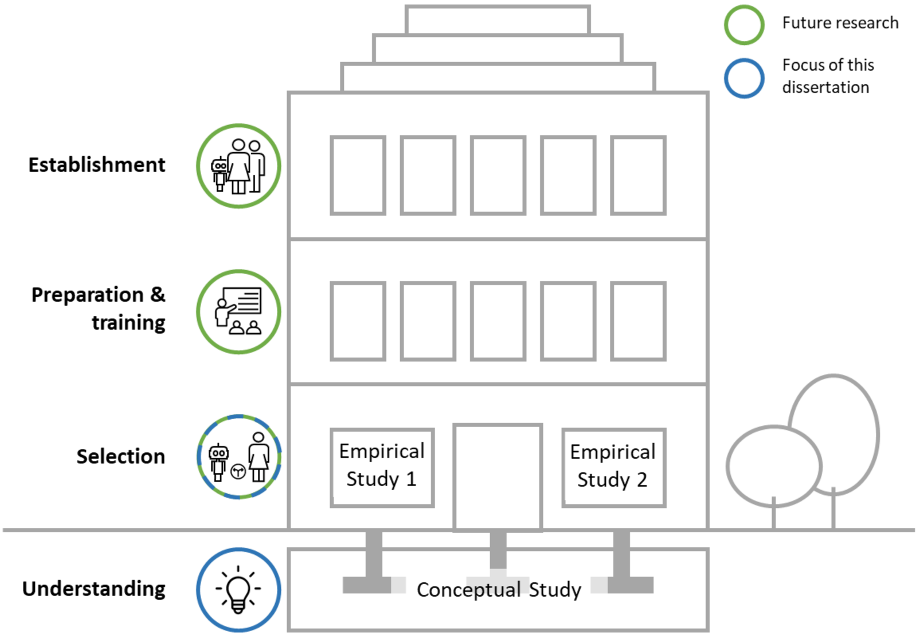


Figure 5-1. Relationship Between the Research Studies Included in This Dissertation, Their Focus, and Avenues for Future Research

Extending the theoretical foundations behind the successful establishment of HRTs with social robots in different team roles is the main *theoretical contribution* of this dissertation. To this end, empirical studies 1 and 2, which thus address overarching RQs 2 and 3, respectively, utilize EDT (Oliver, 1980) to examine the interplay between expectations and experiences of taskwork-/performance-related and teamwork-related /relational measures in decisions for social robots. This theory has already been used in general IS (e.g., S. A. Brown et al., 2014) and HRI (e.g., Horstmann & Krämer, 2020) research and is now applied to team contexts with social robots.

Empirical study 1 further uses the IPO of teams (Gladstein, 1984) to structure the research and and establish an expectation-experience-based model of HRTs. Thereby, it builds on cognitive dissonance (Festinger, 1957), disappointment theory (D. E. Bell, 1985), and reactance theory (Brehm, 1966). In doing so, it shows that these theories can be applied to team contexts with social robots. For robotic and human lower-level (team) managers, empirical study 2 utilizes the TAM (Davis, 1989; Davis et al., 1989) and extends the theory of reasoned action (Fishbein & Ajzen, 1975) prospect theory (Kahneman & Tversky, 1979), and the too-much-of-a-good-thing-effect (Pierce & Aguinis, 2013) to the differentiated consideration of expectations and experiences of both performance-related and relational features of social robots in office work environments. Table 5-2 provides an overview of the theories applied in the empirical studies included in this dissertation and their implications for the research.

Based on the findings for the different roles and measures, the results of this thesis indicate that theories from human-centered research fields such as social psychology or marketing research (e.g., expectation disconfirmation theory, disappointment theory, prospect theory) seem to be a suitable and promising starting point for a sound theoretical understanding of HRTs.

The main *methodological contribution* of this dissertation is the application of the methodological approach based on polynomial regression and RSA proposed by S. A. Brown et al. (2014) to the HRT domain, which is taken up in empirical studies 1 and 2. This approach additionally is extended by providing a new set of test criteria for studying surface values as key features of response surfaces. By applying polynomial regression and RSA, fine-grained statements about the interplay between expectations and experiences of taskwork-/performance-related measure and teamwork-related/relational features in the decision for social robots in HRTs are possible.

This methodological approach is superior to the commonly used difference scores (J. R. Edwards, 2002) in several important aspects: First, by considering expectations and experiences separately, ambiguous results are avoided (J. R. Edwards, 2002) – in contrast to the various types of difference scores that create an artificial dimension reduction by calculating the algebraic, absolute, or squared difference between the values of two constructs (Shanock et al., 2010). Second, this approach avoids imposing implicit constraints on the independent and dependent variables under consideration (J. R. Edwards, 2002). Finally, this approach avoids loss of information and oversimplification and allows for the capture of information about how the full range of differences between expectations and experiences affects the dependent variable (J. R. Edwards, 2002).

In summary, this dissertation contributes to research by providing a better understanding of HRTs as well as fine-grained insights into the underlying mechanisms for the decision for robots in different team roles as central prerequisite for the successful establishment of HRTs.

Table 5-2. Overview of Applied Theories and Their Implications for the Research in This Dissertation

Name of Theory	**Field(s)**	**Important Sources**	**Basic Assumptions**	**Critique**	**Used in Empirical Research Study**	**Implications for Research in This Dissertation**
Expectation Disconfirmation Theory (EDT)	Origin: marketing research Extensions: information systems research	S. A. Brown et al., 2014; Oliver, 1980; Venkatesh & Goyal, 2010	Satisfaction with a product and the resulting intention of repurchasing it are influenced by previous expectations and actual experiences.	• Majority of studies on EDT utilize difference scores, not allowing for a detailed investigation of the interplay between expectations and experiences (S. A. Brown et al., 2014). • Original strong focus on expectations as determining factor of satisfaction is too simplistic, experiences also play a role (Venkatesh & Goyal, 2010).	1, 2	• Theoretical basis for investigation of decisions for social robots in different team roles. • Prediction of positive evaluation of social robots in case expectations are (over-) fulfilled.

Name of Theory	Field(s)	Important Sources	Basic Assumptions	Critique	Used in Empirical Research Study	Implications for Research in This Dissertation
Input-Process-Output (IPO) Model of teams	Organizational psychology research	Gladstein, 1984; Ilgen et al., 2005; Mathieu et al., 2008	Teams receive various inputs, engage in specific processes such as communication and coordination, and produce outputs such as team performance and satisfaction.	The model implies a linear path from input to output, which greatly simplifies teams (Ilgen et al., 2005).	1	Provision of structure for research framework.
Cognitive dissonance	Cognitive social psychology research	Festinger, 1957; Harmon-Jones & Mills, 2019	Individuals try to minimize the difference between their expectations and experiences to reach consonance.	Does not not account for situational factors and individual differences (Harmon-Jones & Harmon-Jones, 2007)	1	Prediction of relatively stable evaluation of social robotic team assistants in case expectations are closely fulfilled.
Disappointment theory	Cognitive social psychology research	D. E. Bell, 1985; Homburg et al., 2004;	Disappointment emerges in situations where the outcome of a decision falls short of initial expectations.	Original theory is focused on lotteries with two outcomes (Loomes & Sugden, 1986)	1	Prediction of positve (negative) evaluation of social robotic team assistants who exceed (do not meet) expectations.

Name of Theory	Field(s)	Important Sources	Basic Assumptions	Critique	Used in Empirical Research Study	Implications for Research in This Dissertation
		Loomes & Sugden, 1986				
Reactance theory	Cognitive social psychology research	Brehm, 1966; Quick & Stephenson, 2008	People have a strong need for freedom and autonomy. When that freedom is threatened, they will react emotionally and behaviorally to restore it.	Does not consider reactance as a personality trait (Miller et al., 2007)	1	Explanation of interplay between expectations and experiences of taskwork skills and robot acceptance of an android team assistant.
Technology Acceptance Model (TAM)	Information systems research	Davis, 1989; Davis et al., 1989; Y. Lee et al., 2003; Venkatesh & Bala, 2008	Actual use of specific IS technology by users can be predicted based on three key variables: (perceived) usefulness, (perceived) ease of use, and attitudes. • Thereby, usefulness and ease of use	• Focus on a limited number of variables to explain technology acceptance (Y. Lee et al., 2003). • Insufficient "actionable guidance" (Venkatesh & Bala, 2008, p. 274) for practice.	2	Identification of usefulness and attitudes as important drivers of robotic lower-level (team) manager (empirical study 2) acceptance.

Name of Theory	Field(s)	Important Sources	Basic Assumptions	Critique	Used in Empirical Research Study	Implications for Research in This Dissertation
			mediate the effects from external variables on behavioral intention.			
Met expectations hypothesis	Organizational psychology research	Porter & Steers, 1973; Wanous et al., 1992	Unmet expectations (i.e., experiences falling short of expectations) lead to dissatisfaction.	• Only focuses on negative disconfirmation (Wanous et al., 1992) • Contrary to original interpretations, met expectations do not need to be associated with high satisfaction (Irving & Montes, 2009)	2	Prediction of positive evaluation of social robotic managers in case expectations of performance-related features are fulfilled.
Equity theory	Social psychology research	Adams, 1963; Wanous et al., 1992	Getting more or less of an outcome than one considers fair leads to dissatisfaction. People try to reduce this dissatisfaction.	Positive and negative affirmations do not necessarily have to be perceived in exactly the same way (Pritchard, 1969)	2	Prediction of decreasing evaluation of social robotic managers in case expectations of performance-related features are overfulfilled.

Name of Theory	Field(s)	Important Sources	Basic Assumptions	Critique	Used in Empirical Research Study	Implications for Research in This Dissertation
Theory of reasoned action	Social psychology research	Ajzen, 1985; Fishbein & Ajzen, 1975; Wilson et al., 2000	A person's behavioral intention has a direct influence on behavioral performance and is influenced by attitudes and subjective norm. Attitudes are thereby determined by a person's salient beliefs, which are in turn determined by experience.	The original theory does not consider control over a situation and thus does not capture situations in which people do not have intentional control (Ajzen, 2020)	2	Prediction of influence of experiences on the evaluation of relational features of social roboic managerts.
Prospect theory	Behavioral economics research	Kahneman & Tversky, 1979; N. Lankton & McKnight, 2012	Negative effects of losses are stronger than positive effects of gains.	The reference point for losses and gains is difficult to determine (Pesendorfer, 2006)	2	Explanation of interplay between expectations and experiences of performance-related features and employees' readiness to work with a robotic manager.

Name of Theory	Field(s)	Important Sources	Basic Assumptions	Critique	Used in Empirical Research Study	Implications for Research in This Dissertation
Too-much-of-a-good-thing-effect	Management reseach	Busse et al., 2016; Grant & Schwartz, 2011; Pierce & Aguinis, 2013	When an underlying positive antecedent is pushed too far, the relationship between that antecedent and an outcome variable can become negative.	The effect may vary depending on contextual factors (Busse et al., 2016)	2	Explanation of interplay between expectations and experiences of performance-related features and employees' readiness to work with a robotic manager.

5.2 Practical Implications

Besides the theoretical implications, this dissertation may also be useful for robot manufacturers and managers in organizations. With robots being established in organizations for decades and advanced AI and robotics continuing to grow, there is undoubtedly a movement towards more social robots in organizations (Noble et al., 2022; Wolf & Stock-Homburg, 2022), which offers robot manufacturers and managers the opportunity to shape the future of work.

The findings from the different research studies included in this dissertation have a number of direct implications for robot manufacturers and managerial practice (see Table 5-3). Robot manufacturers should focus on developing *reliable technologies* for *natural, error-free, and accurate interactions* between social robots and humans, as communication is a key success factor for HRTs and interaction experiences play an important role in decisions for social robots.

Managers should consider both expectations and experiences while finding the right balance between expectation management in advance of interactions and live experiences of social robots in mixed HRTs. This is important because "one size does not fit all" when it comes to different robotic team roles and criteria of interest. In particular, the results of the research in this dissertation show direct implications in threewo ways:

On the one handFirst, since managers should actually *use social robots in their organizations* and encourage their employees to interact with them to create experiences that increase acceptance. At the same time, they should *carefully consider different robots* when making adoption decisions, depending on the individual situation.

Second, managers should consider both expectations and experiences and engage in targeted and tailored *expectation management in advance of interactions* with social robots, taking into account the robot's role in the team and the criterion of interest. Since "the more the better" does not always apply, targeted expectation management that *undersells* robotic teamwork capabilities and accurately communicates performance-related robotic features enables support for positive acceptance of social robtos. To do this, managers need to understand the needs and desires of their employees in terms of social robots in their teams and should seek appropriate dialogues.

Table 5-3. Selected Research Findings and Associated Practical Implications

Research Study	Research Findings	Practical Implications
Conceptual study	Autonomous robots, coordination and communication are important success factors for HRTs.	Robot manufacturers should develop social robots capable of *natural communication* and interactions with humans.
Empirical study 1	Detailed investigation using RSA shows that for humanoid and android social robotic team assistants it is important to focus both on expectations and optimal experiences of the robotic team assistant. For taskwork in case of the humanoid robotic team assistant and teamwork for both robots especially good levels of robot acceptance are achieved in the case of large positive disconfirmation.	Managers should *undersell robotic teamwork capabilities* to achieve positive initial interactions. Managers should *train their employees* with skills to effectively utilize social robots and address user concerns to increase acceptance. Robot manufacturers should develop *reliable technologies* for interactions between humans and social robots.
Empirical study 1 & 2	Android robots are preferred over humanoid robots. For lower-level (team) managers, human managers are preferred overall.	Managers should *carefully consider different robots* when making decisions about adopting them.
Empirical study 2	Detailed investigation using RSA shows that for performance-related characteristics a slight overfulfillment of expectations is associated with the highest levels of readiness. For relational characteristics, the results instead follow a degressive curve for which actual experiences dominate the outcome.	Managers should *use social robots in their organizations* to create experiences that increase their acceptance. At the same time, they should consider both expectations and experiences of both performance-related and relational features and engage in targeted and tailored *expectation management* prior to interactions with social robots.

Third, employees should be actively prepared and *trained* to work with social robots. Ideally, these trainings should be a strategic and permanent part of the overarching field of HR development (Kim, 2022) to ensure the successful establishment and adoption of HRTs in organizations. The trainings should take a differentiated approach that considers the specific situation, e.g., the role in which a social robot will be used, the team context into which the robot will be placed, or employees' concerns towards the use of social robots. This is important to avoid overwhelming employees with this new technology.

From these direct implications, a number of further implications can be derived for the managerial practice. In particular, expectation management has some consequences for the introduction of social robots in organizations. First, the decision to use social robots in teams and the reasoning behind it should be communicated transparently as early as possible to avoid major surprises for employees as much as possible. Furthermore, clear responsibilities and decision-making processes for the implementation of social robots in teams should be established. In particular, it should be clear who is responsible as a contact person and decision maker for questions and concerns.

In summary, managers should be encouraged to seize the opportunity to take the leap into the future of work by deploying social robots in their organizations. A set of implications outlined above can help managers unlock the potential of these new technologies and future-proof their organizations for the long run.

5.3 Limitations and Future Research

This dissertation offers valuable insights for both researchers and practitioners. While the limitations of the individual studies have already been described in detail in the corresponding chapters, two overarching limitations should be mentioned here. At the same time, however, these limitations also provide avenues for future research, which is taken up in two additional points (see Figure 5-1).

First, the two empirical research studies (chapter 3 and 4) in this dissertation methodologically rely on online studies using vignettes rather than real-life studies.[14] Building on the research agenda outlined in the literature review (see chapter 2.4.4), future research could build on these insights and use real-life settings to gain a deeper understanding of the setup of HRTs.

[14] Due to restrictions during the COVID-19 pandemic (several lockdowns, the Technical University of Darmstadt was closed for experiments), real-life studies were not possible when the studies included in this dissertation were conducted.

Second, the empirical research studies 1 and 2 take a perspective that focuses on decisions for robots following typical human selection processes in a work context. In addition to this perspective, which originates from human resource management, researchers could extend the research on the successful setup of HRTs by also considering another perspective with a stronger focus on the technological aspects of robots. In doing so, they could expand research on robot selection, which to date has largely focused on the selection of industrial robots (e.g., Ketipi et al., 2014; Koulouriotis & Ketipi, 2014), to the selection of social robots for organizational HRTs. In this context, the entire selection and decision-making process preceding the establishment of HRTs could be examined and the question of responsibility for the setup and ongoing management of social robots in different team roles in HRTs could be investigated.

Future research should also examine the preparation for HRTs in greater detail, as indicated in the literature review (chapter 2). Appropriate training and communication measures are likely to be a critical success factor for the establishment of HRTs in organizations. These trainings and measures depend on particular contingencies, including environmental factors, and should follow a situational and customized approach (Kim, 2022).

Lastly, as also indicated in the literature review, research on existing HRTs still has a number of gaps. There are a number of promising avenues that future research could take to further advance the understanding of these teams of the future: For example, privacy and data protection are becoming increasingly important as humans increasingly interact with AI and robots in the work environment. Building on research in the context of people analytics and holistic data protection management (Holthaus et al., 2015), future research should explore this highly relevant topic. Further, trust and related privacy considerations in this context, which have already emerged in conjunction with other technologies such as AI (Mesbah et al., 2019) or HRI in the workplace (Stock-Homburg & Hannig, 2020), may be a promising area for future research on HRTs. Future research should moreover have a general focus on conducting studies with social robots in different team roles in real-world settings to obtain robust results and insights.

To conclude, this dissertation has addressed the question of the definition and important characteristics and influencing factors of HRTs, and provided answers to which underlying mechanisms drive the decisions for robotic team members in the establishment of HRTs. With its findings, it has made an important contribution to research on HRTs and provided avenues for future research and management implications for this emerging topic.

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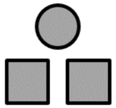
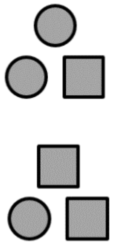
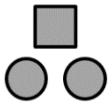
Appendix

List of Tables

Tables

Table 2-1. Overview of Different Team Compositions, Sample Definitions, and Related Research

Team type	Team composition	Sample definition	Related empirical research
Human-directed robot team		“a single human operator can oversee and flexibly intervene in the operation of a team of largely autonomous robots” (Sellner et al., 2006, p. 1425).	*Management:* Pina et al., 2008; Sellner et al., 2006 *Cognitive science*: J. Wang et al., 2008; You & Robert, 2016, 2018a, 2019a, 2019b *HRI:* Alboul et al., 2008; Crandall et al., 2003; Goodrich et al., 2007 *Military*: S. Brown et al., 2005 *Robotics*: Zheng et al., 2013 (*Urban) search and rescue*: Burke & Murphy, 2004, 2007; Kantor et al., 2006; P.-J. Lee et al., 2010; Ranzato & Vertesi, 2017; H. Wang et al., 2010; Yazdani et al., 2016
Human-/Robot-directed mixed team		“human workers … perform physical tasks in coordination with robotic partners” and “human and robot co-leaders [have] identical functions and capabilities, by restricting the human co-leaders’ capabilities such that they were the same as those of the robot” (Gombolay, Gutierrez, et al., 2015, pp. 295–296)	*HRI*: Law et al., 2021 *Management*: Gombolay, Gutierrez, et al., 2015, referring to human and robotic co-leads, human assistants; Gombolay, Huang, & Shah, 2015, referring to human leader, robotic and human assistants
Robot-directed human team		“the partner [robot] … is instructing the primary human … on the task steps to complete. There are no shared decision making tasks” (Harriott et al., 2011, p. 46)[a]	N/A; the only studies with such a team composition refer to robot-directed dyadic task teams

Team type	Team composition	Sample definition	Related empirical research
Autonomous mixed team	○ ○ □	"humans and robots [work] together to accomplish complex team tasks" (Dias et al., 2008, p. 1)	*Cognitive science*: Correia, Mascarenhas, et al., 2019; Jung et al., 2015; Strohkorb Sebo et al., 2020; Traeger et al., 2020 *HRI*: Gervits et al., 2020; Kwon et al., 2019; Tang & Parker, 2006 *Robotics*: Claure et al., 2020; T. Iqbal & Riek, 2017; Marge et al., 2009 *Space*: Fong et al., 2005; Fong et al., 2006 (*Urban) search and rescue*: Dias et al., 2008; Jung et al., 2013

Note: ○ = human, □ = robot. The studies (with team sizes of at least n = 3) are categorized according to a best fit approach, so they might feature aspects of more than one research discipline. Overview over related empirical research is not exhaustive.

[a]Harriott et al. (2011) only consider a dyadic task team

Table 2-2a. Conceptual Studies on Multiple Member HRTs Related to Intra-member Team Characteristics and Their Effects

Author / subcategory /discipline[1)] / team interaction[2)]	Major findings[3), 4)]
Ambrose et al. (2000) / (physical) robot design / VI / T	• Overview of the design of NASA’s Robonaut
Bluethmann et al. (2003) / (physical) robot design / VI / T	• Information on the design of NASA's Robonaut
Fong et al. (2005) / (physical) robot design / VI / T	• Proposal of interaction framework "Human-Robot Interaction Operating System" (HRI/OS) • Proposal of metrics for evaluation of HRTs
Kelly and Watts (2017) / robot behavior / V / T+S	• Position paper that suggests that task-related "inefficiency" in the form of social behavior should be considered when designing social robots
Ramesh et al. (2021) / (physical) robot design / V / T	• Proposal of set of robot vitals to quantify "the performance degradation experienced by a robot" (p. 303)

Note: 1) Disciplines: I = HRI, II = Management, III = military, IV = Cognitive science, V = robotics, VI = space, VII = (urban) search and rescue, VIII = ethics; Studies are categorized based on a “best fit”-approach and might comprise aspects of more than one considered research discipline; 2) Team interaction: T = task interaction, T+S = task & social interaction; 3) None of the studies specified underlying theories. In part of the studies, the robot morphology, robot level, and type of embodiment are not specified. The two studies that provide information (Bluethmann et al., 2003; Fong et al., 2005) use the physical, humanoid “Robonaut” robot on a lower or same level as humans; 4) In most of the studies, the team setup is not specified. Only Kelly and Watts (2017) specify that they focus on a human-directed robot team.

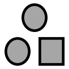
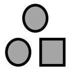
Table 2-2b. Empirical Studies on Multiple Member HRTs Related to Intra-member Team Characteristics and Their Effects

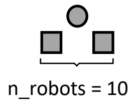
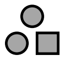
Author / subcategory / discipline[1)]	Robot morphology[2)] / robot level[3)] / type of embodiment	Team interaction[4)] / team setup[5)]	Data basis / participants[6)] / time frame[7)]	Underlying theories	Independent variable(s)[8)]	Dependent variable(s)[8)]	Major findings
Claure et al.(2020) / robot behavior / V	n.i. / ↔ / n.i.	T+S ●●■	n=282 / 156 f, 124 m, 1 other, 1 not disclosed; age: M=36 years (SD=11); mTurk; from the US / C	Equity models, fairness theory	• Robot fairness	• User trust (+ / n.s.) • Perceived robot fairness (n.s.)	• "Fairness of resource allocation has significant effect on user's trust in the system" (p. 299)
Correia, Mascarenhas, et al. (2019) / robot behavior / IV	Humanoid (EMYS robotic head) / ↔ / Physical robot	T+S ●■■	n=70 / 32 f, 37 m, 1 unknown; age: range 22-62 years (M=34.6, SD=11.557)/ C	n.i.	• Prosocial robot behavior	• Perceived robot social attributes (+)	• Prosocial robots are rated more positively in terms of their social attributes (p.143) • "The perception of competence, the responsibility attribution (blame/credit) and the preference for a future partner are only significantly different in the losing condition" (p.143)
Correia, Petisca, et al. (2019) / human preferences and behavior / IV	Humanoid("Emys", "Glin"; both identical physical appearance: EMYS) / ↔ / Physical robot	T+S ●●●■ ●●■■	n_1=30, n_2=61 / 1: 17m, age: range 19-42 years, M=23.03 (SD=4.21), university students; 2: 38 m, age: range 17-32 years, M=23.66	Learning goal theory	• Robot goal orientation (performance-driven vs. learning-driven)	• Competitiveness Index (higher for performance-driven) • McGill Friendship Questionnaire (higher for	• "When a partner is chosen without previous partnering experience, people tend to prefer robots with relationship-driven characteristics as their partners compared with competitive robots" (p. 1)

Author / subcategory / discipline[1)]	Robot morphology[2)] / robot level[3)] / type of embodiment	Team interaction[4)] / team setup[5)]	Data basis / participants[6)] / time frame[7)]	Underlying theories	Independent variable(s)[8)]	Dependent variable(s)[8)]	Major findings
			(SD=3.24), 59 university students, 2 worker / C/L (3 sessions in direct succession)			learning-driven) • Relationship Assessment Scale (higher for learning-driven) • Godspeed Questionnaire (n.s. /higher for learning-driven)	• "After some partnering experience has been gained, the choice becomes less clear and additional driving factors emerge: (2a) participants with higher levels of competitiveness (personal characteristics) tend to prefer Emys [the performance-driven robot], whereas those with lower levels prefer Glin [the learning-driven robot], and (2b) the choice of which robot to partner with also depends on team performance, with the winning team being the preferred choice." (p. 1)

Author / subcategory / discipline[1]	Robot morphology[2] / robot level[3] / type of embodiment	Team interaction[4] / team setup[5]	Data basis / participants[6] / time frame[7]	Underlying theories	Independent variable(s)[8]	Dependent variable(s)[8]	Major findings
Cunningham et al. (2013) / human preferences and behavior / I	Functional (da Vinci surgical system) / ↓ / Physical robot	T / n.i.	n=4 cases (2 in US, 2 in FR) / US: experiences and novice users, FR: novice users (less than 5 procedures) / C	n.i.	• Experience • Workplace culture	• Workflow • Timeline • Roles • Communication patterns • (see study for detailed observations)	• Adapting to robotic technology can be challenging. Experience and workplace culture affect team behavior, with less experience leading to more preparation time and more verbal exchanges
Fraune, Oisted, et al. (2020) / robot behavior / I	Functional (Sociable Trash Box (STB)) / n.i. / Image/video of a robot, physical robot	T+S 1: n_{human} = 0,…, “multiple”; n_{robot} = 1,…,3	n_1=630, n_2=71 / 1: from USA (n=333, 47% f, age M=24.59, SD=9.59) and Japan (n=297, 7% f, age M=21.55, SD=3.35), recruited in universities; 2: from USA (42% f, age M=19.20, SD=1.30), recruited from university / C	Social identity theory	• Robot behavior toward robots (none, social, functional) • Robot behavior toward humans (social, functional) • Country (US, Japan)	• Anthropomorphism of robot (partially + for robot-robot social, n.s. for other conditions) • Emotional and behavioral intention about robot (n.s.) • Entativity of robot (n.s.)	• Social robot-robot behavior increases anthropomorphism, social robot-human behavior increases positive emotions and willingness for interactions (p.1) • Robots that are designed for positive human interaction resp. to be perceived intelligent should behave socially towards humans resp. also towards robots (p.1)

Author / subcategory / discipline[1]	Robot morphology[2] / robot level[3] / type of embodiment	Team interaction[4] / team setup[5]	Data basis / participants[6] / time frame[7]	Underlying theories	Independent variable(s)[8]	Dependent variable(s)[8]	Major findings
					• Robot behavior toward robot (social, functional) • Robot behavior toward human (social, functional)	• Cooperation (n.s.) • Anthropomorphism of robot (partially + or - for robot-robot social) • Emotional and behavioral intention about robot (+ for robot-human social) • Entativity of robot (partially + for robot-human functional)	

Author / subcategory / discipline[1)]	Robot morphology[2)] / robot level[3)] / type of embodiment	Team interaction[4)] / team setup[5)]	Data basis / participants[6)] / time frame[7)]	Underlying theories	Independent variable(s)[8)]	Dependent variable(s)[8)]	Major findings
Gombolay et al. (2017) / robotic behavior, human preferences and behavior / I	Functional (Willow Garage PR2 platform) / ↓ / Physical robot	T+S 	n_1=17, n_2=18, n_3=20 / all: recruited form local university; 1: 6 m, age: range 18-25 years, M=19.5 (SD=1.95); 2: 10 m, age: range 19-45 years, M=27 (SD=7); 3: 10 m, age: range 18-30 years, M=21 (SD=3) / C	Situational awareness	• Degree of robotic autonomy in scheduling decisions	• Situation awareness (-)	• "human participants' awareness of their team's actions decreased as the degree of robot autonomy increased" (p. 614) • "participants preferred working with a robot that included their preferences when scheduling and ... preferred working with a robot that utilized them more frequently" (p. 613)
					• Degree to which participant's preferences are respected by robotic teammate	• Preference to work with robot (+)	
					• Degree to which participant's preferences are respected by robotic teammate • Participant utilization	• Preference to work with robot (+, +)	
Gombolay, Huang, and Shah (2015) /	Functional (Willow Garage PR2 platform)	T+S 	n=17 / n.i. / C	n.i.	• Consideration of human preferences	• Willingness to work (+)	• Humans prefer working with a robotic team mate

Author / subcategory / discipline[1]	Robot morphology[2] / robot level[3] / type of embodiment	Team interaction[4] / team setup[5]	Data basis / participants[6] / time frame[7]	Underlying theories	Independent variable(s)[8]	Dependent variable(s)[8]	Major findings
robot behavior, human preferences and behavior / II	/ ↓ / Physical robot						that considers their preferences • Team efficiency has to be kept in mind when allocating decision-making authority (robot taking decisions can lead to decreased efficiency and belief that the robot is unaware of team goals)
L. Jiang and Wang (2019) / robot behavior / V	n.i. / n.i. / n.i.	T+S 	n.i. / n.i. / n.i.	Regret theory	• Robot decision making (regret-decision model)	• Teaming performance (+)	• More human-like decision-making by robots can help to balance workload and performance in HRTs
Law et al. (2021) / (physical) robot design, robot behavior / I	Humanoid (Willow Garage PR2) / ↔ / Image/video of robots	T+S 	n_1=198, n_2=421 / 1: 95 f, 1 other, age: range 18-77 years (M=34.96, SD=11.47); 2: 162 f, 3 other, age: range 18-81 years (M=36.52, SD=11.85); both: mTurk / C	Emotional intelligence, social role theory	• Robot emotional intelligence (+) • Robot gender (+, male) • Vignette presentation (n.s.) ——— • Robot emotional	• Trust in robot	• Robotic EI influences trust in a robot (p. 1) • "Gender stereotypical expectations related to EI [are] transferred to trust" (p. 1)

Author / subcategory / discipline[1]	Robot morphology[2] / robot level[3] / type of embodiment	Team interaction[4] / team setup[5]	Data basis / participants[6] / time frame[7]	Underlying theories	Independent variable(s)[8]	Dependent variable(s)[8]	Major findings
					intelligence (+) • Robot gender (+, male) • Vignette presentation (+, text) • Participant gender (n.s.) • Participant age (-)		
					• Robot trustworthiness (n.s.) • Robot gender (n.s.)	• Perceived robot EI	
					• Robot trustworthiness (+) • Robot gender (n.s.) • Vignette presentation (+, text) • Order of questionnaires (+, EI first, then trust)	• Trust in robot	

Author / subcategory / discipline[1)]	Robot morphology[2)] / robot level[3)] / type of embodiment	Team interaction[4)] / team setup[5)]	Data basis / participants[6)] / time frame[7)]	Underlying theories	Independent variable(s)[8)]	Dependent variable(s)[8)]	Major findings
Lei and Rau (2020) / human preferences and behavior / IV	Humanoid (Nao) / ↔ / Physical robot	T+S ●●■	n=60 / 30 f; age: M=22.2 years (SD=2.29); (under-) graduate students (40%/60%)/ C	CASA paradigm, common sense psychology, gender studies	• Task outcome (n.s.) • Human gender (-/+)	• Attribution of blame to robot • Attribution of credit to robot	• Gender effects play a role in the attribution of credit and blame to robot team members • "participants attributed more credit and less blame to the robot member than to themselves" (p. 1) • "the robot member was more blamed than the human member, whereas they received similar levels of credit" (p. 1)
Rhim et al. (2019) / robot behavior / IV	Humanoid (Pepper) / ↑ / Physical robot	T / ■ ●●	n=78 (39 teams) / 38% f / C (between-subject)	n.i.	• Robot behavior (positive vs. neutral)	• Participant's mood • Creativeness of story • Robot's impression • Team collaboration • *(see paper for detailed results)*	• "Self-reported valence and arousal increased in human participants when interacting with the affective robot regardless of the robot's perceived mood" (p. 1) • "Participants' likeability of the robot increased when interacting with a positive robot, while likeability decreased when interacting with a neutral robot" (p. 1)

Author / subcategory / discipline[1)]	Robot morphology[2)] / robot level[3)] / type of embodiment	Team interaction[4)] / team setup[5)]	Data basis / participants[6)] / time frame[7)]	Underlying theories	Independent variable(s)[8)]	Dependent variable(s)[8)]	Major findings
Strohkorb Sebo et al. (2018) / robot behavior / IV	Humanoid (Nao) / ↔ (not specified) / Physical robot	T+S ●●●■	n=105 (in 35 teams) / experimental condition: 26/54 m, age: M= 20.13 years (SD=7.13); control condition: 15/51 m, M=21.333 years (SD=11.00); recruited from university campus and surrounding town and summer program./ C	Trust theories	• Robot vulnerability	• Team member interactions with robot (+) • Perceived psychological safety (n.s.) • Team member interactions with other human team members (+)	• Robots making vulnerable statements lead to increased engagement with the robot • In groups with robots making vulnerable statements, human teammates take more actions to reduce tension experienced by the team (e.g., explain failures, laugh together)
Traeger et al. (2020) / robot behavior / IV	Humanoid (Nao) / ↔ / Physical robot	T+S ●●●■	n=153 (in 51 groups of 3 each) / vulnerable condition: 28 f, 26 m, age: M=20.13 years (SD=7.13); neutral condition: 36 f, 15 m, age: M=21.33 years (SD=11.01); silent condition: 31 f, 17 m, age: M=23.94 years (SD=7.36)/ C	n.i.	• Robot vulnerability	• Team member interactions with other human team members (+) • Total talking time (+) • Team perception (+)	• "people in groups with a robot making vulnerable statements converse substantially more with each other, distribute their conversation somewhat more equally, and perceive their groups more positively compared to control groups with a robot that either makes

Author / subcategory / discipline[1)]	Robot morphology[2)] / robot level[3)] / type of embodiment	Team interaction[4)] / team setup[5)]	Data basis / participants[6)] / time frame[7)]	Underlying theories	Independent variable(s)[8)]	Dependent variable(s)[8)]	Major findings
						• Conversation equality (+)	neutral statements or no statements at the end of each round" (p. 6370)

Note: 1) Disciplines: I = HRI, II = Management, III = military, IV = Cognitive science, V = robotics, VI = space, VII = (urban) search and rescue, VIII = ethics; Studies are categorized based on a "best fit"-approach and might comprise aspects of more than one considered research discipline; 2) n.i. = no information provided by author(s); 3) Robot level: ↓ = robot on lower level, ↔ = robot on same level, ↑ = robot on higher level; 4) Team interaction: T = task interaction, T+S = task & social interaction; 5) ◯ = human, □ = robot; 6) f=female, m=male; 7) C = cross-sectional, L = longitudinal; 8) (-) = negative effect, (+) = positive effect, (n.s.) = not significant

Table 2-2c. Empirical Studies on Dyadic HRTs Related to Intra-member Team Characteristics and Their Effects

Author / subcategory / discipline[1]	Robot morphology[2] / robot level[3] / type of embodiment	Team interaction[4] / team setup[5]	Data basis / participants[6] / time frame[7]	Underlying theories	Independent variable(s)[8]	Dependent variable(s)[8]	Major findings
Arnold and Scheutz (2018) / robot behavior / I	Humanoid / ↔ / Image/video of a robot	T+S ● ■	n=332 / 135 f, age: 44.43 years; mTurk; US citizens / C	n.i.	• Positive robot attitude • Robot touch	• Perceived robot capability (+/ n.s.) • Confidence in robot skills (+) • Perceived robot qualification (+ / n.s.) • Perceived robot fairness (+)	• Robot touch leads to better rating of the social performance, skills, fairness of a robot • However, gender effects from survey responses show that robot touch has to be considered with caution as the context and expectations from society can lead to a significantly varying perception of robot touch
Bartneck et al. (2006) / (physical) robot design / I	Android (Tron-X, PKD), animal-like (AIBO) / ↔ / Image/video of a robot	T+S ● ■	n=12 / age: range 21-54 years (M=29.9); Masters's and Ph.D. students in Psychology or Engineering / within subject design, C	CASA paradigm, Uncanny valley paradigm	• Human- /animal-likeness of robot	• Praise (+) • Punishment (-)	• The study results lead to the conclusion that the CASA paradigm holds true for computers • Robots on the other hand were treated differently depending on their physical appearance: very human-like or animal-like robots were

Author / subcategory / discipline[1)]	Robot morphology[2)] / robot level[3)] / type of embodiment	Team interaction[4)] / team setup[5)]	Data basis / participants[6)] / time frame[7)]	Underlying theories	Independent variable(s)[8)]	Dependent variable(s)[8)]	Major findings
							praised more and punished less than computer and human, machine-like robots were treated like computer and human
Ezenyilimba et al. (2023) / robot behaior / VII	n.i. / n.i. / Simulation/ virtual robot	T+S / n.i.	n=48 / university members / C (2 missions; between-subject)	Situation awareness	• Explanation (limited vs. full) • Transparency (static vs. dynamic)	• Situation awareness (lowest for [limited/static], n.s. between others) • Trust in robot (lower for all conditions in 2nd mission) • Trust in team (lowest for [limited/static], n.s. between others; decrease between missions) • Workload (highest for [limited/static] and [full/static],	• "By implementing robot transparency and robot explanations, we found that the driving factors for effective HRTs rely on robot explanations that are context-driven and are readily available to the human teammate." (p. 75)

Author / subcategory / discipline[1)]	Robot morphology[2)] / robot level[3)] / type of embodiment	Team interaction[4)] / team setup[5)]	Data basis / participants[6)] / time frame[7)]	Underlying theories	Independent variable(s)[8)]	Dependent variable(s)[8)]	Major findings
						n.s. between others; increase between missions)	
Hiatt et al. (2011) / robot behavior / IV	Humanoid (Mobile, Dexterous, Social (MDS) robot) / ↔ / Image/video of a robot	T+S	n=35 / n.i. / n.i.	Theory of mind	• Robot explanation	• Perceived robot naturalness (+) • Perceived robot intelligence (+)	• A robot that uses a theory of mind (ToM) approach and offers explanations is perceived both more intelligent and natural than a robot that either shows only simple correction or blindly follows a human (p. 2066) • To utilize the ToM-approach, the robot analyzes different models of human partners and, in case it finds a likely cause of unexpected behavior, articulates his findings (p. 2071)
Natarajan and Gombolay (2020) / robot	Functional (Sawyer), humanoid (Kuri, Pepper, Nao) / n.i. / Physical	T+S	n=75 / 51.47% f; age: range 18-58 (M=25.298,	n.i.	• Perceived anthropomorphism (+)	• Trust	• "Behavior and anthropomorphism of the agent are the most significant

Author / subcategory / discipline[1)]	Robot morphology[2)] / robot level[3)] / type of embodiment	Team interaction[4)] / team setup[5)]	Data basis / participants[6)] / time frame[7)]	Underlying theories	Independent variable(s)[8)]	Dependent variable(s)[8)]	Major findings
behavior / I	robot, video/image of a robot (as condition of experiment)		SD=8.457); from university / C (4x4x2x2; between- and within-subject)		• Robot behavior (+) • Robot presence (n.s.) • Coalition building preface (n.s.)		factors in predicting the trust and compliance with the robot" (p. 33)
Richert et al. (2016) / (physical) robot design, robot behavior / II	Functional, humanoid / n.i. / Simulation/ virtual robot	T+S / n.i.	n.i. / n.i. / n.i.	CASA paradigm, embodiment theories	• Personal characteristics • Robot characteristics	• Task performance (not reported)	• Proposal of experiments to gain insights into cooperation between humans and robots based on robot appearance and robot accuracy
N. Wang et al. (2016a) / robot behavior / III	Functional / n.i. / Simulation/virtual robot	T+S ● ■	n=220 / mTurk, USA / C	n.i.	• Robot explanations	• Transparency (+) • Trust (+) • Performance (+)	• A better understanding of decision-making processes of a robot can help improve trust • Explanations based on POMDP (Partially Observable Markov Decision Processes) can be a way to achieve this goal

Author / subcategory / discipline[1)]	Robot morphology[2)] / robot level[3)] / type of embodiment	Team interaction[4)] / team setup[5)]	Data basis / participants[6)] / time frame[7)]	Underlying theories	Independent variable(s)[8)]	Dependent variable(s)[8)]	Major findings
N. Wang et al. (2016b) / robot behavior / III	Functional / n.i. / Simulation/virtual robot	T+S	n=220 / mTurk, USA / C (between-subject)	n.i.	• Robot explanations	• Transparency (+) • Trust (+) • Performance (+)	• A better understanding of decision-making processes of a robot can help improve trust in HRTs (similar experiment as in "The impact of POMDP-generated explanations on trust and performance in human-robot teams")
N. Wang et al. (2018) / robot behavior / IV	Animal-like, functional / ↓ / Simulation/virtual robot (online HRI test bed)	T+S	n=61 / 14 f; age: range 18-23 (M=19.2); years higher-education military school in the US, participants received extra course credit for participation / C (2 sessions, 120 mins	n.i.	• Embodiment (n.s.) • Communication strategy in case of error (n.s.) • Explanations (+)	• Trust • Transparency • Transparency test score • Compliance • No. of correct decisions made	• Explanations by robots (even if they don't indicate which components of a robot are faulty) have significant effects on transparency and self-reported trust of participants and result in better decision-making of a human team mate • Robot embodiment and acknowledgement of mistakes only have a marginally or no

Author / subcategory / discipline[1)]	Robot morphology[2)] / robot level[3)] / type of embodiment	Team interaction[4)] / team setup[5)]	Data basis / participants[6)] / time frame[7)]	Underlying theories	Independent variable(s)[8)]	Dependent variable(s)[8)]	Major findings
			total, 8 missions)				significant impact on self-reported trust, transparency or correct decisions

Note: 1) Disciplines: I = HRI, II = Management, III = military, IV = Cognitive science, V = robotics, VI = space, VII = (urban) search and rescue, VIII = ethics; Studies are categorized based on a "best fit"-approach and might comprise aspects of more than one considered research discipline; 2) n.i. = no information provided by author(s); 3) Robot level: ↓ = robot on lower level, ↔ = robot on same level, ↑ = robot on higher level; 4) Team interaction: T = task interaction, T+S = task & social interaction; 5) ◯ = human, ▯ = robot; 6) f=female, m=male; 7) C = cross-sectional, L = longitudinal; 8) (-) = negative effect, (+) = positive effect, (n.s.) = not significant

Table 2-3a. Conceptual Studies on Multiple Member HRTs Related to Inter-member Team Characteristics and Their Effects

Author / subcategory / discipline[1)] / team interaction[2)]	Underlying theories	Major findings[3), 4)]
Abrams and Rosenthal-von der Pütten (2020) / team perceptions / IV / T+S	In-group identification (e.g., social identity theory); cohesion theories (e.g., group development theory); entativity theory (e.g., formation of perceived entativity)	• In-group identification, cohesion, and entitativity (I-C-E) framework can be used as a theoretical basis for research on human-robot groups • Multi-agent groups are similar but not the same as all-human groups • Dyads have unique processes that differ from group and team processes
Bradshaw et al. (2012) / autonomy and control / III / T	n.i.	• Autonomy and coordination in human-agent-robot teamwork should be in the focus of future research to solve current problems
Dudenhoeffer et al. (2001) / autonomy and control / III / T+S	Shared mental models, situational awareness	• Simulations are widely used in HRT and HRI research and can help to gain insights into this field, esp. when many robots are involved
Fusaro et al. (2021) / roles of humans and robots / V / T	n.i.	• Proposal and validation of integrated method for task allocation and planning in mixed HRTs that treats individual jobs as sets of "different tasks with temporal and logic constraints" (p. 534) thus working with simplified sub-problems that are optimized
Gladden (2014) / leaderhip / I / T+S	French and Raven's bases of power	• Charismatic robotic leaders (w/ charismatic authority being a manifestation of referent power) will probably emerge naturally • Introduction of three possible ways of charismatic robotic leaders
Groom and Nass (2007) / roles of humans and robots / III / T+S	Shared mental models	• Robots should be evaluated as complements to human team members (rather than duplicates) to take advantage of individual abilities of humans and robots
Hari et al. (2020) / roles of humans and robots / III / T	n.i.	• Proposal of algorithm for task allocation, sequencing and scheduling problem
Makarius et al. (2020) / roles of humans and robots / II / T+S	Socio-technical systems theory	• Proposal of model of AI (and robot integration)
Manikonda et al. (2007) / autonomy and control/ V / T	n.i.	• Proposal of framework for communication and collaboration in HRTs (strong technical focus)

Author / subcategory / discipline[1)] / team interaction[2)]	Underlying theories	Major findings[3), 4)]
Musić and Hirche (2018) / autonomy and control / V / T	n.i.	• Proposal of control approach for robot teams
Nikolaidis and Shah (2012) / team perceptions / IV / T	Shared mental models	• Proposal to use shared mental models also for HRTs
E. Phillips et al. (2012) / team perceptions / III / T+S	Shared mental models	• "relevant human–animal team capabilities (…) can inform and guide the design of next-generation human–robot teams" (p. 1553)
E. Phillips et al. (2016) / team perceptions / I / T+S	Shared mental models, interdependence theory	• Human-animal teams can be used as analogous examples for the development/set-up of effective HRTs
Samani and Cheok (2011) / leadership / II / T+S	n.i.	• Ideas on emotion-laden robotic leadership, advantages of robotic leaders, modes of robotic leadership
Scheutz et al. (2017) / team perceptions / IV / T+S	Shared mental models	• Proposal of formal and computational framework for development and usage of shared mental models in HRTs based on all-human teams
Sierhuis et al. (2003) / autonomy and control / VI / T	n.i.	• Discussion of perspective on teamwork and sliding autonomy
Talamadupula et al. (2014) / team perceptions / V / T	Shared mental models	• Proposal of "automated planning problem instance" (p. 2957)
Yazdani et al. (2016) / autonomy and control / VII / T	n.i.	• Proposal of cognition-enabled robot-control framework to foster a more natural communication between humans and robots

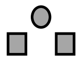
Note: 1) Disciplines: I = HRI, II = Management, III = military, IV = Cognitive science, V = robotics, VI = space, VII = (urban) search and rescue, VIII = ethics; Studies are categorized based on a “best fit”-approach and might comprise aspects of more than one considered research discipline; 2) Team interaction: T = task interaction, T+S = task & social interaction; 3) In most of the studies, the robot morphology, robot level, and type of embodiment are not specified. The six studies that provide information (Abrams & Rosenthal-von der Pütten, 2020; Dudenhoeffer et al., 2001; Gladden, 2014; Manikonda et al., 2007; Talamadupula et al., 2014; Yazdani et al., 2016) focus on functional robots (e.g., Growbot (Dudenhoeffer et al., 2001), Pioneer P3-AT (Talamadupula et al., 2014)) and indicate different robot levels (lower/same and higher level) and embodiments (physical robot; simulation); 4) In most of the studies, the team setup is not specified. The two studies that provide information focus on human-directed robot teams (Musić & Hirche, 2018; Yazdani et al., 2016).

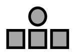
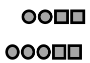
Table 2-3b. Conceptual Studies on Dyadic HRTs Related to Inter-member Team Characteristics and Their Effects

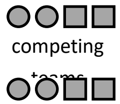
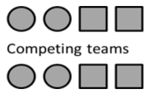
Author / subcategory / discipline[1)] / team interaction[2)]	Underlying theories	Major findings[3)]
Bankins and Formosa (2020) / team perceptions / IV / T+S	Psychological contract theory, social exchange theory, reciprocity	• Bankins and Formosa see a potential for human-robot psychological contracts that can also influence how humans work together
M. Demir et al. (2020) / roles of humans and robots / VII / n.i.	Shared mental models	• "results indicate that effective team interaction and shared cognition play an important role in human-robot dyadic teaming performance." (p. 1)

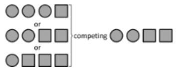
Note: 1) Disciplines: I = HRI, II = Management, III = military, IV = Cognitive science, V = robotics, VI = space, VII = (urban) search and rescue, VIII = ethics; Studies are categorized based on a "best fit"-approach and might comprise aspects of more than one considered research discipline; 2) Team interaction: T = task interaction, T+S = task & social interaction, n.i.= no information provided by author(s); 3) Robot morphology, robot level, and type of embodiment as well as team setup are not specified.

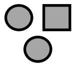
Table 2-3c. Empirical Studies on Multiple Member HRTs Related to Inter-member Team Characteristics and Their Effects

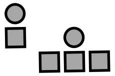
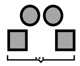
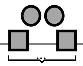
Author / subcategory / discipline[1)]	Robot morphology[2)] / robot level[3)] / type of embodiment	Team interaction [4)] / team setup[5)]	Data basis / participants[6)] / time frame[7)]	Underlying theories	Independent variable(s)[8)]	Dependent variable(s)[8)]	Major findings
Burke and Murphy (2004) / roles of humans and robots / VII	Functional / ↓ (Inuktun Micro Variable Geometry Tracked Vehicle (n=32), Inuktun Microtracs robot (n=1)) / Physical robot	**T** 	n=33 (two field studies) / experienced firefighters seeking USAR certification / C	Shared mental models, situational awareness	• Operator situational awareness (+) • Goal-oriented team communicatio n (+)	• Task performance	• "a minimum 2:1 human-to-robot ratio is required for effective robot-assisted technical search in USAR" (p. 307) • Goal-oriented team communication and a shared mental model of the search space and the task lead to better task performance
Chang et al. (2021) / team perceptions / I	Humanoid / n.i. / Simulation/virt ual robot	T / n.i.	n=95 / 30 f; age: M=38.55 (SD=12.25) / C (online user study, 2x2 between-subject)	Fairness	• Equality of capability (balanced vs. unbalanced) • Equality of time (balanced vs. unbalanced)	• Equality of workload • Equality of time • Equality of capability • Perspective-taking *(see major findings and study for detailed results and interaction effects)*	• Proposal and validation of metrics for people's perception of fairness in HRTs • "There are bleed-over effects in people's assessment of fairness. When asked to rate fairness based on the amount of time that the robot spends working with each person, participants used two factors (fairness based on the robot's time and

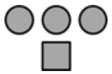
Author / subcategory / discipline[1]	Robot morphology[2] / robot level[3] / type of embodiment	Team interaction [4] / team setup[5]	Data basis / participants[6] / time frame[7]	Underlying theories	Independent variable(s)[8]	Dependent variable(s)[8]	Major findings
							teammates' capabilities)" (p. 905)
Charisi et al. (2021) / roles of humans and robots / IV	Neither zoomorphic nor humanoid (Haru robot) / ↔ / Physical robot	T / 	n=84 / 34 f; age: range 5-8 years (M=6.71, SD=0.99); no previous experience with chosen task and any robotic platform / C (2X2 repeated-measures between-subjects with 4 sessions)	n.i.	• Cognitive reliability (sub-optimal vs. optimal • Socia positioning (neutral vs. expressive) • Team-role of the robot (turn-taking vs. voluntary)	• Task performance • Social interaction • Help-seeking behavior • Pre-intervention trust-belief *(see study for detailed results)*	• "Children who interacted with the reliable robot had a better task performance but children who interacted with the unreliable robot exhibited more task-related social interactions." (p. 9439)
Crandall et al. (2003) / autonomy and control / I	n.i. / ↓ / n.i.	**T** 	n_1=13, n_2=23 / n.i. / C (six 5-minute sessions each)	n.i.	• n.i.	• n.i.	• Proposal of performance prediction algorithm for HRTs
Dias et al. (2008) / autonomy and control / VII	Functional (Pioneer, Segway ER1) / ↓, ↔ / Physical robot	**T** 	n.i. / n.i. / C (15 minutes run)	Sliding autonomy methodolo gy	• Sliding autonomy	• Performance (+)	• Challenges of enabling sliding autonomy in HRTs can be overcome by the presence of six key capabilities (requesting help, maintaining

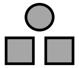
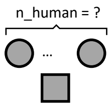
Author / subcategory / discipline[1]	Robot morphology[2] / robot level[3] / type of embodiment	Team interaction [4] / team setup[5]	Data basis / participants[6] / time frame[7]	Underlying theories	Independent variable(s)[8]	Dependent variable(s)[8]	Major findings
							coordination, situational awareness, granularity, prioritization, learning)
Fraune et al. (2017) / team perceptions / IV	Functional (Mugbot) / ↔ / Physical robot	T+S 	n = 48 / 21 f / C	Group theory, social identity	• Group (ingroup, outgroup) • Agent (human, robot)	• Liking (higher for in-group and humans in most cases) • Anthropomorphism (higher for ingroup in all cases)	• "participants favored the ingroup over the outgroup, and humans over robots. Group had a greater effect than Agent, so participants preferred ingroup robots to outgroup humans." (p. 1432)
Fraune (2020) / team perceptions / IV	Humanoid (Nao), functional (iRobot Creates) / ↔ / Physical robot	T+S / 	n=81 / age: M=19.15 / C (2 × 2 × 2 mixed-design)	Group theory, social identity	• Group membership (ingroup vs. outgroup; + for ingroup) • Agent type (human vs. robot; + for human)	• Moral behavior (measured via noise blast volume)	• "Participants favored the ingroup over the outgroup and humans over robots—to the extent that they favored ingroup robots over ingroup humans" (p. 1) • Results further indicate "that patterns of responses toward humans were more closely mirrored by anthropomorphic than mechanomorphic robots" (p. 1)

Author / subcategory / discipline[1)]	Robot morphology[2)] / robot level[3)] / type of embodiment	Team interaction [4)] / team setup[5)]	Data basis / participants[6)] / time frame[7)]	Underlying theories	Independent variable(s)[8)]	Dependent variable(s)[8)]	Major findings
(Fraune, Šabanović, & Smith, 2020) / team perceptions / IV	Functional (Mugbot) / ↔ / Physical robot	T+S / 	n=102 / recruited at university / C (2x2x3 mixed design)	Group theory, social identity	• Group membership (ingroup vs. outgroup) • Agent type (human vs. robot)	• Moral behavior (measured via noise blast volume)	• "Participants favored the ingroup over the outgroup and humans over robots - to the extent that they favored ingroup robots over outgroup humans. Interestingly, people differentiated more between ingroup than outgroup humans and robots" (p. 303)
Fuse and Tokumaru (2020) / roles of humans and robots / IV	Humanoid (RoBoHoN) / n.i. / Physical robot	T+S 	n=14 / Japanese university students / C (5 rounds)	n.i.	• Presence of robot considering group norms (vs. no robot)	• Change in answers given (+ for change between round 1 and 2, for others n.s.)	• "robots attempt to comply with a group norm affects human's decision-making" (p. 56081)
Gervits et al. (2020) /team perceptions / I	Humanoid (PR2 by Willow Garage) / ↔ / Simulation/virtual robot	**T** 	n=26 (from 36 originally recruited) / 19 m; age: M=24.9 years (SD=8.6); from University campus / C	Shared mental models	• Robot shared mental models	• Performance (+)	• Shared mental models help to improve performance and efficiency of HRTs

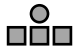
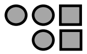
Author / subcategory / discipline[1)]	Robot morphology[2)] / robot level[3)] / type of embodiment	Team interaction [4)] / team setup[5)]	Data basis / participants[6)] / time frame[7)]	Underlying theories	Independent variable(s)[8)]	Dependent variable(s)[8)]	Major findings
Gombolay, Gutierrez, et al. (2015) / autonomy and control / II	Functional / ↔,↑ / Physical robot	**T+S** 	n=24 / 14 m, 10 f; age: range 20-42 (mean age of 27±7 years); recruited via email and around a university campus / C	n.i.	• Presence of robot • Robot decision-making authority	• Team efficiency (+/ +) • Perceived likeability, appreciation, and understanding of co-leader (-/+)	• “an autonomous robot can outperform a human worker in the allocation of part of or all tasks that have to be completed” (p. 293) • People prefer to give control authority to the robot • "People value human teammates more than robotic teammates, however, providing robots authority over team coordination more strongly improves their perceived value compared to giving similar authority to a human team mate" (p. 293) • People tend to "assign a disproportionate amount of work to themselves when working with a robot (...) rather than human team mates only" (p.293)

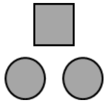
Author / subcategory / discipline[1]	Robot morphology[2] / robot level[3] / type of embodiment	Team interaction [4] / team setup[5]	Data basis / participants[6] / time frame[7]	Underlying theories	Independent variable(s)[8]	Dependent variable(s)[8]	Major findings
Goodrich et al. (2007) / autonomy and control / I	n.i. / ↓ / Simulation/virtual robot; physical robot	**T** / 	n=80 (in four experiments with 16, 23, 11, 30 participants resp.) / n.a. / C	n.i.	• Attention management aids (+) • Adaptive autonomy (+) • Information abstraction (+)	• Individual and team autonomy	• Individual and team autonomy benefit from adjustable and adaptive autonomy • Adjusting autonomy should also allow for shifting between management styles
Kwon et al. (2019) / leadership / I	n.i. / ↔, ↓, ↑ / No embodiment	T  n_humans = {3,…,6}	n.i. / n.i. / n.i.	Adaptive leadership theory	• Robot intervention (use of leader-follower graph)	• Leadership scores (+) • Task execution time (+) • Success rate (+)	• Leader-follower graphs enable robots to influence human teams through "redirect[ion of] a leader-follower relationship, distract[ion of the] team, or lead[ing of] a team towards the optimal goal" (p. 2)
P.-J. Lee et al. (2010) / autonomy and control / VII	Functional (Pioneer P2-AT robots) / ↓ / Simulation/virtual robot (USARSim robotic simulation)	**T**  n_robots=2	n=120 (in 60 teams) / University of Pittsburgh community, paid, no previous experience with robot control / C	n.i.	• Robot autonomy (+) • Team organization (+/-)	• System performance	• "Automating path planning improved system performance. Effects of team organization were equivocal." (p. 438)
Lewis et al. (2010) /	Functional (Pioneer P2-	**T**  n robots=24	n=120 (in 60 teams) /	n.i.	• Robot autonomy (+)	• System performance	• Automation of path planning in USAR HRTs

Author / subcategory / discipline[1]	Robot morphology[2] / robot level[3] / type of embodiment	Team interaction [4] / team setup[5]	Data basis / participants[6] / time frame[7]	Underlying theories	Independent variable(s)[8]	Dependent variable(s)[8]	Major findings
autonomy and control / VII	AT) / ↓ / Simulation		University of Pittsburgh community, paid, no previous experience with robot control / C		• Shared team authority (+)		helps to improve performance • "effects of team organization favored operator teams who shared authority for the pool of robots" (p. 1617)
Li et al. (2021) / leadership / I	n.i. / ↔, ↓, ↑ / No embodiment	T /  n_humans = {3,…,6}	n.i. / n.i. / n.i.	Adaptive leadership theory	1&2 • Robot intervention (use of leader-follower graph)	1: • Leadership scores (+) • Task execution time (+) • Success rate (+) 2: • Collision time (+)	• Proposal and validation of framework for leaders & followers in HRTs • Leader-follower graphs enable "better planning and an optimization for robot actions" (p. 970)
Lopes et al. (2021) / leadership / II	Humanoid (EMYS) / ↑ / Physical robot	T / 	n=108 (divided into 36 teams of 3 each) / 52.8% f; age: M=37.40 (SD=11.09) / C	n.i.	• Robotic leadership style (transformational vs. transactional)	• Team productivity (+ for transactional) • Team engagement (+ for transformational)	• "Both [transformational and transactional] leadership styles can have positive impacts in organizational outcomes, although in different aspects" (p. 258)

Author / subcategory / discipline[1]	Robot morphology[2] / robot level[3] / type of embodiment	Team interaction [4] / team setup[5]	Data basis / participants[6] / time frame[7]	Underlying theories	Independent variable(s)[8]	Dependent variable(s)[8]	Major findings
						• Role ambiguity (n.s.) • Human-robot trust (n.s.)	
Musić et al. (2019) / autonomy and control/ V	Functional (KUKA LWR 4+) / ↔, ↓ / Physical robot	T 	n=48 / 12 f / C (experiment was performed 10 times/particip ant)	n.i.	• Type of feedback (no vs. binary vs. relative)	• Task performance (n.s. / +)	• Proposal of control architecture for HRTs • Feedback through wearable fingertip devices helps to increase performance
Ranzato and Vertesi (2017) / roles of humans and robots / VII	Functional / ↓ / Physical robot (remote!)	T+S 	n=30 (6 teams of 5 each with 3:2 gender ratio) / n.i. / C	n.i.	• Team organizational structure (loose)	• Efficiency (+) • Communicat ion (+) • Teammate trust (+)	• Loosely coupled teams were found to be the most successful compared to tightly coupled hierarchical and consensus groups
Savela, Kaakinen, et al. (2021) / team perceptions / II	n.i. / ↔ / n.i.	n.i. / setups ranging from 1H4R to 4H1R (study 1) / 2H3R (2) to 5H	n_1=1003, n_2=969 / 1: 51.11% f; age: M=37.36 (SD=11.80); 2: 51.15% f; age: M=37.15 (SD=11.35); both: Amazon Mechanical turk / C	Social identity theory	• 1 & 2: Experimental group (1H4R, 2H3R, 5H; 1: - for more robots on team, 2: n.s.)	1 & 2: • In-group identification	• "Having a robot on the work team had a nega-tive impact on in-group identification." (p. 1) • "The results suggest that when humans are members of minority subgroup within a work team, their subgroup

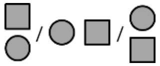
Author / subcategory / discipline[1]	Robot morphology[2] / robot level[3] / type of embodiment	Team interaction [4] / team setup[5]	Data basis / participants[6] / time frame[7]	Underlying theories	Independent variable(s)[8]	Dependent variable(s)[8]	Major findings
			(between subject)				identity is threatened." (p. 1) • These results "indicate that introducing a robot as a teammate may affect in-group identification process negatively with some individual differences." (p. 1)
Savela, Oksanen, et al. (2021) / team perceptions / II	n.i. / ↔ / n.i.	n.i. / setups ranging from 1H4R (study 1 & 2 & 3) to 4H1R (1) to 2H3R (2) to 5H (1 & 2 & 3)	n_1=1003, n_2=969, n_3=1059 / 1: 48.16% m; age: M=37.36 (SD=11.80); 2: 48.08% m; age: M=37.15 (SD=11.35); 3: 48.29% m; age: M=37.97 (SD=11.75); all: Amazon mechanical Turk / C (between-subject)	Theories of prejudice	1 & 2: • Experimental group (see team setup; 1: - for more robots on team, 2: n.s.) 3: • Experimental group (framing as teammates vs. coworkers; - for R teammates (as compared to H teammates); n.s. for pairwise	1 & 2 & 3: • Sentiments of written social media posts	• "People are less enthusiastic about working with robots than with humans"(p. 1) • Further, the "results suggest these more negative reactions stem from feelings of oddity in an unusual situation and the lack of social interaction" (p.1) • "The same robot product could be received differently depending on the social status and group membership it is given" (p. 12)

Author / subcategory / discipline[1]	Robot morphology[2] / robot level[3] / type of embodiment	Team interaction [4] / team setup[5]	Data basis / participants[6] / time frame[7]	Underlying theories	Independent variable(s)[8]	Dependent variable(s)[8]	Major findings
					comparison of all groups)		
Sellner et al. (2006) / autonomy and control / I	Functional (Roving Eye, Mobile Manipulator, Crane) / ↓ / Physical robot	T 	n_1=2, n_2=32 /1: expert users of the robotic system; 2: n.i. / C	Situational awareness, concept of sliding autonomy	• Autonomy	• Time to completion (-) • Success rate (+) • Human workload (-)	• Robots purposefully asking for help result in more efficient and robust systems and enable human operators to gain situational awareness
					• Autonomy • Extent of information provision	• Average response time (-/+)	
Strohkorb Sebo et al. (2020) / roles of humans and robots / I	Humanoid (Jibo) / ↔ (not specified) / Physical robot	T+S / Round 1:  Round 2: 	n=78 (in 26 teams) / 38 f; age: M=16.82 years (SD=0.72); from high school program held at Yale University / C	Social identity theory	• Specialized robot liaison (-) • Robot supportive utterances (+ / n.s.)	• Human inclusion	• "specialized roles may hinder human team member inclusion, whereas supportive robot utterances show promise in encouraging contributions from individuals who feel excluded." (p. 309)

Author / subcategory / discipline[1)]	Robot morphology[2)] / robot level[3)] / type of embodiment	Team interaction [4)] / team setup[5)]	Data basis / participants[6)] / time frame[7)]	Underlying theories	Independent variable(s)[8)]	Dependent variable(s)[8)]	Major findings
Yam et al. (2022) / leadership / IV	Functional/humanoid / ↑ / Physical robot	T+S / 	n_1=179; n_2=164 / 1: 51.4% f; age: M=21.08 (SD=2.01); 2: 51.2% f; age: M=20.20 (SD=1.62); both: undergraduate students from large university in China / C (laboratory)	Ming perception theory	• Robot supervisor anthropomorphism (+)	• Supervisor-directed retaliation	• In the context of delivering negative feedback to an employee through a robotic supervisor, anthropomorphism leads to higher supervisor-directed retaliation

Note: 1) Disciplines: I = HRI, II = Management, III = military, IV = Cognitive science, V = robotics, VI = space, VII = (urban) search and rescue, VIII = ethics; Studies are categorized based on a "best fit"-approach and might comprise aspects of more than one considered research discipline; 2) n.i. = no information provided by author(s); 3) Robot level: ↓ = robot on lower level, ↔ = robot on same level, ↑ = robot on higher level; 4) Team interaction: T = task interaction, T+S = task & social interaction; 5) ◯ = human, □ = robot; 6) f=female, m=male; 7) C = cross-sectional, L = longitudinal; 8) (-) = negative effect, (+) = positive effect, (n.s.) = not significant

Table 2-3d. Empirical Studies on Dyadic HRTs Related to Inter-member Team Characteristics and Their Effects

Author / subcategory / discipline[1]	Robot morphology[2] / robot level[43] / type of embodiment	Team interaction[4] / team setup[5]	Data basis / participants[6] / time frame[7]	Underlying theories	Independent variable(s)[8]	Dependent variable(s)[8]	Major findings
Abendschein et al. (2021) / roles of humans and robots / IV	n.i. / all configurations: ↑, ↔, ↓ / Image/video of robot	T+S 	n = 215 / 134 f, 77m; age: range 18-69 years (M = 24, SD = 8.67) / C	n.i.	• Team roles (human lead, robotic assistant; robotic lead, human assistant; co-teaching) (+ for all DVs in human-led teaching team)	• Credibility • Task and social attraction • Social presence • Affective learning	• "Students rated the human-led team as more appealing and having more credibility than the robot-led team" (p. 123) • "The current findings are unique in that they compare the individual roles and power structures of human-robot teams leading a course" (p. 123)
Chang et al. (2020) / team perceptions / I	Functional / ↔ / Physical robot	T+S / 	n=30 / 9f; university students / C (2x2 within-subject)	Fairness	• Fluency (absent vs. present) • Effort (absent vs. present)	• Objective measures: total task time, ratio of total tasks, ratio of math tasks, ratio of pickup tasks, ratio of strength tasks • Participant's perception of fairness *(see major findings and*	• "Effort and fluency help improve fairness without making a trade-off with efficiency" (p. 1251) • Proposal of "three notions of fairness for effective human-robot teamwork: equality of workload, equality of apability, equality of task type" (p.1251)

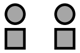
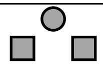
Author / subcategory / discipline[1)]	Robot morphology[2)] / robot level[43] / type of embodiment	Team interaction[4)] / team setup[5)]	Data basis / participants[6)] / time frame[7)]	Underlying theories	Independent variable(s)[8)]	Dependent variable(s)[8)]	Major findings
						study for detailed results and interaction effects)	
Eyssel and Kuchenbrandt (2012) / team perceptions / I	Humanoid / ↔ / Video/image of robot	T+S / n.i.	n=78 / German university students, 37 m, 40 f; age: M=23.27 (SD=3.29) / C	Social identity theory	• Robot in in-group (vs. out-group)	• Warmth (+) • Mind attribution (+) • Psychological closeness (+) • Contact intentions (+) • Design preference (+)	• Participants "rated the in-group robot more favourably … [and] also anthropomorphized it more strongly than the out-group robot" (p. 724)
Jong et al. **(2021)** / roles of humans and robots / IV	Functional (Cozmo), humanoid (Nao) / ↔ / Image/video of a robot	T+S / 	n_1=81, n_2=37 (without robots); n_3=87, n_4=93 / 3: 52% f, 46% m, age: M=35.52 (SD=12.42); 4: age: M=29.11 (SD=9.32) / C	Social identity theory	3 & 4: • Results (+) • Group membership (+) • Agent type (n.s.)	3 & 4: • Intergroup empathy • Intergroup schadenfreude	• "People felt more empathy towards ingroup members than outgroup members and more schadenfreude towards outgroup members. The existence of an intergroup bias did not depend on the nature of the agent:" (p. 1) • "Similar empathy and schadenfreude biases were

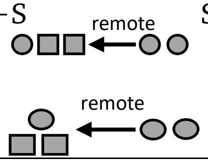
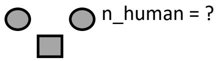
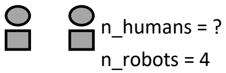
Author / subcategory / discipline[1]	Robot morphology[2] / robot level[43] / type of embodiment	Team interaction[4] / team setup[5]	Data basis / participants[6] / time frame[7]	Underlying theories	Independent variable(s)[8]	Dependent variable(s)[8]	Major findings
			(2 (results) x 2 (group membership) x 2 (agent type) within design)				observed for both humanoid and mechanoid robots" (p. 1)
Kuchenbrandt et al. (2013) / team perceptions / IV	Humanoid (Nao) / n.i. / Physical robot	T+S / n.i.	n=45 / 25 m, 18 f, age: M=24.81 years (SD=5.00), German university students / C	Social identity	• Robot in in-group (vs. out-group)	• Implicit anthropomorphization of robot (+) • Explicit anthropomorphization of robot (+) • Acceptance of robot (+) • General willingness to interact with robot (+)	• "Perceived in-group membership with the robot resulted in a greater extent of anthropomorphic inferences about the robot and more positive evaluations." (p. 409) • Additionally, participants with the robot in their in-group "showed greater willingness to interact with robots in general." (p. 409)
Marble et al. (2004) / autonomy and control / VII	Functional / ↓ / Physical robot	T+S	n=11 /1 f, 10 m; 4 expert users, 7 no or some prior experience; INEEL employees / L (4 sessions in	n.i.	• Dynamic robot autonomy	• Target detection (+) Situation awareness (+)	• Autonomy of a robot should be adjustable to allow for situation awareness and task completion • Participants varied greatly in their ability to trust a robot (i.e., allow autonomy)

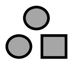
Author / subcategory / discipline[1)]	Robot morphology[2)] / robot level[43] / type of embodiment	Team interaction[4)] / team setup[5)]	Data basis / participants[6)] / time frame[7)]	Underlying theories	Independent variable(s)[8)]	Dependent variable(s)[8)]	Major findings
			direct succession)				• Performance benefits from practice

Note: 1) Disciplines: I = HRI, II = Management, III = military, IV = Cognitive science, V = robotics, VI = space, VII = (urban) search and rescue, VIII = ethics; Studies are categorized based on a "best fit"-approach and might comprise aspects of more than one considered research discipline; 2) n.i. = no information provided by author(s); 3) Robot level: ↓ = robot on lower level, ↔ = robot on same level, ↑ = robot on higher level; 4) Team interaction: T = task interaction, T+S = task & social interaction; 5) ◯ = human, ▯ = robot; 6) f=female, m=male; 7) C = cross-sectional, L = longitudinal; 8) (-) = negative effect, (+) = positive effect, (n.s.) = not significant

Table 2-4a. Conceptual Studies on Multiple Member HRTs Related to Team Processes and Their Effects

Author / subcategory / discipline[1)]	Robot morphology[2)] / robot level[3)] / type of embodiment	Team interaction[4)] / team setup[5)]	Underlying theories	Major findings
Alboul et al. (2008) / (physical) coordination / I	n.i. / ↓ / Physical robot	T 	n.i.	• Proposal of theoretical framework for navigation in HRTs
Bradshaw et al. (2009) / (physical) coordination / I	n.i. / n.i. / n.i.	T+S / n.i.	Coordination theory	• Coordination in human-agent-robot teams as an essential ingredient of joint activities: Fulfillment of teamwork model & resulting expectations towards communication (towards leader and colleagues) will allow robots to be seen as team mates
S. Brown et al. (2005) / (physical) coordination / III	n.i. / ↓ / n.i.	T 	n.i.	• Proposal of reference framework for HRTs
Bruemmer et al. (2002) / collaboration / III	Functional (augmented ATRVJR) / ↓, (↔, ↑) / Physical robot	T / n.i.	Role theory, shared mental models	• Proposal of a framework for mutual-initiative in HRTs
Bruemmer and Walton (2003) / collaboration / III	Functional (augmented ATRVJR) / n.i. / n.i.	T / n.i.	Shared mental models	• Discussion of approach for control architecture for human-robot teams in a military context
Fiore et al. (2011) / collaboration / III	n.i. / n.i. / n.i.	T+S / n.i.	n.i.	• Successful interactions in HRTs are based on organizational (and corresponding roles), social, and cultural models • Research has to work on gaining insights into how robots fit into such models and how they can understand organizational, social, and cultural factors

Author / subcategory / discipline[1)]	Robot morphology[2)] / robot level[3)] / type of embodiment	Team interaction[4)] / team setup[5)]	Underlying theories	Major findings
Gervasi et al. (2020) / collaboration / I	n.i. / ↑, ↔, ↓ / n.i.	T+S / n.i.	n.i.	• Proposal of conceptual framework for the evaluation of collaboration in HRTs
Hayes and Scassellati (2014) / collaboration / I	n.i. / n.i. / n.i.	T+S / n.i.	n.i.	• Proposal of four research questions on collaboration in HRTs
Kruijff, Janíček, et al. (2014) / communication / VII	Functional ("Generaal", P3-AT; NIFTi UGV andUAV) / ↓ / Physical robot	T+S 	Situational awareness	• Proposal and validation of "user-centric design methodology in developing systems for human-robot teaming in Urban Search and Rescue" (p. 1) • Robot acceptance is important
Kruijff et al. (2012) / communication /III	Functional / ↓ / Physical robot	T 	Situational awareness	• Proposal of experience and communication model to support shares human-robot activities
Kruijff-Korbayová et al. (2015) / communication /IV	Functional (NIFTi UGV and UAV) / ↓ / Physical robot	T 	Situational awareness	• Description of the project "TRADR: long-term human-robot teaming for robot assisted disaster response" (p. 193) and the user centric design approach that is used
Nakano and Goodrich (2015) / communication / V	n.i. / n.i. / n.i.	n.i. / n.i.	n.i.	• Proposal of "new interface concept, a Graphical Narrative Interface (GNI)" (p. 634) • "We hypothesize that the GNI allows users to search and analyze spatiotemporal information more easily and quickly than a typical GUI." (p. 634)
Nourbakhsh et al. (2005) /	n.i. / n.i. / n.i.	T / n.i.	n.i.	• Proposal of an agent-based "architecture for Urban Search and Rescue and a methodology for mixing real-world and simulation-based testing" (p. 72)

Author / subcategory / discipline[1)]	Robot morphology[2)] / robot level[3)] / type of embodiment	Team interaction[4)] / team setup[5)]	Underlying theories	Major findings
communicatin / VII				
Norton et al. (2022) / communication / I	Functional / ↓ / n.i.	T / n.i.	Situation awareness,	• Proposal of metrics for proficiency-based HRI
Schwartz et al. (2016) / collaboration / I	Humanoid (Aila), functional (Artemis, Compi) / n.i. / n.i.	n.i. / n.i.	n.i.	• Discussion of setup of teams with robots, virtual agents and humans as team members ("hybrid teams")
Stewart et al. (2012) / collaboration / IV	n.i. / n.i. / n.i.	n.i. / n.i.	Decision theory	• Proposal of decision-making model for HRTs
Tang and Parker (2006) / collaboration / I	n.i. / ↔ / n.i.	T / n.i.	Information invariance theory, schema theory	• Proposal of human-robot teaming approach ASyMTRe, dealing "with the issue of how to organize robots into subgroups to accomplish tasks collectively based upon their individual capabilities" (p. 27)
Woods et al. (2004) / (physical) coordination / III	n.i. / n.i. / n.i.	T / n.i.	n.i.	• Exploration of issues with human-robot coordination
Yi and Goodrich (2014) / collaboration / V	n.i. / ↓ / n.i.	T 	Shared mental models	• Proposal of collaboration model using shared mental models

Note: 1) Disciplines: I = HRI, II = Management, III = military, IV = Cognitive science, V = robotics, VI = space, VII = (urban) search and rescue, VIII = ethics; Studies are categorized based on a "best fit"-approach and might comprise aspects of more than one considered research discipline; 2) n.i. = no information provided by author(s); 3) Robot level: ↓ = robot on lower level, ↔ = robot on same level, ↑ = robot on higher level; 4) Team interaction: T = task interaction, T+S = task & social interaction, n.i. = no information provided by author(s); 5) ◯ = human, ▯ = robot

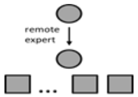
Table 2-4b. Conceptual Studies on Dyadic HRTs Related to Team Processes and Their Effects

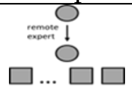
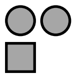
Author / subcategory / discipline[1)]	Robot morphology[2)] / robot level[3)] / type of embodiment	Team interaction[4)] / team setup[5)]	Underlying theories	Major findings
Breazeal, Brooks, et al. (2004) / collaboration / I	Humanoid (Leonardo) / ↔ / Physical robot	T+S	Collaborative discourse theory, joint intention theory	• The authors follow a perspective "of a balanced partnership where the human and robot maintain and work together on shared task goals" (p. 270) • Paper gives an overview of the different robotic features of the robot
Breazeal, Hoffman, and Lockerd (2004) / collaboration / I	Humanoid (Leonardo) / ↔ / Physical robot	T+S	Collaborative discourse theory, joint intention theory	• Presentation of approach for collaborative human-robot teamwork
Oh et al. (2015) / (physical) coordination / V	n.i. / n.i. / n.i. (*no robot involved in experiments*)	T+S / n.i.	n.i.	• Proposal and validation of model for indirect perception in HRTs
Ososky et al. (2013) / trust / IV	n.i. / ↔ / Physical robot	T+S	Shared mental models	• Trust in HRTs should not simply be maximized, the goal should be to have appropriate trust (both in intention and ability)
Shah and Breazeal (2010) / (physical) coordination / IV	n.i. / n.i. / n.i. (*no robot involved in experiments*)	T+S / n.i.	Shared mental models	• Implicit and explicit communication in HHT give insights into how robots in HRTs could act • "a robot should respond to communications differently, depending on whether they are implicit, explicit, verbal only, nonverbal only (gesture), or combined." (p. 244)
Visser et al.(2020) / trust / IV	n.i. / ↔ / n.i.	T+S / n.i.	Theory of mind, trust theories	• Proposal of Human-robot team trust model that has a longitudinal perspective on the development and calibration of trust in HRTs

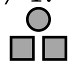
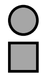
Note: 1) Disciplines: I = HRI, II = Management, III = military, IV = Cognitive science, V = robotics, VI = space, VII = (urban) search and rescue, VIII = ethics; Studies are categorized based on a "best fit"-approach and might comprise aspects of more than one considered research discipline; 2) n.i. =

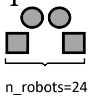
no information provided by author(s); 3) Robot level: ↓ = robot on lower level, ↔ = robot on same level, ↑ = robot on higher level; 4) Team interaction: T = task interaction, T+S = task & social interaction, n.i. = no information provided by author(s); 5) ◯ = human, ▯ = robot

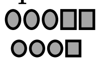
Table 2-4c. Empirical Studies on Multiple Member HRTs Related to Team Processes and Their Effects

Author / subcategory / discipline[1]	Robot morphology[2] / robot level[3] / type of embodiment	Team interaction[4] / team setup[5]	Data basis / participants[6] / time frame[7]	Underlying theories	Independent variable(s)[8]	Dependent variable(s)[8]	Major findings
Aggravi et al. (2021) / (physical) coordination / VII	Functional / ↓ / Simulation/virtual robot	T / 	n = 12 / 1 f; age: range 23–32 years / C (16 trials per user)	Concept of decentralized control	• Haptic feedback (vs. visual) • Separate information provision (vs. joint)	• Avg task completion time (- / -) • Avg length (- / -) • Linear velocity of simulated human agent (- / -) • Avg connectivity force commanded to human operator (- / n.s.) • Avg connectivity level of whole formation (- /n.s.)	• Proposal and validation of "decentralized haptic-enabled connectivity-maintenance control framework" (p. 4843) for HRTs • "Providing haptic feedback showed increased performance w.r.t. providing visual information only" (p. 4843)
Aggravi et al. (2022) / (physical) coordination) / VII	Functional / ↓ / Simulation/virtual robot	T /	n_1=15, n_2 = 16, n_3=1 / 1: 2f, age: range 23-29 years, naive	Concept of decentralized control	• 1: Feedback modality (no feedback vs. vibrotactile feedback vs.	1&2: Performance • Avg task completion time	• Proposal and validation of "decentralized connectivity-maintenance control framework" (p. 3109) for HRTs

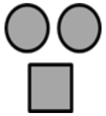
Author / subcategory / discipline[1)]	Robot morphology[2)] / robot level[3)] / type of embodiment	Team interaction[4)] / team setup[5)]	Data basis / participants[6)] / time frame[7)]	Underlying theories	Independent variable(s)[8)]	Dependent variable(s)[8)]	Major findings
		 (third experiment without remote expert)	participants; 2: 2f, age: range 23-29 years, naive participants; 3: 1m, age: 30 years, expert / C (within-subject)		auditory feedback) • 2: Feedback modality (vibrotactile feedback vs. auditory feedback) • 3: n.i. • *(see paper for detailed results)*	• Avg connectivity force commanded to human operator • Avg total force commanded to robots • Max. total force commanded to robots • Number of targets reached • User's experience • User's perceived effectiveness • 3: n.i.	• "Providing either haptic or audio feedback for conveying information about the team connectivity significantly improves the performance of the considered tasks, although users significantly preferred receiving haptic stimuli w.r.t. the audio ones" (p. 3109)
Burke and Murphy (2007) / collaboration / VII	Functional (Inuktun Micro Variable Geometry Tracked Vehicle (VGTV) robot)	T 	n=62 / 90% m; majority between 35-54 years; NASA USAR task-force personnel / L (two runs á 20	Shared mental models, situational awareness	• Remote shared visual presence (+) • Visual contact (n.s.)	• Team performance	• Remote shared visual presence may help remote USAR HRTs "to perform as effectively as collocated teams" (p. 161)

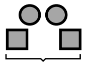
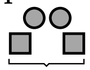
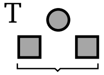
Author / subcategory / discipline[1]	Robot morphology[2] / robot level[3] / type of embodiment	Team interaction[4] / team setup[5]	Data basis / participants[6] / time frame[7]	Underlying theories	Independent variable(s)[8]	Dependent variable(s)[8]	Major findings
	/ ↓ / Physical robot		minutes over 2-day period; final n=50 (# teams completing both runs))				
Canning et al. (2014) / communication / I	Humanoid & Functional (Xitone Design MDS, Willow Garage PR2, VGo, iRobot Create) / ↓/ Simulation/virtual robot, Video/image of robot	T / 1:  2 & 3: 	n_1= 24, n_2=137, n_3=183 / mTurk; 1: 12 f, age: range 18-31 years, M=20.88 (SD=2.59), all right-handed, fluent in English; 2: 48 f, age: range: 18-60 years, median=31, US residents; 3: 91 f, age: range: 18-60 years, median=31, US residents / C	n.i.	• Video feed type (real vs. simulated)	• Task performance (n.s.) • Perceived collaboration (+ for real video) • Perceived utility (+ for real video)	• Examination of robot perceptions in remote team settings • "realism of the [video]feed becomes important when the human teammate knows about the robot's appearance and they work together on a task" (p. 4361) • See study for details on results and interaction effects of study 3
					• Video feed type (real vs. simulated) • Introduction of robot	• Task performance (n.s.) • Perceived collaboration (n.s.) • Perceived utility (n.s.) • Perceived competence (n.s.) • Perceived warmth (n.s.)	

Author / subcategory / discipline[1)]	Robot morphology[2)] / robot level[3)] / type of embodiment	Team interaction[4)] / team setup[5)]	Data basis / participants[6)] / time frame[7)]	Underlying theories	Independent variable(s)[8)]	Dependent variable(s)[8)]	Major findings
Fong et al. (2006) / communication / VI	Functional, humanoid (K10 rover, Robonaut) / ↓, ↔ / Physical robot	T 	n.i. / n.i. / C	n.i.	• Reliability of robots (independence, as a result of understanding of communication)	• Productivity (amount of useful work, exposure time in space) (+)	• Software frameworks are being developed (e.g., HRI/OS) to allow for effective work of humans and robots
Gao et al. (2012) / (physical) coordination / VII	n.i. / ↓ / Simulation/virtual robot (USARsim)	T 	n=48 / 19 f; age: range 19-47 years, M=26.6 (SD=5.5); 33 of them students / C	n.i.	• Team structure (pooled, sector) • Search guidance (no, suggestion, enforced)	• Task performance (n.s.) • Task completion time (- for suggested guidance in sector teams; n.s. for other conditions) • Subjective workload (- for pooled teams)	• Automated search guidance neither increased nor decreased performance" (p. 81) • Search guidance decreased average task completion time in Sector teams" (p. 81) • "pooled teams experienced lower subjective workload than sector teams" (p. 81)
T. Iqbal et al. (2015) / collaboration / V	Functional (Turtlebot) / ↔ / Physical robot	T 	n=2 / n.i. / n.i.	n.i.	• n.i.	• n.i.	• Proposal of an event-based model to enable robotic action perception in HRTs

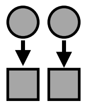
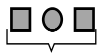
Author / subcategory / discipline[1)]	Robot morphology[2)] / robot level[3)] / type of embodiment	Team interaction[4)] / team setup[5)]	Data basis / participants[6)] / time frame[7)]	Underlying theories	Independent variable(s)[8)]	Dependent variable(s)[8)]	Major findings
T. Iqbal et al. (2016) / (physical) coordination / V	Functional (turtlebot) / ↔ / Physical robot	T / pilot:  main: 	n_pilot=7, n_main=27 (in 9 groups) / pilot: 3 f; main: 14 f, age: M=22.93 (SD=3.98), mainly students / C	n.i.	• Robot movement based on synchronization-index based anticipation (vs. based on event cluster-based anticipation)	• Synchronization (+) • Robot Timing Appropriateness (+)	• Proposal and validation of "approach to enable robots to perceive human group motion in real time to anticipate future actions and synthesize their own motion accordingly " (p. 909) • * "the robot performs better when it has an understanding of high-level group behavior than when it does not" (p. 909)
T. Iqbal and Riek (2017) / (physical) coordination / V	Functional (Turtlebot) / ↔ / Physical robot	T 	n= 18 (in 6 groups) / 11 f; age: M=24.7 years (SD=4.5); undergrad and grad students / C	n.i.	• n.i.	• n.i.	• "results might suggest that an addition of a robot with heterogeneous behavior to a group significantly reduces the overall group coordination, and might be an important indicator of human-robot group dynamics." (p. 1716)
Jung et al. (2013) / communication / VII	Humanoid (Maddox and Nexi), functional (UAV, not specified) / ↔ / Physical robot	T+S 	n=73 / age: range 18-40 years (M=25.0, SD=6.19); from university community / C	Back-channeling, social signaling	• Back-channeling	• Team functioning (+) • Perceived robot engagement (+)	• "subtle backchanneling by robots in human-robot teams helped team functioning (lower stress, lower cognitive load) and perceived engagement of the robots, especially when

Author / subcategory / discipline[1)]	Robot morphology[2)] / robot level[3)] / type of embodiment	Team interaction[4)] / team setup[5)]	Data basis / participants[6)] / time frame[7)]	Underlying theories	Independent variable(s)[8)]	Dependent variable(s)[8)]	Major findings
						• Perceived robot competence (-)	the task was complex, but at the same time lead to robots being seen as less competent." (p. 1563) • "the biggest benefits from backchanneling in human-robot teams may be seen when tasks are demanding and complex." (p. 1563)
Jung et al. (2015) / communication / IV	Functional (Pioneer 3 robot base + OWI robot arm + arm-control board + speaker) / ↔ / Physical robot	T+S	n=106 (in 53 teams)/ 55 m; age: range 18-65 years (M=24.5, SD=8.0); recruited from university / C	n.i.	• Robot intervention	• Awareness of conflict (+) • Affect (+/n.s.) • Perceptions of team members' contributions (n.s.) • Team performance (n.s.)	• "we found that the robot's repair interventions increased the groups' awareness of conflict after the occurrence of a personal attack thereby acting against the groups' tendency to suppress the conflict." (p. 229)s
Kantor et al. (2006) / communication / VII	Functional / ↓ / Physical robot	T	n.i. / n.i. / C	n.i.	• n.i.	• n.i.	• Sensor networks can be used by robots and humans to extend their joint capabilities
Kruijff, Kruijff-Korbayová,	Functional (NIFTi UGV	T	n.i. / n.i. / n.i.	Situational awareness	• n.i.	• n.i.	• Description of the experiences in designing,

Author / subcategory / discipline[1)]	Robot morphology[2)] / robot level[3)] / type of embodiment	Team interaction[4)] / team setup[5)]	Data basis / participants[6)] / time frame[7)]	Underlying theories	Independent variable(s)[8)]	Dependent variable(s)[8)]	Major findings
et al. (2014) / communication / VII	and UAV) / ↓ / Physical robot						developing and deploying systems for USAR
R. Liu et al. (2021) / (physical) coordination / I	Functional (Sawyer) / ↓ / Physical robot	T / 	n=90 / 34% f, 46% m; age: M=23 / C (5 completed repetitions per participant)	n.i.	• Scheduling approach (exploitation, explore-exploit, annealed explore-exploit)	• Makespan improvement • Subject skill • Subject idle time • Robot trust • Human-robot working alliance • Perceived team competence • Perceived robot performanc *(see study for detailed results)*	• Proposal and validation of coordination algorithm • "Human-robot working alliance […] and human performance […] are maximized when the robot dedicates more time to exploring the capabilities of human teammates" (p. 1)
Marge et al. (2009) / communication / V	Functional (Pioneer P2-DX, Segway Robotic Mobility Platform	T+S 	n.i. / n.i. / n.i.	n.i.	• n.i.	• n.i.	• Description of the human-robot interface TeamTalk

Author / subcategory / discipline[1]	Robot morphology[2] / robot level[3] / type of embodiment	Team interaction[4] / team setup[5]	Data basis / participants[6] / time frame[7]	Underlying theories	Independent variable(s)[8]	Dependent variable(s)[8]	Major findings
	(RMP)) / ↔ / Simulation/virtual robot						
Nevatia et al. (2008) / / collaboration / VII	Functional / ↓ / / Simulation/virtual robot	T  n_robots = {2, 3, 4, 5}	n.i. / n.i. / n.i.	n.i.	• n.i.	• n.i.	• Proposal and validation of an "integrated system for semiautonomous cooperative exploration, augmented by an intuitive user interface for efficient human supervision and control" (p. 2103) • "having a human in the loop improves task performance, especially with larger numbers of robots" (p.2103)
H. Wang et al. (2010) / (physical) coordination / VII	Functional (Pioneer P2-AT) / ↓ / Simulation/virtual robot (USARSim robotic simulation)	T  n_robots=24	n=60 participants (acting in teams of 2 -> 30 teams) / University of Pittsburgh, paid, no previous experience with robot control / C	Situational awareness	• Automated path planning (+) • Team organization (shared authority for robots) (+)	• System performance	• For USAR tasks, automated path planning helps to improve team accuracy and performance • Sharing authority for robots during team organization also helps to improve performance (re/ accuracy and finding)
J. Wang et al. (2008) / (physical)	Functional (P2DX robots, Zergs) / ↓ /	T  n_robots = 6	n=19 / age: range 19-33 years, from	Crandall's neglect tolerance	• Needed physical proximity	• Team performance (-)	• "Automating cooperation [by using subteams] reduced CD [coordination

Author / subcategory / discipline[1)]	Robot morphology[2)] / robot level[3)] / type of embodiment	Team interaction[4)] / team setup[5)]	Data basis / participants[6)] / time frame[7)]	Underlying theories	Independent variable(s)[8)]	Dependent variable(s)[8)]	Major findings
coordination / IV	Simulation/virtual robot		Pittsburgh university / C	model , situational awareness		• Coordination demands (n.s.)	demands] and improved performance." (p. 9)
					• Automation of cooperation	• Team performance (+) • Coordination demands (+)	
Williams et al. (2015) / communication / IV	Functional (VGo, Roompi) / ↓ / Physical robot	T	n_1=28, n_2 = 28 / 1&2: 14 f, age: range 18-65, mostly students / C	n.i.	• Robot-robot communication (verbal, silent)	• Perceived creepiness of the robot (1: n.s.; 2: + for silent communication) • Perceived trustworthiness of the robot (1 & 2: n.s.) • Perceived efficiency of the robot (1 & 2: n.s.) • Perceived cooperativity	• "silent communication of task-dependent, human-understandable information among robots is perceived as creepy by cooperative, co-located human teammates" (p. 24) • "increased natural language interaction with a robot enhances humans' general perceptions of that robot" (p. 38)

Author / subcategory / discipline[1]	Robot morphology[2] / robot level[3] / type of embodiment	Team interaction[4] / team setup[5]	Data basis / participants[6] / time frame[7]	Underlying theories	Independent variable(s)[8]	Dependent variable(s)[8]	Major findings
						of the robot (1 & 2: n.s.)	
You and Robert (2016) / (physical) coordination / IV	Functional/humanoid (adapted from the LEGO® Mindstorms® EV3 sets) / ↓ / Physical robot	T 	n=60 / 36 f; age: M=22.86 years (SD=4.51); from university in US / C	n.i.	• Training	• Individual performance (+/n.s.) • Team performance (+/n.s.)	• "training minimized the negative impacts of curiosity and heightened the positive impacts of control on task involving the use of a robot." (p.449)
Zheng et al. (2013) / communication / V	Humanoid (Robovie-II) / ↔ / customer & operator: n.a.; simulation: simulation/virtual robot; case study: physical robot	T 	n_customer=15, n_operator=16; n_simulation=15; n_case study=n.i. / customer: 8 f, age: M=22 years; operator: 7 f, age: M=21 years; simulation: 6 f, age: M=20 years; case study: n.i.; all: Japanese undergrad students / C	n.i.	• n.i.	• n.i.	• Introduction of simulation tool for "models for operation timing, customer satisfaction and customer–robot interaction" (p. 843), and "techniques for managing interaction flow and operator task assignment" (p. 843)

Note: 1) Disciplines: I = HRI, II = Management, III = military, IV = Cognitive science, V = robotics, VI = space, VII = (urban) search and rescue, VIII = ethics; Studies are categorized based on a "best fit"-approach and might comprise aspects of more than one considered research discipline; 2) n.i. = no information provided by author(s); 3) Robot level: ↓ = robot on lower level, ↔ = robot on same level, ↑ = robot on higher level; 4) Team interaction: T = task interaction, T+S = task & social interaction, n.i. = no information provided by author(s); 5) ◯ = human, ▯ = robot; 6) f=female, m=male; 7) C = cross-sectional, L = longitudinal; 8) (-) = negative effect, (+) = positive effect, (n.s.) = not significant

Table 2-4d. Empirical Studies on Dyadic HRTs Related to Team Processes and Their Effects

Author / subcategory / discipline[1)]	Robot morphology[2)] / robot level[3)] / type of embodiment	Team interaction[4)] / team setup[5)]	Data basis / participants[6)] / time frame[7)]	Underlying theories	Independent variable(s)[8)]	Dependent variable(s)[8)]	Major findings
Ali et al. (2022) / trust / I	n.i. / n.i. / No embodiment	T+S /	n.i. / n.i. / n.i.	n.i.	• n.i.	• n.i.	• Proposal and validation of "task allocation method for heterogeneous human–robot teams based on artificial trust from a robot that can learn agent capabilities over time and allocate both existing and novel task. Tasks are allocated to the agent that maximizes the expected total reward. The expected total reward incorporates trust in the agent to successfully execute the task as well as the task reward and cost associated with using that agent for that task." (p. 15304)

Author / subcategory / discipline[1)]	Robot morphology[2)] / robot level[3)] / type of embodiment	Team interaction[4)] / team setup[5)]	Data basis / participants[6)] / time frame[7)]	Underlying theories	Independent variable(s)[8)]	Dependent variable(s)[8)]	Major findings
Bozcuoglu et al. (2015) / communication / VII	Functional (Quadcopter) / ↓, ↔ / Simulation/virtual robot	T+S	n.i. / n.i. / n.i.	n.i.	• n.i.	• n.i.	• Transparency on robotic behavior and reactions through communication helps to increase the success of HRTs
Breazeal et al. (2005) / communication / I	Humanoid ("Leo(nardo)")/ ↓, ↔ / Physical robot	T+S	n=21 / 10m; age: range 20-40; local campus, no interaction with robot before / C	Shared mental models	• Non-verbal social cues and behavior	• Task performance (understandability of the robot, efficiency of task performance, robustness to errors that arise from miscommunication) (+)	• Non-verbal communication plays an important role also in the effectiveness of HRTs
M. Chen et al. (2020) / trust / V	Functional / n.i. / Simulation/virtual robot, Physical robot	T+S	n_1=201 (simulation), n_2=20 (real robot) / 1: age: range 18-65 years, mTurk, from the US, 2: age: range 21-65 years, from University / C	n.i.	• Trust	• Team performance (+/-; appropriate level of trust needed for best performance)	• Proposal of computational model to integrate trust into robotic behavior • "maximizing trust alone does not always lead to the best performance" (p. 9:1)
Ciocirlan et al. (2019) /	Humanoid (TIAGo) / n.i. /	T+S / n.i.	n=71 / 40 m, 30 f; age:	Trust theories	• communication (no	• trust (+ for task communication)	• "the decrease in trust when the

Author / subcategory / discipline[1)]	Robot morphology[2)] / robot level[3)] / type of embodiment	Team interaction[4)] / team setup[5)]	Data basis / participants[6)] / time frame[7)]	Underlying theories	Independent variable(s)[8)]	Dependent variable(s)[8)]	Major findings
communication / IV	Simulation/virtual robot		range 14-53 years, M=24 years (SD=6) / C		communication, text and verbal task communication, text and verbal informal communication)		robot fails to perform the task is lower when [there] is text and verbal interaction between the robot and the participant" (p. 7) • "trust at the end of the experiment was higher than the initial trust when the participants had a text and verbal interaction communication related to the task" (p. 7)
Freedy et al. (2007) / trust / III	Functional (unmanned ground vehicle) / ↓ / Simulation/virtual robot	T+S 	n=12 / 4 f; age: range 18-25 years, most with several years of gaming	Collaborative performance model	• Robot competency	• Time to complete mission (-) • Operator intervention (-) • Workload (-)	• Introduction of an objective measure of trust dependent on the number of operator

Author / subcategory / discipline[1)]	Robot morphology[2)] / robot level[3)] / type of embodiment	Team interaction[4)] / team setup[5)]	Data basis / participants[6)] / time frame[7)]	Underlying theories	Independent variable(s)[8)]	Dependent variable(s)[8)]	Major findings
			experience, 1.5 hours of training / L (15 trials/participant, 5 trials of 3 competency levels in firing behavior each)		• Trust	• Human intervention (-/+-; appropriate level of trust needed)	overrides/interventions • Knowledge about robot competencies and characteristics (e.g., level of performance) can help to foster trust
Hoffman and Breazeal (2004) / collaboration / I	Humanoid ("Leo")/ ↓, ↔ / Physical robot	T+S ● ■	n.i. / n.i. / C	Dialog theory, joint intention theory	• n.i.	• n.i.	• Proposal of a framework for dynamic collaboration • To establish successful HRTs, robots and humans have to share the same goals, communicate with each other and show commitment to jointly reach their goals
Hoffman and Breazeal (2007) / collaboration /I	Functional (Symon, forklift-like) / ↔ / Simulation/virtual robot	T+S ● ■	n=32 / 15 f; MIT community, laboratory / C	n.i.	• Robot anticipatory action	• Task efficiency (+/n.s.) • Perceived robot contribution to team fluency (+)	• Anticipatory action of a robotic teammate helps to increase task efficiency and improves "the perceived

Author / subcategory / discipline[1)]	Robot morphology[2)] / robot level[3)] / type of embodiment	Team interaction[4)] / team setup[5)]	Data basis / participants[6)] / time frame[7)]	Underlying theories	Independent variable(s)[8)]	Dependent variable(s)[8)]	Major findings
						• Perceived robot contribution to team success (+) • Perceived robot commitment (+)	commitment of the robot to the team and its contribution to team's fluency and success" (p. 1)
Koppula et al. (2016) /collaboration / I	Functional / ↓ / Physical robot (Kodiak (PR2)) / simulation/virtual robot	T+S ● ■	n=5 / n.i. / n.i.	n.i.	• Anticipatory planning	• Perceived robot collaboration (+) • Perceived robot timing (+) • Satisfaction with robot (+) • Willingness to work with the robot (+) • Time savings (+ / not stated explicitly)	• Proposal of graphical model to anticipate human actions
Lo et al. (2020) / communication / V	Functional / ↔ / Physical robot	T+S ● ■	n=16 / 8 f, visitors or students at the campus / C	n.i.	• Robot motion planning approach (nested inference for corroborative acts (NICA) vs. legible motion)	• Perceived clarity of intent (+) • Motion predictability and naturalness (+) • Perceived social appropriateness (+) • Perceived safety, intelligence, capabilities,	• Proposal of model for multi-agent planning based on partner's knowledge and behavior (NICA) • Experiment shows that NICA "is perceived as significantly more natural, socially

Author / subcategory / discipline[1]	Robot morphology[2] / robot level[3] / type of embodiment	Team interaction[4] / team setup[5]	Data basis / participants[6] / time frame[7]	Underlying theories	Independent variable(s)[8]	Dependent variable(s)[8]	Major findings
						thoughtfulness, and fluency to team with of the robot (n.s. / +)	appropriate, and fluent to team with, while being both more predictable and intent-clear" (p. 326)
Marble et al. (2003) / collaboration /VII	Functional (ATRVJr) / ↓ / Physical robot	T+S	n=11 / 1 f, 10 m; 4 expert users, 7 no or some prior experience; INEEL employees / C	n.i.	• Mixed-initiative interaction	• Adaptation to autonomy (not reported) • Perceived ease to predict outcome of control (not reported)	• Utilization of robot autonomous capabilities depends on previous robotic experience of users (inexperienced users utilize autonomy more willingly) • Control challenges should be considered
Nikolaidis et al. (2015) / (physical) coordination / IV	Functional / ↓ / Simulation/virtual robot, Physical robot	T+S	n_1=36, n_2=24 / 1: recruited from MIT; 2: n.i. / C	Shared mental models	• team training (human-robot cross-training)	• mental model convergence (+) • robot trustworthiness (+) • team fluency (+)	• "cross-training yields statistically significant improvements in quantitative team performance measures, as well as significant differences in

Author / subcategory / discipline[1]	Robot morphology[2] / robot level[3] / type of embodiment	Team interaction[4] / team setup[5]	Data basis / participants[6] / time frame[7]	Underlying theories	Independent variable(s)[8]	Dependent variable(s)[8]	Major findings
					• team training (human-robot cross-training) without learning component in algorithm	• objective and subjective measures of team fluency and participant's satisfaction (n.s.	perceived robot performance and human trust" (p.1711) • "This study supports the hypothesis that the effective and fluent teaming ofa human and a robot may best be achieved by modeling known, effective human teamwork practices." (p. 1711)
Nikolaidis and Shah (2013) / (physical) coordination / IV	Functional / ↓, ↔ / Physical robot	T+S	n=36 / recruited from MIT / C	Shared mental models	• Team training (human-robot cross-training)	• Mental model convergence (+) • Mental model similarity (+) • Team fluency (concurrent motion, idle time) (+) • Perceived robot performance (+) • Human trust (+)	• A good way to achieve effective and fluent human-robot teaming may be to model effective practices for human teamwork (p. 33) • Human-robot cross-training leads to "statistically significant improvements in

Author / subcategory / discipline[1)]	Robot morphology[2)] / robot level[3)] / type of embodiment	Team interaction[4)] / team setup[5)]	Data basis / participants[6)] / time frame[7)]	Underlying theories	Independent variable(s)[8)]	Dependent variable(s)[8)]	Major findings
							quantitative team performance measures" (p. 33) (compared to standard reinforcement learning techniques)
Nikolaidis et al. (2018) / communication / I	Humanoid (HERB) / ↔ / Video/image of a robot (video playback)	T+S	n_1=151 (from initial 200-exclusions) / 1: 60% female, age: M=35 years, from US, mTurk / C	Game theory	• Robot communication	• Trust in the robot (+ / n.s.) • Adaption to robot (+ / n.s.)	• "enabling the robot to issue verbal commands is the most effective form of communicating objectives, while retaining user trust in the robot." (p. 22:1)
Shah et al. (2011) / (physical) collaboration / I	Humanoid (Nexi, a Mobile-Dexterous-Social (MDS) robot) / ↔ / Physical robot	T+S	n=16 subjects / 10 m; age: M=29.4 years (SD = 16.1), recruited from the MIT and Greater Boston area / C	n.i.	• Usage of robot plan execution system Chaski	• Human idle time (-) • Time to complete task (n.s.) • Robot trustworthiness (+) • Team fluency (n.s.) • Perceived robot performance (n.s.)	• Chaski (task-level executive for robots) is able to reduce human idle time significantly and by this supports the hypothesis that it can help to increase team performance

Author / subcategory / discipline[1)]	Robot morphology[2)] / robot level[3)] / type of embodiment	Team interaction[4)] / team setup[5)]	Data basis / participants[6)] / time frame[7)]	Underlying theories	Independent variable(s)[8)]	Dependent variable(s)[8)]	Major findings
						• Sharing of common goals (n.s.)	

Note: 1) Disciplines: I = HRI, II = Management, III = military, IV = Cognitive science, V = robotics, VI = space, VII = (urban) search and rescue, VIII = ethics; Studies are categorized based on a "best fit"-approach and might comprise aspects of more than one considered research discipline; 2) n.i. = no information provided by author(s); 3) Robot level: ↓ = robot on lower level, ↔ = robot on same level, ↑ = robot on higher level; 4) Team interaction: T = task interaction, T+S = task & social interaction, n.i. = no information provided by author(s); 5) ◯ = human, ▯ = robot; 6) f=female, m=male; 7) C = cross-sectional, L = longitudinal; 8) (-) = negative effect, (+) = positive effect, (n.s.) = not significant

Table 2-5a. Studies Related to Moderating Effects in Multiple Member HRTs

Author / Discipline[1)] / Main Category	Independent variable(s)[2)]	Dependent variable(s)[2)]	Moderator variable(s)	Moderating effect[2)]
Claure et al. (2020) / V / Cat. 1	• Robot fairness	• User trust • Perceived robot fairness	• Human capabilities	• (+ for weak performers; n.s. otherwise)
Correia, Petisca, et al. (2019) / IV / Cat. 1	• Robot goal orientation (performance-driven vs. learning-driven)	• Competitiveness Index • McGill Friendship Questionnaire • Relationship Assessment Scale • Godspeed Questionnaire	• Session number	• Mixed results, see study for details
Fraune (2020) / IV / Cat. 2	• Group membership (ingroup vs. outgroup) • Agent type (human vs. robot)	• Moral behavior (measured via noise blast volume)	• Robot appearance (anthropomorphic vs. mechanomorphic)	• Anthropomorphic robots were treated more similarly to humans
Fraune, Šabanović, and Smith (2020) / IV / Cat. 2	• Group membership (ingroup vs. outgroup) • Agent type (human vs. robot)	• Moral behavior (measured via noise blast volume)	• Team composition (1H3R vs. 2H3R vs. 3H1R)	• Softer noise blasts are given to ingroup (than outgroup) members
Jung et al. (2013) / VII / Cat. 3	• Back-channeling	• Team functioning • Perceived robot engagement • Perceived robot competence	• Task complexity	• (+) • (+) • (n.s.)
You and Robert (2016) / IV / Cat. 3	• Training	• Individual performance • Team performance	• Curiosity • Control	• (+ /n.s.) • (n.s. /-)

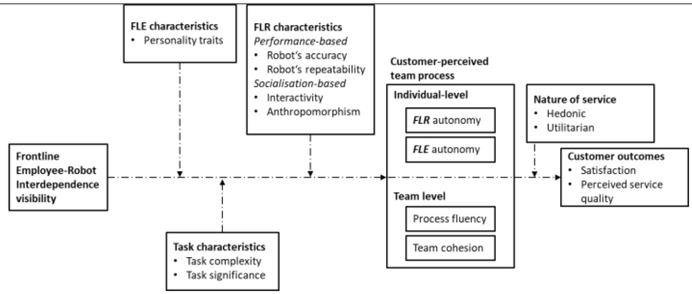
Note: 1) Disciplines: I = HRI, II = Management, III = military, IV = Cognitive science, V = robotics, VI = space, VII = (urban) search and rescue, VIII = ethics; Studies are categorized based on a "best fit"-approach and might comprise aspects of more than one considered research discipline; 2) (-) = negative effect, (+) = positive effect, (n.s.) = not significant

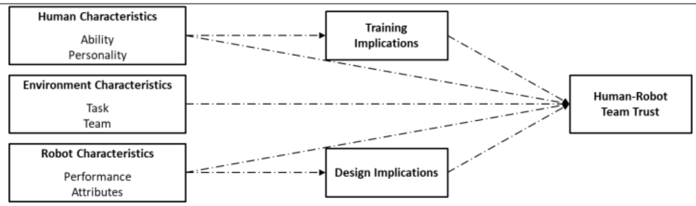
Table 2-5b. Empirical Studies Related to Moderating Effects in Dyadic HRTs

Author / Discipline[1] / Main Category	Independent variable(s)[2]	Dependent variable(s)[2]	Moderator variable(s)	Moderating effect[2]
Marble et al. (2004) / VII / 2 (dyad)	• Dynamic robot autonomy	• Target detection • Situation awareness	• Session number	• (+) • (+)
Marble et al. (2003) / VII / 3 (dyad)	• Mixed-initiative interaction	• Adaptation to autonomy • Perceived ease to predict outcome of control	• Remote system experience	• n.s • (-)
Richert et al. (2016) / II / 1	• Personal characteristics • Robot characteristics	• Task performance	• Subjective behavior: ○ Stress ○ Cooperation	• Not reported

Notes: 1) Disciplines: I = HRI, II = Management, III = military, IV = Cognitive science, V = robotics, VI = space, VII = (urban) search and rescue, VIII = ethics; Studies are categorized based on a "best fit"-approach and might comprise aspects of more than one considered research discipline; 2) (-) = negative effect, (+) = positive effect, (n.s.) = not significant

Table 2-6a. Conceptual Integrative and Overarching Studies on Multiple Member HRTs

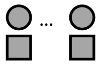
Author / subcategory / discipline[2)] / team interaction[2)]	Underlying theories	Research framework[3)]	Major findings[4)]
Arnold and Scheutz (2017) / ethics / VIII / T+S	n.i.	n.i.	• There are many ethical questions currently unsolved in HRI • "Robots do not have to be teammates to work with a team, especially given the ethical and empirical question of how the whole range of physical presence with a robot can affect others." (p. 449)
Le et al. (2023) integrative study / II / T+S	Interdependence theory		• Proposal of a framework for frontline employee-robot interdependence with a focus on customer perspective
Ma et al. (2018) / HRT design / I / T+S	n.i.	n.i.	• Overview of important considerations for the design of HRTs, including team and teamwork components
Ma et al. (2022) / metrics/HRT design / I / T+S	n.i.	n.i.	• Proposal of metrics for HRTs that combines traditional HRI and new teamwork metrics
Oleson et al. (2011) / integrative	n.i.		• Inappropriate levels of trust can lead to disuse and/or misuse of robots • Proposal of a framework for human-robot trust

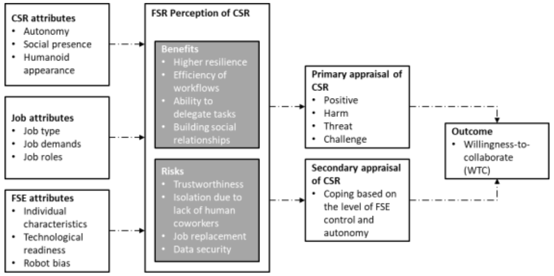
Author / subcategory / discipline[2)] / team interaction[2)]	Underlying theories	Research framework[3)]	Major findings[4)]
study / IV / T+S			
L. P. Robert, Jr. (2018) / integrative study / IV / T+S	Motivational theories of individual and team motivation	n.i.	• Proposal of "Motivational Theory of Human–Robot Teamwork" based on: emotional stability, extraversion, openness to experience, agreeableness, conscientiousness of a robot
Seeber et al. (2020) / integrative study / I / T+S	n.i.	n.i.	• Proposal of "research agenda for exploring the potential risks and benefits of machines [including (social) robots] as teammates"
Smids et al. (2020) / ethics / IV / T+S	Theories of meaningfulness in life and work	n.i.	• "Robotization of the workplace can have both significant negative and positive effects on meaningful work" (p. 503) • Thereby, meaningful work includes five key aspects: "pursuing a purpose, social relationships, exercising skills ald self-development, self-esteem and recognition, and autonomy" (p. 503)
Tamburrini (2009) / ethics / VIII / T+S	n.i.	n.i.	• Robot ethics is a growing field that gains importance with the developments of new robots and technology

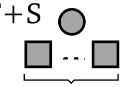
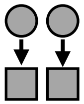
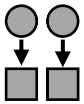
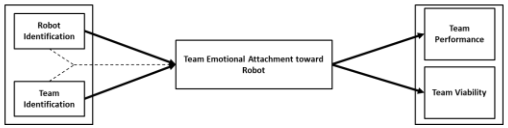
Author / subcategory / discipline[2)] / team interaction[2)]	Underlying theories	Research framework[3)]	Major findings[4)]
You and Robert (2018c) / integrative study / I / T+S	IPO model, trust theories	n.i.	• Proposal of working framework for HRTs based on IMOI (inputs-mediators-outputs-inputs) framework

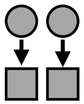
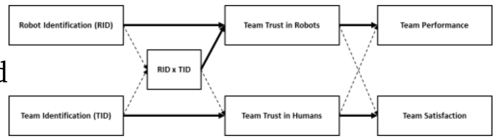
Note: 1) Disciplines: I = HRI, II = Management, III = military, IV = Cognitive science, V = robotics, VI = space, VII = (urban) search and rescue, VIII = ethics; Studies are categorized based on a "best fit"-approach and might comprise aspects of more than one considered research discipline; 2: Team interaction: T = task interaction, T+S = task & social interaction; 3) ➡ = positive effect, ⟶ = negative effect, ⇢ = not significant, –·→ = effect not reported; 4) None of the studies provide information on robot morphology, robot level, or type of embodiment. Only two studies provide information on team setup, focusing on autonomous mixed teams (Ma et al., 2018) and human-directed robot teams (You & Robert, 2018c), respectively.

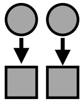
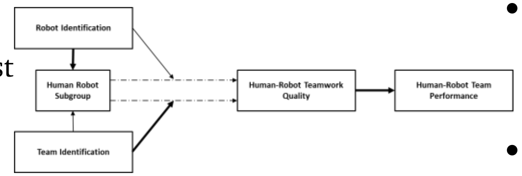
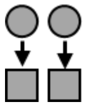
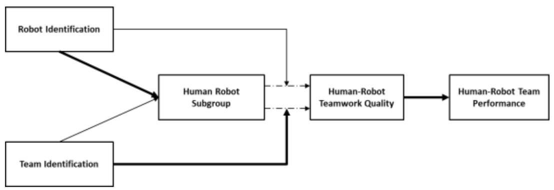
Table 2-6b. Empirical Integrative and Overarching Studies on Multiple Member HRTs

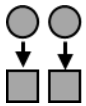
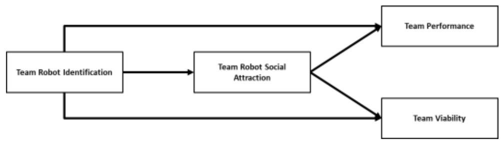
Author / subcategory / discipline[2)]	Robot morphology[2)] / robot level[3)] / type of embodiment	Team interaction[4)] / team setup[5)]	Data basis / participants[6)] / time frame[7)]	Underlying theories	Research framework[8)]		Major findings
Burke et al. (2008) / metrics / I	Functional (Telemax UGV, Matilda UGV, Dragonrunner UV, AirRobot UAV) / ↓ / Physical robot	T 	n=31 / participants from FEMA USAR teams in the US / C (in 2 phases)	n.i.	n.i.		• Proposal and validation of measurement instruments for assessment of usability (team member), incidents (observer) and team processes (observer) in HRTs
Giachetti et al. (2013) / integrative study / III	n.i. / n.i. / Simulation/virtual robot	T / Combinations of n_robot={2, 4} & n_team={6, 12}	n.i. / n.i. / n.i.	Shared mental models	• Number of robots (2,4) • Team size (6,12) • Team centralization (low, high) • Danger level (30%, 70%) • Robot reliability (6, 10 hours)	• Performance • Effectiveness (see major findings and study for detailed results and interaction effects)	• Proposal and validation of agent-based simulation model for the examination of team designs • "there are limits to the number of robots that a team can effectively manage" (p. 25) • "larger teams have more robust performance over the noise [i.e., not controllable] factors" (p. 15)

Author / subcategory / discipline[2)]	Robot morphology[2)] / robot level[3)] / type of embodiment	Team interaction[4)] / team setup[5)]	Data basis / participants[6)] / time frame[7)]	Underlying theories	Research framework[8)]	Major findings
						• "robot reliability is critical to the formation of human-robot teams" (p. 15) • "high centralization of decision-making authority created communication bottlenecks at the commander in large teams" (p. 15)
Paluch et al. (2022) / integrative study / II	n.i. / n.i. / n.i.	T+S / n.i.	n=36 / 58% f, age: 24-61 years, experience with service robots, working in service industry / C (qualitative interviews)	Appraisal theory		• Proposal of a framework on the willingness to work with robots to better understand employee-robot interactions, identifying attributes and employee personas that shape the appraisal of service robots in service contexts

Author / subcategory / discipline[2)]	Robot morphology[2)] / robot level[3)] / type of embodiment	Team interaction[4)] / team setup[5)]	Data basis / participants[6)] / time frame[7)]	Underlying theories	Research framework[8)]	Major findings
Pina et al. (2008) / metrics / I	n.i. / ↓ / n.i.	T+S  n_robots = {2,	n=16 / age: range 19-49 years / C (four 8-minute sessions with different robotic team sizes)	n.i.	n.i.	• Proposal of generalizable metric classes for the evaluation of HRTs and illustration of need for these with case study
L. P. Robert, Jr. and You (2015) / integrative study / IV	Functional/humanoid (adapted from the LEGO® Mindstorms® EV3 sets) / ↓ / Physical robot	T+S 	n=30 (15 teams) / 14 f; age: M=24.7 (SD=7.48); from large university in US / C (laboratory)	n.i.	n.i.	• "subgroups formed between humans and their robots were negatively correlated with various team outcomes" (p. 1)
You and Robert (2018a) / integrative study / IV	Functional/humanoid (adapted from the LEGO® Mindstorms® EV3 sets) / ↓ / Physical robot	T+S 	n=114 (in 57 teams) / 51 m; age: M=23 years (SD=5.3); from online	Media richness (channel expansion theory, cognitive model of media choice,		• Emotional attachment of teams to robots leads to better performance • "Both robot and team identification increased a team's

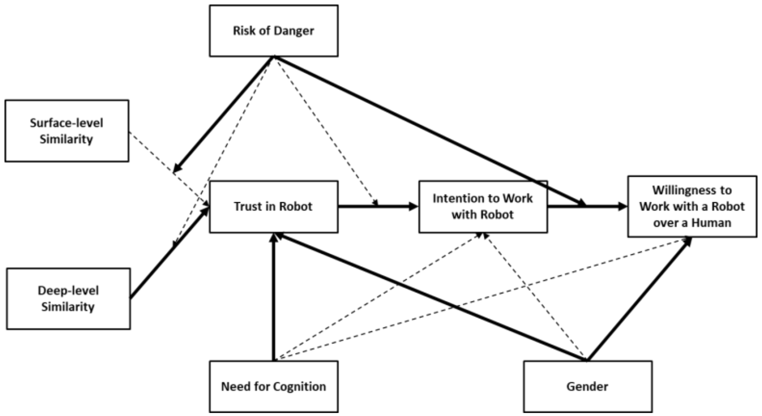
Author / subcategory / discipline[2]	Robot morphology[2] / robot level[3] / type of embodiment	Team interaction[4] / team setup[5]	Data basis / participants[6] / time frame[7]	Underlying theories	Research framework[8]	Major findings
			subject pool at a Midwestern university in US / C (duration with robots approx. 25-30 minutes) (between-subjects)	media synchronicity), technology acceptance model, unified model of technology acceptance and use of technology, social identity theory		emotional attachment to its robots" (p. 377)
You and Robert (2019b) / integrative study / IV	Functional/humanoid (adapted from the LEGO® Mindstorms® EV3 sets) / ↓ / Physical robot	T+S 	n=108 (54 teams) / 54 men; age: M=24 years; from subject pool at a Midwestern university in US / C (duration approx. 25-30 minutes)	Social categorization and attraction theories, trust theories		• "robot identification increased trust in robots and team identification increases trust in one’s teammates" (p. 244) • "Trust in robots increases team performance while trust in teammates increases satisfaction" (p. 244)

Author / subcategory / discipline[2)]	Robot morphology[2)] / robot level[3)] / type of embodiment	Team interaction[4)] / team setup[5)]	Data basis / participants[6)] / time frame[7)]	Underlying theories	Research framework[8)]	Major findings
You and Robert (2019a) / integrative study / IV	Functional/humanoid (adapted from the LEGO® Mindstorms® EV3 sets) / ↓ / Physical robot	T+S 	n=88 (44 teams) / 42 f; age: M=23.6 (SD=4.1); from large university in US / C (duration approx. 25-30 minutes)	Social identity theory, trust theories		• Subgroups can form in HRTs (when humans identify with their robots) • "Robot identification and team identification moderate … negative effects of subgroup formation on teamwork quality and subsequent team performance" (p. 1)
You and Robert (2022a) / integrative study / IV	Functional/humanoid (adapted from the LEGO® Mindstorms® EV3 sets) / ↓ / Physical robot	T+S / 	n_1=88 (44 teams), n_2=112 / 1: 42 f; age: M=23.6 (SD=4.1); from large university in US; 2: 44f; age: M=41.2 (SD=11.5); experienced in	n.i.	1:  2: Qualitative online study	• "As physically embodied AI, robots are able to elicit strong emotional bonds from humans, leading to subgroups in human– robot teams." (p. 14)

Author / subcategory / discipline[2)]	Robot morphology[2)] / robot level[3)] / type of embodiment	Team interaction[4)] / team setup[5)]	Data basis / participants[6)] / time frame[7)]	Underlying theories	Research framework[8)]	Major findings
			working with robots / C (laboratory, between-subjects; survey)			
You and Robert (2022b) / integrative study / IV	Functional/humanoid (adapted from the LEGO® Mindstorms® EV3 sets) / ↓ / Physical robot	T+S / 	n=60 (30 teams) / 32 f, age: M=24 years (SD= 5.88 years) / C (laboratory, between-subject)	Team identification theory		• Proposal and validation of theoretical framework of team robot identification theory (TRIT) • Team identification in HRTs leads to better performance and team viability

Note: 1) Disciplines: I = HRI, II = Management, III = military, IV = Cognitive science, V = robotics, VI = space, VII = (urban) search and rescue, VIII = ethics; Studies are categorized based on a "best fit"-approach and might comprise aspects of more than one considered research discipline; 2) n.i. = no information provided by author(s); 3) Robot level: ↓ = robot on lower level, ↔ = robot on same level, ↑ = robot on higher level; 4) Team interaction: T = task interaction, T+S = task & social interaction; 5) ◯ = human, ▯ = robot; 6) f=female, m=male; 7) C = cross-sectional, L = longitudinal; 8) ➡ = positive effect, ⟶ = negative effect, - - -▸ = not significant, —·→ = effect not reported

Table 2-6c. Empirical Integrative and Overarching Studies on Dyadic HRTs

Author / subcategory / discipline[1)]	Robot morphology[2)] / robot level[3)] / type of embodiment	Team interaction[4)] / team setup[5)]	Data basis / participants[6)] / time frame[7)]	Research framework[8)]	Major findings[9)]
Visser et al. (2006) / metrics / I/III	n.i. / ↓ / n.i.	T+S	n=12 / 4 f, age: range 18-25 years / C (3x5x6 mixed factorial design (2 within, 1 between))	n.i.	• Proposal and validation of measurement methodology for team performance of HRTs
You and Robert (2018b) / integrative study / II	Functional (PR2) / ↓ / Image/video of robot	T+S	n=200 / 77 m, age: range 18-68 years (M= 36.5, SD= 10.77), mTurk, US / C		• Human-robot (work-style) similarity helps to increase trust in a robot, leading to willingness to work with robots and ultimately to preference for robotic co-worker rather than human co-worker

Note: 1) Disciplines: I = HRI, II = Management, III = military, IV = Cognitive science, V = robotics, VI = space, VII = (urban) search and rescue, VIII = ethics; Studies are categorized based on a “best fit”-approach and might comprise aspects of more than one considered research discipline; 2) n.i. = no information provided by author(s); 3) Robot level: ↓ = robot on lower level, ↔ = robot on same level, ↑ = robot on higher level; 4) Team interaction: T = task interaction, T+S = task & social interaction; 5) ◯ = human, □ = robot; 6) f=female, m=male; 7) C = cross-sectional, L = longitudinal; 8) = positive effect, = negative effect, = not significant, = effect not reported ; 9) None of the studies indicated underlying theories

Supplementary Material A

This supplementary material details the literature review and coding process, including information on

(1) Search terms and publication organs reviewed.

(2) Exclusion criteria.

(3) Efforts to address potential biases.

(4) Coding scheme.

Search terms and reviewed publication organs

As mentioned in the introduction (chapter 2.1), we conducted online searches through Google and EBSCO using the search terms listed below. Further, we searched HRI, robotics, and computer science conferences and journals for relevant studies. We also conducted forward and backward searches in any manuscripts initially identified in the search.

Search Terms on Google and EBSCO

“human-robot team AND collaboration”

“human-robot team AND cooperation”

“human-robot team AND communication”

“human-robot team collaboration”

“human-robot team cooperation”

“human-robot team communication“

“human-robot team performance”

“human-robot team”

“robot AND collaboration”

“robot AND group”

“robot AND team”

Reviewed Conferences

AAAI Fall Symposia

AAAI Spring Symposia

ACM/IEEE International Conference on Human-Robot Interaction (HRI)

IEEE International Conference on Robotics and Automation (ICRA)

IEEE International Conference on Systems, Man and Cybernetics

IEEE International Multi-Disciplinary Conference on Cognitive Methods in Situation Awareness and Decision Support (CogSIMA)

IEEE International Symposium on Safety, Security, and Rescue Robotics (SSRR)

IEEE International Workshop on Safety, Security and Rescue Robotics

IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)

IEEE-RAS International Conference on Humanoid Robots (Humanoids)

International Conference on Automation Science and Engineering (CASE)

International Conference on Autonomous and Intelligent Systems (AIS)

International Conference on Autonomous Robots and Agents

International Conference on Control Automation Robotics & Vision

International Conference on Robot and Human Interactive Communication (RO-MAN)

International Symposium on Collaborative Technologies and Systems

RO-MAN

Reviewed Journals

ACM Computing Surveys

ACM Transactions on Human-Robot Interaction

ACM Transactions on Human-Robot Interaction

ACM Transactions on Intelligent Systems and Technology

ACM Transactions on Interactive Intelligent Systems

Advances in Human-Computer Interaction

Artificial Intelligence Review

Autonomous Robots

Cognition, Technology and Work

Cognitive Systems Research

Computer Speech and Language

Computers in Human Behavior

Engineering Applications of Artificial Intelligence

Group & Organization Management

IEEE Access

IEEE Intelligent Systems

IEEE Robotics and Automation Letters

IEEE Sensors Journal

IEEE Transactions on Automation Science and Engineering

IEEE Transactions on Control Systems Technology

IEEE Transactions on Cybernetics

IEEE Transactions on Haptics

IEEE Transactions on Human-Machine Systems

IEEE Transactions on Industrial Electronics

IEEE Transactions on Robotics

IEEE Transactions on Systems, Man, and Cybernetics

Intelligent Service Robotics

International Journal of Computer Vision

International Journal of Human-Computer Studies

International Journal of Humanoid Robotics

International Journal of Robotics Research

International Journal of Social Robotics

Journal of Artificial Intelligence Research

Journal of Field Robotics

Journal of Intelligent and Robotic Systems

Journal of Management Information Systems

Journal of Strategic Information Systems

Proceedings of the ACM on Human-Computer Interaction

Proceedings of the IEEE

Robotics and Autonomous Systems

Exclusion Criteria

For the selection of studies (see chapter 2.1 and Figure 2-1), manuscripts were excluded according to the following criteria:

I. Type of Study

   a. Workshop proposal/extended abstract: These papers tend to present little to no empirical research and instead provide an overview or brief introduction to a topic. Due to their brevity and specific focus, we exclude them.

   b. Reviews/surveys: Excluding these publications helps ensure that we focus directly on conceptual and empirical studies of human-robot teams (HRTs).

c. Books/dissertations: Many books and dissertations do not undergo rigorous peer review, so we excluded them.

d. Press/praxis articles: In order to focus the literature review on scholarly contributions, we excluded press/praxis articles.

II. Embodiment of Robots

a. Studies of conversational agents: We limit our review to studies that investigate embodied robots, rather than conversational agents. Disembodied agents have limited communication channels compared to embodied agents (Deng et al., 2019), which in turn may limit the generalizability of results. However, in our review we include physical robots as well as simulations/virtual robots and videos/images of robots, which are often used in online studies.

b. Studies of intelligent machines or computers: We exclude studies of intelligent machines or computers, in order to focus our review on HRTs with both human and robotic team members.

III. Focus Areas

a. Studies of human–robot interaction and human–robot collaboration: As we explain in chapter 2.2.2.3 , significant differences mark HRI, human-robot collaboration (HRC), and HRTs. With our focus on HRTs, we exclude studies of HRI or HRC.

b. Studies of robot–robot teams: In order to focus on studies of teams that include both human and robot members, we exclude studies that include teams of robots only.

IV. Team Size & Interaction Focus

Some aspects of task interdependence may arise in dyadic task teams, in which one robot and one human interact to achieve their goals, but they represent the broader field of HRC, so we do not consider studies of dyadic task teams in depth. Details of these studies can be found in supplementary material B.

These exclusion criteria left us with studies in the following categories:

- Conceptual articles of *multiple member* HRTs, including articles on measurement/taxonomy development.

- Conceptual articles on *dyadic collaborative* HRTs, including articles on measurement/taxonomy development.
- Experimental studies with functional, humanoid, or android robots engaged in *multiple-member* HRTs.
- Experimental studies with functional, humanoid, or android robots engaged in *dyadic collaborative* HRTs.

Considerations of Biases

During our literature review we considered a number of biases (selection bias, data extraction bias, publication bias) in an effort to minimize them (see chapter 2.4.3). Detailed considerations are presented below.

Selection bias

To minimize selection bias, which is related to including only major studies in a domain or studies that are most consistent with a researcher's views (Nightingale, 2009), we established specific search, exclusion, and inclusion criteria, as detailed above, and reviewed all studies that explicitly mentioned human–robot teams, as detailed in the "Human–Robot Teams" section, providing an overview of the different viewpoints identified in previous research. The first search step was thus independent of our derived definition of human–robot teams.

Data extraction bias

Data extraction bias "can arise during the process of the review when data are extracted from included studies" (Nightingale, 2009, p. 382). The author team carefully discussed and compared individual findings from the studies during the process of writing the overview.

Publication bias

Publication bias results from an unbalanced, unrepresentative inclusion of published studies, relative to all studies conducted, which can often impose a bias toward studies with significant results (Rothstein et al., 2006). It is difficult to avoid completely (Jager et al., 2020), but because conferences publish more preliminary research and even non-significant results, we expect a less pronounced publication bias among these submissions and explicitly include conference publications in our review (see the list of reviewed conferences). However, as publication bias occurs before and during the scientific review process, we acknowledge the continued possibility that our review suffers from a publication bias.

Coding Scheme

We coded the studies and papers we found in our literature research according to the IPO framework. As a first step, we used a keyword search of the IPO framework subcategories in the abstract and main bodies of the papers and reviewed the papers in order to assign them to the framework elements (see Figure 2-5). It was possible for papers to be assigned to more than one element of the framework. In this case, coding results were discussed until a concensus was reached.

Subsequent analogous keyword searches were used to identify disciplines (cognitive science, ethics, HRI, management, military, robotics, space, (urban) search and rescue), robot morphology (functional, humanoid, android, animal-like), and type of embodiment (physical robot, simulation/virtual robot (interaction), image/video of robot (observation), no embodiment).

For the robot level (robot on lower level, robot on same level, robot on higher level), team interaction (task interaction, task & social interaction), team setup, and study time frame (cross-sectional, longitudinal), study designs described in the papers were reviewed.

Supplementary Material B

This supplementary material includes details on the reviewed studies that claim to be on the topic of HRTs but only consider dyadic task teams (see definition in chapter 2.2.2.3). As described in chapter 2.2.2.3 and in supplementary material A, while some aspects of task interdependence might be present in these dyads, they overall fall into the broader field of general human-robot collaboration and are therefore excluded from our review. Since some researchers consider such dyadic task teams to be HRTs, we nonetheless wanted to provide interested readers with the study details. The structure of this supplementary material follows the proposed framework from our manuscript (see chapter 2.2.3).

Table B1. Empirical Studies on Dyadic Task Teams Related to Intra-member Team Characteristics and Their Effects

Author / subcategory / discipline[1)]	Robot morphology[2)] / robot level[3)] / type of embodiment	Team interaction[4)] / team setup[5)]	Data basis / participants[6)] / time frame[7)]	Underlying theories	Independent variable(s)[8)]	Dependent variable(s)[8)]	Key findings
S. D. Jiang (2019) / robot behavior / VII	Functional (simulated Pioneer 3-AT robot) / ↓ / Simulation/virtual robot	T	n=35 / 16 f, age: range 18-36, mostly students / C	Regret theory	• Human-robot teaming strategy (guarded-teleop, mixed -initiative)	• Task performance (+ for mixed-initiative) • Operator's interaction with robot (+ / n.s. for mixed-initiative)	• "search performance of the human-robot team was improved when the robot is allowed to seize initiative from the human operator" (p. 355) • "robot interventions were not seen as interference, and majority of the participants commented robot interventions were “useful”" (p. 355)
Singh and Heard (2022) / robot behavior, human preferences and behavior / V	n.i. / n.i. / n.i.	n.i. / n.i.	n=9 (2 excluded in final results) / 4f; age: M=26.3 / C (15 min training + 52.5 min trial + 5 min break + 52.5 min trial; mixed design)	n.i.	• Workload (underload, normal load, overload; only used to test the system architecture, not connected to DV) • Reinforcement learning agent type (task + interaction , task +	• NASA-TLX (highest for task + interaction + human workload) • Comfort (n.s. difference between agents) • Trust (n.s. difference	• Proposal and validation of human-aware system architecture using reinforcement learning that "incorporates human states into the robot's decision-making process to achieve more fluid human-robot team dynamics and improve the overall team performance" (p. 268)

Author / subcategory / discipline[1)]	Robot morphology[2)] / robot level[3)] / type of embodiment	Team interaction[4)] / team setup[5)]	Data basis / participants[6)] / time frame[7)]	Underlying theories	Independent variable(s)[8)]	Dependent variable(s)[8)]	Key findings
					interaction + human workload)	between agents)	

Note: 1) Disciplines: I = HRI, II = Management, III = military, IV = Cognitive science, V = robotics, VI = space, VII = (urban) search and rescue, VIII = ethics; Studies are categorized based on a "best fit"-approach and might comprise aspects of more than one considered research discipline; 2) n.i. = no information provided by author(s); 3) Robot level: ↓ = robot on lower level, ↔ = robot on same level, ↑ = robot on higher level; 4) Team interaction: T = task interaction, T+S = task & social interaction; 5) ◯ = human, ▯ = robot; 6) f=female, m=male; 7) C = cross-sectional, L = longitudinal; 8) (-) = negative effect, (+) = positive effect, (n.s.) = not significant

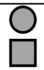
Table B2a. Conceptual Studies on Dyadic HRTs Related to Inter-member Team Characteristics and Their Effects

Author / subcategory / discipline[1)]	Robot morphology[2)] / robot level[3)] / type of embodiment	Team interaction[4)] / team setup[5)]	Key findings[6)]
Noormohammadi-Asl et al. (2022) / roles of humans and robots, leadership / II	n.i. / n.i. / n.i.	T / n.i.	• Proposal and validation of "a task selection and planning algorithm that enables the robot to consider the human's preference to lead, as well as the team and the human's performance, and adapts itself accordingly by taking or giving the lead" (p. 1244)

Note: 1) Disciplines: I = HRI, II = Management, III = military, IV = Cognitive science, V = robotics, VI = space, VII = (urban) search and rescue, VIII = ethics; Studies are categorized based on a "best fit"-approach and might comprise aspects of more than one considered research discipline; 2) n.i. = no information provided by author(s); 3) Robot level: ↓ = robot on lower level, ↔ = robot on same level, ↑ = robot on higher level; 4) Team interaction: T = task interaction, T+S = task & social interaction, n.i. = no information provided by author(s); 5) ◯ = human, ▯ = robot; 6) None of the studies indicated underlying theories

Table B2b. Empirical Studies on Dyadic HRTs Related to Inter-member Team Characteristics and Their Effects

Author / subcategory / discipline[1]	Robot morphology[2] / robot level[43] / type of embodiment	Team interaction[4] / team setup[5]	Data basis / participants[6] / time frame[7]	Independent variable(s)[8]	Dependent variable(s)[8]	Key findings[9]
Hoeniger (1998) / roles of humans and robots, autonomy and control / V	Functional / ↓ / n.i.	T	n.i. / n.i. / n.i.	• n.i.	• n.i.	• Proposal of robot control scheme to find the optimal mix between robot autonomy and HRI
Howard and Cruz (2006) / leadership / II	n.i. / ↓ / Simulation/virtual robot	T	n unknown / n.i. / C	• Directive leadership	• Task execution time (-) • Human workload (+)	• To determine appropriate leadership styles and robot behavior in HRTs, human leadership approaches based on the situational context can be used as a basis
Schermerhorn and Scheutz (2009) / autonomy and control / I	Functional (Pioneer P3AT) / ↓ / Simulation/virtual robot	T	n=10 / undergrad students/ C (within-subject design)	• Autonomy of robot (based on independent decision making and acting)	• Task performance (+)	• "humans not only accept robot autonomy in the interest of the team, but also view the robot more as a team member and find it easier to interact with, despite a very minimalist graphical/speech interface. Moreover, we find evidence that dynamic autonomy reduces human cognitive load." (p. 63)

Author / subcategory / discipline[1]	Robot morphology[2] / robot level[43] / type of embodiment	Team interaction[4] / team setup[5]	Data basis / participants[6] / time frame[7]	Independent variable(s)[8]	Dependent variable(s)[8]	Key findings[9]
Shanks et al. (2021) / roles of humans and robots / II	Humanoid (Nao) / ↑, ↔, ↓ / Pre: Physical robot, 1, 2, 3: Image/video of robot	T / 	n_pre=13, n_1=97, n_2=200, n_3=120 / pre: 100% f, age: M=83.62; 1: 45% f, age: M=20.78; 2: 48% f, age: M=34.80; 3: 57% f, age: M=35.02 / C (pre: survey; 1: lab experiment, 2,3: online experiment)	• Pre: Presence of robot • 1: Leader (human vs. robot) • 2: Leader (human vs. robot) • 3: Leader (human vs. robot)	• Pre: Favorability (-) • Behavioral response (-) • 1: Behavioral intentions (- for robot) • Power relative to assistant (- for robot) • 2: Behavioral intentions (+ for human) • 3: Behavioral intention (switch to different team) (+ for robot)	• Dyadic medical HRTs with robotic assistants are preferred over such teams with a robotic leader. Customers further are willing to pay more to upgrade from a robot-led team to a human-led team when their first interaction is with a robot-led team.
J. Wang and Lewis (2007) / autonomy and control / VII	Functional (P2DX robots) / ↓ / Simulation/virtual robot	T 	n=14 / age: range 19-35, recruited from University of Pittsburgh community, none with prior	• Mixed initiative (+) • Human interaction (+)	• Performance	• Mixed initiative teams of robots are able to perform better (w.r.t. search radius and identified victims) than teams in which an operator controls robots individually

Author / subcategory / discipline[1)]	Robot morphology[2)] / robot level[43] / type of embodiment	Team interaction[4)] / team setup[5)]	Data basis / participants[6)] / time frame[7)]	Independent variable(s)[8)]	Dependent variable(s)[8)]	Key findings[9)]
			experience with robot control / C			

Note: 1) Disciplines: I = HRI, II = Management, III = military, IV = Cognitive science, V = robotics, VI = space, VII = (urban) search and rescue, VIII = ethics; Studies are categorized based on a "best fit"-approach and might comprise aspects of more than one considered research discipline; 2) n.i. = no information provided by author(s); 3) Robot level: ↓ = robot on lower level, ↔ = robot on same level, ↑ = robot on higher level; 4) Team interaction: T = task interaction, T+S = task & social interaction; 5) ◯ = human, ▯ = robot; 6) f=female, m=male; 7) C = cross-sectional, L = longitudinal; 8) (-) = negative effect, (+) = positive effect, (n.s.) = not significant; 9) None of the studies indicated underlying theories

Table B3a. Conceptual Studies on Dyadic HRTs Related to Team Processes and Their Effects

Author / subcategory / discipline[1)]	Robot morphology[2)] / robot level[3)] / type of embodiment	Team interaction[4)] / team setup[5)]	Key findings[6)]
Angleraud et al. (2019) / (physical) coordination / V	Functional / ↔ /n.i.	T ○ □	• Proposal and first tests of model for action plan generation and dynamic adaption
DelPreto and Rus (2019) / (physical) coordination, collaboration / V	Functional / ↔ / Physical robot	T ○ □	• Proposal and validation of a control system to support lifting tasks in HRTs
Hoeniger et al. (1997) / (physical) coordination / V	Functional / ↓ / n.i.	T ○ □	• HRTs are seen as “solution for meeting future requirements in highly flexible manufacturing systems” (p. 899)
T. Iqbal et al. (2018) / collaboration / V	n.i. / ↓ / n.i.	T ○ □	• Presentation of a "supervised activity segmentation algorithm that can detect the start and end time of activities" (p. 1)
Laengle et al. (1997) / collaboration / I	n.i. / ↓, ↔ / Physical robot	T ○ □	• Concept of human-robot teams • Four key issues to be analyzed: communication, interpretation of transmitted data, coordination, cooperation
C. Liu and Tomizuka (2014) / (physical) coordination / V	Functional / ↔ / Simulation	T ○ □	• Combination of human flexibility and robotic productivity in manufacturing is promising. A challenge to be solved is the safety of an environment. (p. 1386) • Proposal of a two-layer interaction model as basis for the modeling and controller design method of cooperative robots (p. 1391)

Note: 1) Disciplines: I = HRI, II = Management, III = military, IV = Cognitive science, V = robotics, VI = space, VII = (urban) search and rescue, VIII = ethics; Studies are categorized based on a “best fit”-approach and might comprise aspects of more than one considered research discipline; 2) n.i. = no information provided by author(s); 3) Robot level: ↓ = robot on lower level, ↔ = robot on same level, ↑ = robot on higher level; 4) Team interaction: T = task interaction, T+S = task & social interaction, n.i. = no information provided by author(s); 5) ○ = human, □ = robot; 6) None of the studies indicated underlying theories

Table B3b. Empirical Studies on Dyadic HRTs Related to Team Processes and Their Effects

Author / subcategory / discipline[1]	Robot morphology[2] / robot level[3] / type of embodiment	Team interaction[4] / team setup[5]	Data basis / participants[6] / time frame[7]	Independent variable(s)[8]	Dependent variable(s)[8]	Key finding[9]
Anima et al. (2019) / collaboration / I	Humanoid (Baxter) / ↔ / Physical robot	T / n.i.	n.i. / n.i. / n.i.	• n.i.	• n.i.	• Proposal and validation of human-robot collaborative architecture that enables dynamic task allocation
Chan et al. (2022) / collaboration / V	Chan et al. (2022) / collaboration / V	T / ● ■	n=26 / 7f / C	• Interaction method (human-only vs. joystick-predefined vs. AR-predefined vs. joystick-unspecified s. AR-unspecified)	• Task completion time (- for AR-unspecified) • Robot utilization (+ for AR-unspecified) • NASA-TLX (- for AR-unspecified) • System Usability Scale (+ for AR-unspecified) • User Experience Questionnaire (+ for both AR-conditions)	• Proposal and validation of a "wearable augmented reality (AR) system" (p. 1) • Findings indicate that "subjectively, the AR interface feels more novel and a standard joystick interface feels more dependable to users. However, the AR interface was found to reduce physical demand and task completion time, while increasing robot utilization." (p. 1)

Author / subcategory / discipline[1]	Robot morphology[2] / robot level[3] / type of embodiment	Team interaction[4] / team setup[5]	Data basis / participants[6] / time frame[7]	Independent variable(s)[8]	Dependent variable(s)[8]	Key finding[9]
Guznov et al. (2020) / communication / IV/VII	Guznov et al. (2020) / communication / IV/VII	T /	n=88 / 50f, age: M=27.61 (SD=9.49) / C (2 (transparency) x 2 (team orientation) mixed design)	• Transparency • Team orientation	• Participants' supervisory performance (+,n.s.) • State trust (n.s., -) • Perceived accuracy (n.s., n.s.) • Situation awareness (n.s., -) • Workload (+,-)	• Increased transparency can have both benefits and limitations and should thus be implemented carefully • "Team orientation manipulation showed to be ineffective (and potentially detrimental)" (p. 650)
Harriott et al. (2011) / collaboration / III	Functional (Pioneer 3-DX robot teammate) / ↑ / Physical robot	T	n=28 / 14 m, age: M=25.2 years (range 18-57); at least college education, recruited by flyers around Vanderbilt area, average robotic experience: 2.7 (scale 1-9) / C (90 minutes)	• Team constellation (HHT vs. HRT)	• Correctness of responses to the secondary task questions (n.s.) • Workload ratings (-) • Post-experimental NASA-TLX responses (n.s.) • Physiological data (-)	• Working in a HRT was able to reduce the workload compared to a human team • Human Performance Moderator Functions (HPMFs) might be used also for HRTs

Author / subcategory / discipline[1)]	Robot morphology[2)] / robot level[3)] / type of embodiment	Team interaction[4)] / team setup[5)]	Data basis / participants[6)] / time frame[7)]	Independent variable(s)[8)]	Dependent variable(s)[8)]	Key finding[9)]
Harriott et al. (2013) / collaboration / I	Functional (Pioneer 3-DX) / ↔ / Physical robot	T	n_1=28, n_2=36 / 1: 14m, age: range 18-57 years; H-H condition: M=24.2 (SD=10.3),H-R condition: 26.2 (SD=7.8); 2: 19 m, age: range 18-56 years; H-H condition: M=27.4 (SD=8.4),H-R condition: 24.1 (SD=4.6) / C (mixed-design)	• Presence of robot	• Objective workload measurement (+) • Subjective workload measurement (-)	• Participants perceived the physical workload in human-human teams as higher than in human-robot teams • Physilogically measured physical workload was higher for human-robot teams than for human-human teams
Kennedy et al. (2007) / collaboration /III	Functional (iRobot B21r) / ↔ / Physical robot	T	n.i. / n.i. / n.i.	• n.i	• n.i	• Proposal of model using spatial information for collaboration between humans and robots
Kwon et al. (2020) / collaboration / I	Functional (Fetch, Fetch Robotics) / ↔ / Image/video of robot; physical robot	T	n_online=50, n_lab=10 / online: 32% f; age: median=33 years, participants from Stamford and mTurk; lab: 2 f; age: range 20-36 years, participants from Stamford / C	• Risk-aware human model	• Safety of collaboration (+) • Efficiency of collaboration (+)	• A risk-aware model helps to predict suboptimal human behavior and "to improve safety and efficiency during collaboration" (p. 8)

Author / subcategory / discipline[1]	Robot morphology[2] / robot level[3] / type of embodiment	Team interaction[4] / team setup[5]	Data basis / participants[6] / time frame[7]	Independent variable(s)[8]	Dependent variable(s)[8]	Key finding[9]
Ramakrishnan et al. (2017) / (physical) coordination / V	Functional (PR2) / ↔ / Simulation/virtual robot, Physical robot	T	n=48 / recruited from university / C	• adaptive perturbation training (AdaPT)	• Performance (+)	• "perturbation-trained teams using AdaPT outperformed perturbation-trained teams using Q-learning with regard to both objective [...] and subjective measures of performance for multiple task variants" (p. 535)
Reed and Peshkin (2008) / collaboration / I	n.i. (probably functional based on descriptions) / ↔ / Physical robot	T	n_1= 22, n_2=22 / 1: 7 m, 1 left-handed, age: range 18-24 years, 2: 10 m, 8 left-handed, age: range 18-24 years; from Northwestern University's Psychology participant pool / C	• Work with partner (human vs. robot)	• Speed of task execution (- / n.s. for human / robot)	• Specialization (and resulting better performance) in human teams can be done through only haptic communication • Haptic interaction with robots did not lead to similarly good results (participants were slower and not as specialized)

Author / subcategory / discipline[1)]	Robot morphology[2)] / robot level[3)] / type of embodiment	Team interaction[4)] / team setup[5)]	Data basis / participants[6)] / time frame[7)]	Independent variable(s)[8)]	Dependent variable(s)[8)]	Key finding[9)]
Riedelbauch and Henrich (2017) / (physical) coordination / V	Functional (KUKA LWR IV) / ↔ / Physical robot	T	n.i. / n.i. / n.i.	• n.i.	• n.i.	• Proposal of framework and system architecture for coordination in HRTs through local world state observation
Scheggi et al. (2016) / (physical) coordination / V	Functional (Pioneer LX robot) / ↑, ↔ / Physical robot	T	n=15 / 12 m; age: range 23-52 years, 13 right-handed / C	• n.i.	• n.i.	• Proposal of haptic navigation in HRTs with wearable haptic feedback devices for human partners
Schoen et al. (2020) / collaboration / V	Functional (UR5) / ↔ / simulation / physical robot	T /	n_1=8, 22_2=8 / 1: 3f; age: M=27.63 (SD=21.61); 2: 2f; age: M=21 (SD=0.93); both: holding/pursuing a degree in either industrial or mechanical engineering / C	• n.i.	• n.i.	• Proposal and validation of an "end-to-end task authoring environment that assists […]in translating existing manual tasks into plans applicable for human-robot teams" (p. 1194)
Talamadupula et al. (2010) / (physical) coordination / VII	Functional (Pioneer P3-AT) / n.i. / n.i.	T	n.i. / n.i. / n.i.	• n.i.	• n.i.	• Proposal and experimental validation of an open world planner for HRTs

Author / subcategory / discipline[1]	Robot morphology[2] / robot level[3] / type of embodiment	Team interaction[4] / team setup[5]	Data basis / participants[6] / time frame[7]	Independent variable(s)[8]	Dependent variable(s)[8]	Key finding[9]
Unhelkar et al. (2020) / communication / V	Functional (Universal Robot 10 with Robotiq gripper) / ↔ / Physical robot	T	n=15 / 5 m, age: median=26 years / C	• Robot communication	• Shared team reward (+)	• Proposal of communication famework for roobts "to decide if, when, and what to communicate while performing sequential tasks with humans." (p. 336) • Confirmation of framework capabilities in experiments
van Zoelen, van den Bosch, and Neerincx (2021) / collaboration / VII	Functional / ↔ / Simulation/virtual robot	T /	n=24 (of which 4 were completely or partially excluded from final analyses) / 17 f; age: M=24.8 (SD=2.47); with university degree in STEM field; most with no to little experience with HRC / C (8 runs in total, mixed design)	• n.i. (analysis of screen captures and notes for identification of interaction pattern)	• n.i.	• "More participant adaptation improved robot learning and thus team level learning" (p. 1) • "The identification of interaction patterns support awareness among team members, providing the foundation for human-robot communication

Author / subcategory / discipline[1)]	Robot morphology[2)] / robot level[3)] / type of embodiment	Team interaction[4)] / team setup[5)]	Data basis / participants[6)] / time frame[7)]	Independent variable(s)[8)]	Dependent variable(s)[8)]	Key finding[9)]
						about the co-adaptation" (p. 1)
van Zoelen, van den Bosch, Rauterberg, et al. (2021) / (physical) coordination / VII	Functional / ↑, ↔, ↓ (all configurations occured during experiment) / Physical robot	T / / /	n=18 / 9 f, age: M=23 (SD=2.9), students at university / C (four rounds per participant)	• n.i. (video analysis for identification of interaction patterns)	• n.i.	• Call for development of a "language of interaction patterns that can be used to describe tacit co-adaptation in human-robot collaborative contexts" (p. 1) in further studies
Vats et al. (2022) / collaboration / V	Functional (Franka-Emika Panda robot) / n.i. / Simulation/virtual robot, Physical robot	T / n.i.	n.i. / n.i. / n.i.	• n.i.	• n.i.	• Proposal and validation of classifier to help facilitate learning and task allocation in HRTs
F. Zhao et al. (2020) / collaboration / I	Functional (UR3e collaborative robot) / ↔ / Physical robot	T /	n=31 / 6 f, age: range 18–21 years (M = 20.87 , SD = 2.42), students with manufacturing experience or majoring in mechanical or industrial engineering / C	• Level of task interdependence (pooled, sequential, reciprocal)	• Human worker's mental states (stress, - for reciprocal) • Task performance (+ for reciprocal)	• "In teams with reciprocal interdependence, participants perceived the robot more as a teammate and completed the task more efficiently" (p. 1149)

Author / subcategory / discipline[1)]	Robot morphology[2)] / robot level[3)] / type of embodiment	Team interaction[4)] / team setup[5)]	Data basis / participants[6)] / time frame[7)]	Independent variable(s)[8)]	Dependent variable(s)[8)]	Key finding[9)]
			(laboratory, between-subject)		• Perceptions of the robot (safety, n.s.)	

Note: 1) Disciplines: I = HRI, II = Management, III = military, IV = Cognitive science, V = robotics, VI = space, VII = (urban) search and rescue, VIII = ethics; Studies are categorized based on a "best fit"-approach and might comprise aspects of more than one considered research discipline; 2) n.i. = no information provided by author(s); 3) Robot level: ↓ = robot on lower level, ↔ = robot on same level, ↑ = robot on higher level; 4) Team interaction: T = task interaction, T+S = task & social interaction, n.i. = no information provided by author(s); 5) ◯ = human, ▯ = robot; 6) f=female, m=male; 7) C = cross-sectional, L = longitudinal; 8) (-) = negative effect, (+) = positive effect, (n.s.) = not significant; 9) Most of the studies did not indicate underlying theories, only Kwon et al. (2020) indicate reliance on cumulative prospect theory, Ramakrishnan et al. (2017) on learning theory, and (Talamadupula et al., 2010) on decision theory.

Table B4. Empirical Studies Related to Moderating Effects in Dyadic HRTs

Author / Discipline[1] / Main Category	Independent variable(s)[2]	Dependent variable(s)[2]	Moderator variable(s)	Moderating effect[2]
Reed and Peshkin (2008) / I / 3 (dyad)	• Work with partner (human vs. robot)	• Speed of task execution	• Presence of human confederate (not part of the active team)	• (-)
Shanks et al. (2021) / II / Cat. 2 (dyad)	• 2: Leader (human vs. robot)	• 2: Behavioral intentions (+ for human)	• 2: Power distance belief	• (- for lower PDB levels)

Notes: 1) Disciplines: I = HRI, II = Management, III = military, IV = Cognitive science, V = robotics, VI = space, VII = (urban) search and rescue, VIII = ethics; Studies are categorized based on a "best fit"-approach and might comprise aspects of more than one considered research discipline; 2) (-) = negative effect, (+) = positive effect, (n.s.) = not significant

Table B5a. Conceptual Integrative and Overarching Studies on Dyadic HRTs

Author / subcategory / discipline[1)]	Robot morphology[2)] / robot level[3)] / type of embodiment	Underlying theories[4)]	Key findings[5)]
Johnson et al. (2014) / HRT design / VII	Humanoid (Atlas) / ↓ / Simulation/virtual robot	Joint activity theory, organizational theory	• Proposal and validation of human-robot system model supporting interdependence through coactive design

Note: 1) Disciplines: I = HRI, II = Management, III = military, IV = Cognitive science, V = robotics, VI = space, VII = (urban) search and rescue, VIII = ethics; Studies are categorized based on a "best fit"-approach and might comprise aspects of more than one considered research discipline; 2) n.i. = no information provided by author(s); 3) Robot level: ↓ = robot on lower level, ↔ = robot on same level, ↑ = robot on higher level; 4) The study did not specify the research framework; 5) While the study did not report a specific team setup, it is indicated that is focuses on dyadic task teams.

Table B5b. Empirical Integrative and Overarching Studies on Dyadic HRTs

Author / subcategory / discipline[1)]	Robot morphology[2)] / robot level[3)] / type of embodiment	Team interaction[4)] / team setup[5)]	Data basis / participants[6)] / time frame[7)]	Research framework[8)]	Key findings[9)]
Barnes et al. (2011) / HRT design / III	Functional (unmanned vehicles) / ↓ / Simulation/virtual robot / physical robot	T ◯ □	n.i. / n.i. / n.i.	n.i.	• Identification of empirical based guidelines on interface design, procedural issues, individual differences and training implications for HRI
Wen et al. (2022) / ethics / IV	Humanoid / ↓ / Video/image of robot	T / ◯ □	n=120 / 56 f, 57 m, 1 gender-fluid, 5 non-binary, 1 other, age: range 18-68 years (M=35.21, SD=13.50), most with little to no experience with robots and AI / C (within-subject)	Independent variables: • Explanation type (action vs. contextual vs. role vs. contextual role; + for role and context) Relational role (friend vs. subordinate vs. teacher vs. teammate; + [see key findings])	Dependent variables: • Human trust (reliability, capability, ethicality, sincerity) • Understanding confidence • Perceived intelligence

Note: 1) Disciplines: I = HRI, II = Management, III = military, IV = Cognitive science, V = robotics, VI = space, VII = (urban) search and rescue, VIII = ethics; Studies are categorized based on a "best fit"-approach and might comprise aspects of more than one considered research discipline; 2) n.i. = no information provided by author(s); 3) Robot level: ↓ = robot on lower level, ↔ = robot on same level, ↑ = robot on higher level; 4) Team interaction: T = task interaction, T+S = task & social interaction; 5) ◯ = human, □ = robot; 6) f=female, m=male; 7) C = cross-sectional, L = longitudinal; 8) The study did not specify its research framework; 9) The study did not indicate underlying theories

Appendix for Chapter 4

Appendix C: Additional Information on Literature Review

All items were measured using a 7-point Likert scale, anchored by (1) “totally disagree” and (7) “totally agree”, unless noted otherwise.

Search Terms

We conducted online searches using Google and EBSCO using the search terms listed below for our literature review. We also conducted forward and backward searches in any manuscripts initially identified during the search.

Search Terms on Google and EBSCO

- “human-robot team AND lead*”
- “human-robot team AND manage*”
- “robot AND team AND lead*”
- “robot AND team AND manage*”
- “robot leader AND acceptance”
- “robot manager AND acceptance”
- “robot manager AND readiness”
- “robot leader AND readiness”
- “robot manager AND performance”
- “robot leader AND performance”
- “robot manager AND relation*”
- “robot leader AND relation*”

Exclusion Criteria

For the selection of studies, we screened keywords and abstracts of the manuscripts we found during the search. We excluded studies based on the following criteria

I. Role of robot: The studies in focus of our literature review all have robots in the the role of a manager or leader15, thus, we excluded studies that mentioned management/leadership but did not consider the robot(s) in this role.

II. Team setting: We focus our literature review on studies of human-robot teams. We thus excluded studies set outside HRTs or a dyadic team context (e.g., only focused on groups of robots or HRI).

III. Team-internal focus: We focus our literature review on studies with a team internal focus, i.e., employees interacting with robotic managers/leaders. We thus excluded studies with other foci, e.g., customer/patient perceptions or general firm-level considerations.

IV. Type of study: We excluded extended abstracts and reviews from our literature review as these works either present very little empirical research or offer a broader overview over a topic. We rather mentioned the reviews and their foci at the beginning of our literature review.

Appendix D: Online Study Setup Rationale and Script of Video Interaction

Online Study Setup Rationale

Our online study is based on a paper people study, using an experimental vignette methodology and questionnaire (Aguinis & Bradley, 2014). A vignette is “a short, carefully constructed description of a person, object, or situation, representing a systematic combination of characteristics” (Atzmüller & Steiner, 2010, p. 128). Specifically, we utilize a combination of a written vignette and videos as proxies for actual interactions. We use this method as, although social robots appear to be capable of taking on managerial positions (Young & Cormier, 2014), companies have hardly integrated robots as lower-level managers; that is, the scenarios we investigate are yet to be realized in the future working world at large. Compared to a traditional

[15] Extant literature often uses the term robotic manager and robotic interchangeably. Therefore, we review literature on both robotic managers and robotic leaders

survey that only includes a questionnaire, the use of the vignette allows for a more life-like guided scenario by providing explanations and contextual factors (Atzmüller & Steiner, 2010). Vignettes and specifically video vignettes further allow to capture perceptions and experiences (Aguinis & Bradley, 2014; N. Chen et al., 2022; Chita-Tegmark et al., 2019; Law et al., 2021; Nørskov et al., 2020). Online studies are also a well-established research method (Feil-Seifer et al., 2021; Leiner, 2019), with a number of advantages, including access to larger samples, reduced experimenter influences, and greater generalizability (Aguinis et al., 2021). Previous research has further found that results of online studies involving robots are comparable to analogous laboratory studies (Babel et al., 2022).

As part of the online study participants received a monetary compensation to compensate them for their time. The results from the study did not have any influence on participants' compensation. Studies have shown that compensation for work on Amazon MTurk does not have implications on results (Auer et al., 2021).

We chose an international company as setting of our study to reflect the globalized nature of business operations and the diverse environments in which robotic managers could be implemented (Bannon, 2023; Dixon et al., 2019; Thrivikraman Nair, 2022).

Script of Video Interaction

CORPORATE MEETING ROOM

Human-robot team with three human and one robotic member sits around a large conference table in a corporate office meeting room. On the table there are laptops, documents, pens, and coffee cups. In one corner of the room is a flipchart, in another one a plant. The human-team members are all looking in the direction of the robot

ROBOT

<name of team member 1>, you're still busy working on the design of the sales channels until Friday.

Human team member 1 nods.

ROBOT

<name of human team member 2>, you're supposed to be preparing the presentation for the investors' meeting and budgeting for the project.

Human team member 2 nods. They check their laptop in front of them.

HUMAN TEAM MEMBER 2

I'm already working on the presentation. When do you need the budget done?

ROBOT

It would be good if you could send me the budget by noon.

Human team member 2 checks their laptop in front of them.

HUMAN TEAM MEMBER 2

I'm sorry, but I have a meeting from 11 to 1 pm. But I can send you the budget until 4 pm. Would that be all right with you and can you give me feedback on it later?

ROBOT

Oh, sorry, I forgot your meeting. Sure, yes, I will.

Robot looks into direction of human team member 3.

ROBOT

<name of human team member 3>, can you set up a meeting for us?

Team member 3 nods.

FADE OUT.

Appendix E: Additional Information on the Sample

Online Study Setup Rationale

A total of 8,764 participants participated and completed the questionnaire. We had to exclude 1,703 participants (approximately 19.4%) for various reasons: 80 indicated that they were not located in the United States, 476 did not meet the employment criterion (employee, freelancer, or business owner). 853 failed at least two of the three attention check questions (instructed response items scattered throughout the questionnaire). 58 participants completed the survey too quickly (Leiner, 2019) and 236 experienced video or audio problems. This left us with 7,061 valid paricipants for the analyses.

These participants worked in a wide range of industries, including IT services (29.5%), banking/finance/insurance (12.5%), healthcare (9.3%), retail (5.6%), and education (5.3%). In terms of occupational status, most were employed (86.6%) and self-employed (9.5%).

Participants' experiences with robots come mainly from seeing robots in movies or online (66.4%), in real life (56.2%), or interacting with them (40.1%). Few participants have programmed robots (18.6%), previously worked with them (15.1%), or owned them (8.3%) (multiple selections were possible).

Appendix F: Response Surface Analysis – Applications, Implications, and Extensions for This Study

Response Surface Analysis

In this study, we adopt a polynomial regression analysis and response surface analysis (RSA), as described by J. R. Edwards and Parry (1993) and adapted by S. A. Brown et al. (2014). In this approach, the results of a polynomial regression analysis are used as input for a corresponding response surface, which is then analyzed.

This approach is superior to difference scores (J. R. Edwards, 2002) in several important ways. First, by considering employees' expectations and experiences separately we can avoid ambiguous results (J. R. Edwards, 2002). In contrast, difference scores produce an artificial reduction of dimensionality by calculating the algebraic, absolute, or squared difference between the values of two constructs (Shanock et al., 2010). Second, this approach avoids constraints such as the assumed relationship of regression coefficients that are implicitly imposed on the independent and dependent variables (J. R. Edwards, 2002). Third, a RSA prevents the loss of information and oversimplification found in difference scores due to considering only the difference (rather than capturing both values), while capturing the full range of differences between expectations and experiences and the effects on readiness to work with robotic lower-level manager (J. R. Edwards, 2002).

With this approach, models with different levels of complexity can be investigated. First-order models assume linear relationships between expectations and experiences (i.e., the more [expectations/experiences], the better the outcome). The resulting three-dimensional surfaces in such models are planes. Different first-order models would produce differently sloped planes, depending on their assumptions about the interplay of expectations and experiences (S. A. Brown et al., 2014). Figure F1a shows an example.

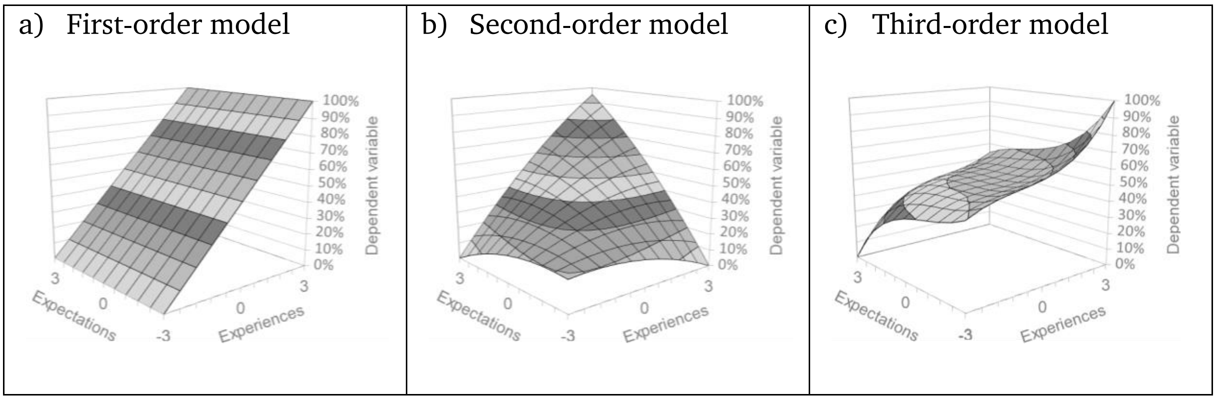


Figure F1. Exemplary Response Surfaces for Models with Different Orders (S.A. Brown et al., 2014)

Instead, second-order models predict that differences between expectations and experiences lead to symmetric outcomes. Specifically, a negative disconfirmation would be valued similarly to a positive disconfirmation. Second-order models, such as the generalized-negativity model proposed by S. A. Brown et al. (2014), are characterized by symmetric surfaces that follow an (inverted) U-shape along the line of perfect confirmation where expectations are equal to experiences (see Figure F1b).

Finally, third-order models capture relationships that cannot be investigated with the simpler approaches (Humberg et al., 2020). These complex relationships include asymmetric and level-dependent effects of the interplay between expectations and experiences on the outcome. For example, high levels of positive or negative disconfirmation have a stronger influence on outcomes than low levels of disconfirmation (S. A. Brown et al., 2014; see Figure F1c).

As an example, a third-order regression equation can be written as

$$Z = b_0 + b_1X + b_2Y + b_3X^2 + b_4XY + b_5Y^2 + b_6X^3 + b_7X^2Y + b_8XY^2 + b_9Y^3, \qquad \text{(F1)}$$

with Z = readiness to work with the agent, X = experiences, Y = expectations, and regression coefficients $b_0, b_1, \ldots, b_9$ that are used as input for the response surface.

According to J. R. Edwards and Parry (1993), there are three key features of response surfaces: First, stationary points, i.e., points where the slope of the surface is zero in all directions, are local or global minima or maxima of the response surface. Second, so-called principal axes which intersect at the stationary point and are perpendicular to each other. These axes “describe the orientation of the response surface with respect to the X,Y [in this study: U_1, U_2 for investigation of usefulness and A_1, A_2 for investigation of employees’ attitude as independent variable, respectively] plane” (J. R. Edwards, 2002, p. 378). Third, the slope of the surface along certain lines of interest on the surface. These lines include the line of perfect confirmation ($Y =$

X-line, where experiences of the robot equal expectations towards it) and the line of perfect disconfirmation ($Y = -X$-line, where experiences assume opposite values of expectations). A number of surface values describing linear, quadratic, and cubic slopes of the surface along these lines are defined (J. R. Edwards, 2002; J. R. Edwards & Parry, 1993) based on the regression results (see Equation F1), see Table F1.

To test our hypotheses, we focus on the latter and utilize the tests of the regression coefficients and response surface values for models of different complexities proposed by S. A. Brown et al. (2014). We adopt an approach offered by (Shanock et al., 2010, 2014) building on rules for linear combinatons of random variables (Cohen et al., 2003) to test the significance of the surface values and compare surface values with each other.

We present the test results for all three lower-level managers (android robot, humanoid robot, human) and independent variables (usefulness, attitude), in the following tables.

Table F1. Surface Values Along Lines of Interest

Surface value	**Description**
$a_{x,0} = b_1 + b_2$	Slope of the response surface along the line Y=X at the point X=0
$a_{y,0} = b_1 - b_2$	Slope of the response surface along the line Y=-X at the point X=0
$a_{x,0}^2 = b_3 + b_4 + b_5$	Curvature of the response surface along the Y=X line at the point X=0
$a_{y,0}^2 = b_3 - b_4 + b_5$	Curvature of the response surface along the Y=-X line at the point X=0
$a_{x,0}^3 = b_6 + b_7 + b_8 + b_9$	Cubic slope of the response surfacec aong the Y=X line at the point X=0
$a_{y,0}^3 = b_6 - b_7 + b_8 - b_9$	Cubic slope of the response surfacec aong the Y=X line at the point X=0

Usefulness

We present the test results for the generalized-negativity model proposed by S. A. Brown et al. (2014), that follows a perfect and symmetrical inverted U-shape, for the robotic lower-level managers (android robot, humanoid robot) in Table F2.

In order to test the S-shape of the response surface, we developed a new set of test criteria that are detailed in Table F3. The results for both robotic lower-level managers can be found in chapter 4.5.

Table F2. Results of Test Criteria for Generalized-Negativity Model (Brown et al., 2014)

Test Criteria	**Results for Android Robot**	**Results for Humanoid Robot**
1) $\lvert b_3\rvert, \lvert b_4\rvert, or\ \lvert b_5\rvert > 0$	Supported	Supported
2) $b_1 = b_2$	Not supported	Not supported
3) $a_{x,0} > 0, a_{y,0} = 0$	Partially supported	Partially supported
4) $a_{y,0}^2 < 0$	Supported	Supported
5) $a_{x,0}^2 = 0$	Not supported	Not supported
6) $b_3 < 0, b_4 > 0, b_5 < 0$	Partially supported	Supported

Table F3. Details on Test Criteria for S-curve (Self-developed)

Test Criteria	**Explanation**
1) $b_1 > b_2$	S-curve has an emphasis on experiences. Thus, experiences should have a higher impact on the outcome than expectations.
2) $a_{x,0} > 0, a_{y,0} > 0$	Higher values of confirmation and low positive disconfirmation should lead to higher outcome values.
3) $\lvert b_6\rvert, \lvert b_7\rvert, \lvert b_8\rvert, or\ \lvert b_9\rvert > 0$	The S-shape of the surface requires at least one cubic coefficient to be significantly different from zero and the cubic slope along the line of perfect disconfirmation to be significantly negative.
4) $a_{y,0}^3 < 0$	
5) $a_{x,0}^2 < 0$	S-curve requires a concave shape for both positive values of confirmation and positive disconfirmation. Thus, the quadratic slopes should be significantly negative.
6) $a_{y,0}^2 < 0$	

7) $\lvert a_{y,neg.\,disc.} \rvert >$ $\lvert a_{y,pos.\,disc.} \rvert$	The absolute value of the linear slope of negative disconfirmation should be greater than the absolute value of the linear slope of positive disconfirmation.
8) $a_{y,3} < 0$	The linear slope for maximum positive disconfirmation along the line of perfect disconfirmation is required to be negative to achieve the S-shape.

Note. $a_{y,\,neg.\,disc.} = (b_1 - b_2) - 3 * (b_3 - b_4 + b_5) + 9 * (b_6 - b_7 + b_8 - b_9)$; $a_{y,\,pos.\,disc.} = (b_1 - b_2) + 3 * (b_3 - b_4 + b_5) + 9 * (b_6 - b_7 + b_8 - b_9)$; $a_{y,3} = (b_1 - b_2) + 6 * (b_3 - b_4 + b_5) + 27 * (b_6 - b_7 + b_8 - b_9)$

Attitude

Table F4 presents the test results for the robotic lower-level managers (android robot, humanoid robot) for the experienes-only model characterized by a linear surface focused on experiences proposed by S. A. Brown et al. (2014).

To test the degressive shape of the response surface, we developed a new set of test criteria that are detailed in Table F5. The results for both robotic lower-level managers can be found in the main body of the manuscript.

Table F4. Results of Test Criteria for Experiences-only Model (Brown et al., 2014)

Test Criteria	Results for Android Robot	Results for Humanoid Robot
1) $b_1 > 0$	Supported	Supported
2) $b_2 = 0$	Partially supported	Not supported
3) $\lvert a_{x,0} \rvert = \lvert a_{y,0} \rvert$	Not supported	Not supported
4) $a_{x,0} > 0, a_{y,0} = 0$	Supported	Supported

Table F5. Details on Test Criteria for Degressive Curve (Self-developed)

Test Criteria	Explanation
1) $a_{x,0} > a_{y,0}$	Experiences have bigger influence on outcome evaluations than expectations; at the same time there is an interaction between expectations and experiences.
2) $a_{x,0} > 0, a_{y,0} > 0$	Higher values of confirmation and low positive disconfirmation should lead to higher outcome values.
3) $\lvert b_6 \rvert, \lvert b_7 \rvert, \lvert b_8 \rvert, or \lvert b_9 \rvert > 0$	

4) $a^3_{y,0} = 0$	The shape of the surface requires at least one cubic coefficient to be significantly different from zero and the cubic slope along the line of perfect disconfirmation to be zero.
5) $a^2_{x,0} < 0$	Degressive curve requires concave shape along both the line of perfect confirmation and line of perfect disconfirmation. Thus, the quadratic slopes should be significantly negative.
6) $a^2_{y,0} < 0$	
7) $a_{x,3} = 0$	The slope for both maximum positive disconfirmation and maximum confirmation along the respective line of interest should be zero to achieve the degressive shape.
8) $a_{y,3} = 0$	

Note. $\mathrm{a}_{\mathrm{x},3} = (\mathrm{b}_1 + \mathrm{b}_2) + 6 * (\mathrm{b}_3 + \mathrm{b}_4 + \mathrm{b}_5) + 27 * (\mathrm{b}_6 + \mathrm{b}_7 + \mathrm{b}_8 + \mathrm{b}_9)$

Appendix G: Supplemental Analyses for Human Control Condition

For the human lower-level manager, the usefulness regression analysis indicates that a first-order model is most appropriate ($R^2 = .073$, adjusted $R^2 = .072$; $\Delta R^2 = .062$; $p < 0.01$; $F\ (4{,}7056) = 138.697$, $p < 0.01$). It is represented by the following equation:

$$Z = 77.352 + 5.094\ U_1 + 0.907\ U_2, \qquad \text{(G1)}$$

with the same variable definitions as in equations (1) and (2) in the main body of the manuscript. Tests of regression coefficients and surface values for first-order models indicate that both experience and expectations play a significantly positive role ($b_1 = 5.094, p < 0.01$; $b_2 = 0.907, p < 0.05$). At the same time, experiences have a significantly greater influence on employees' readiness to work with the human lower-level manager than previous expectations ($p < 0.01$). The linear slopes along both lines of interest are positive ($a_{x,0} = 6.001, p < 0.01$; $a_{y,0} = 4.187, p < 0.01$) and the slope along the line of perfect confirmation is greater than the slope along the line of perfect disconfirmation ($p < 0.05$) (see Figure G1a and Table G1).

The regression analysis for expected and experienced attitudes identifies a third-order model as most appropriate ($R^2 = .104$, adjusted $R^2 = .102$; $\Delta R^2 = 0.001$, $p < 0.05$; $F(11{,}7049) = 74.153$, $p < 0.01$). It is described by the equation:

$$Z = 74.411 + 5.887\ A_1 + 1.919\ A_2 - 1.354\ A_1^2 + 0.232\ A_1 A_2 + 0.053\ A_2^2 + 0.314\ A_1^3 - 0.111\ A_1^2 A_2 + 0.069\ A_1 A_2^2 + 0.013\ A_2^3, \qquad \text{(G2)}$$

with the same variable definitions as in equations (3) and (4) in the main body of the manuscript. Tests for the degressive curve model confirm that the response surface follows such a model imperfectly; not all tests are fully supported (see Figure G1b and Table G2).

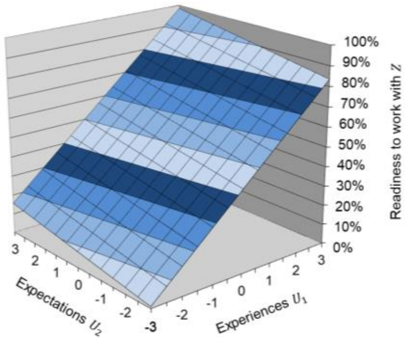
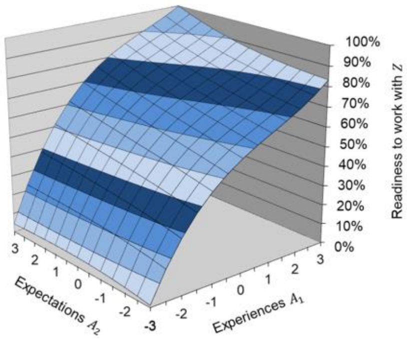
<table>
<tr><th></th><th>Performance-related feature (usefulness)</th><th>Relational feature (attitude)</th></tr>
<tr><td>Human lower-level manager (control condition)</td><td>a.

</td><td>b.

</td></tr>
</table>

Figure G1. Three-Dimensional Response Surfaces for Human Lower-Level Managers

Table G1. Results of Test Criteria for First-order Regression Coefficients and Response Surface Values

Test Criteria	Results for Human
1) $b_1 > 0, b_2 > 0$	Supported
2) $b_1 > b_2$	Supported
3) $a_{x,0} > 0, a_{y,0} > 0$	Supported
4) $a_{x,0} > a_{y,0}$	Supported

Table G2. Results of Test Criteria for Degressive Curve (Self-developed)

Test Criteria	Results for Human
1) $a_{x,0} > a_{y,0}$	Supported
2) $a_{x,0} > 0, a_{y,0} > 0$	Supported
3) $\lvert b_6\rvert, \lvert b_7\rvert, \lvert b_8\rvert, or \lvert b_9\rvert > 0$	Supported
4) $a^3_{y,0} = 0$	Supported
5) $a^2_{x,0} < 0$	Supported

6) $a_{y,0}^2 < 0$	Supported
7) $a_{x,3} = 0$	Not supported
8) $a_{y,3} = 0$	Supported

Appendix H: Supplemental Analyses to Control for Gender Differences

To control for gender differences, we separately considered sub-samples of only male and female participants. The sub-sample sizes were $n = 3523$ for male participants and $n = 3517$ for female participants. Due to the small sub-sample size of $n = 21$ for participants who indicated their gender as "diverse", we did not calculate the response surfaces for this sub-group.

The response surfaces for male and female participants follow the shapes of the response surfaces for the whole sample (Figure H1). A qualitative difference is observeable for the android robot and the performance-related feature of usefulness. For this, the response surface for the female participants showed a less pronounced decline for increasing positive disconfirmation as compared to the response surface for the male participants (Figure H1a and H1c).

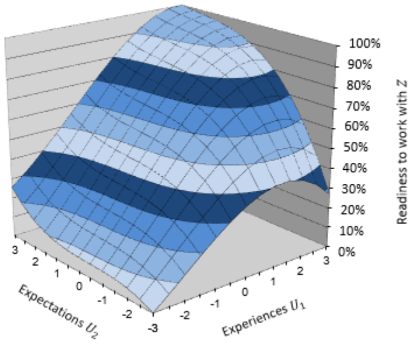
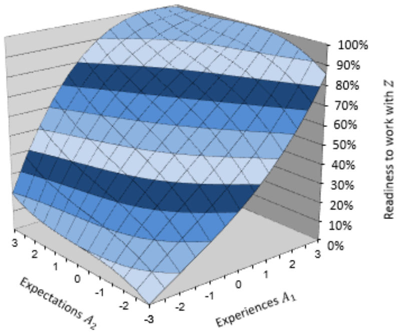
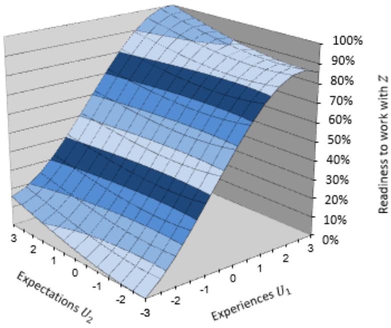
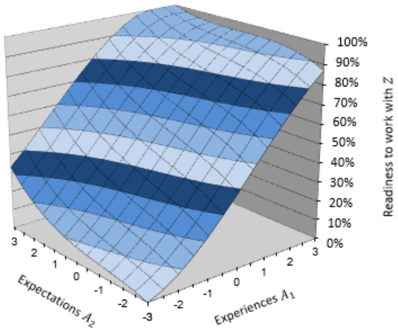
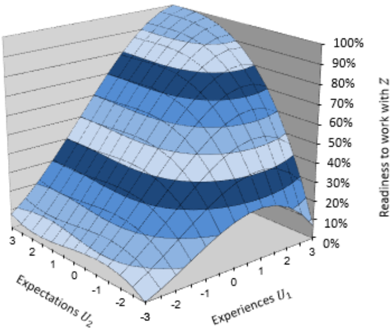
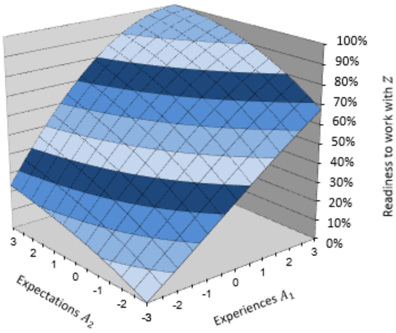
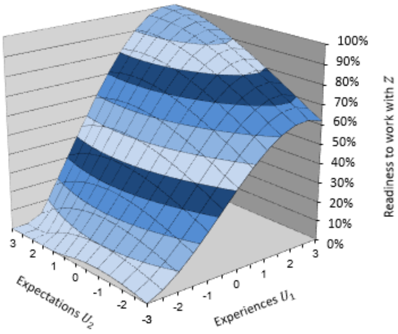
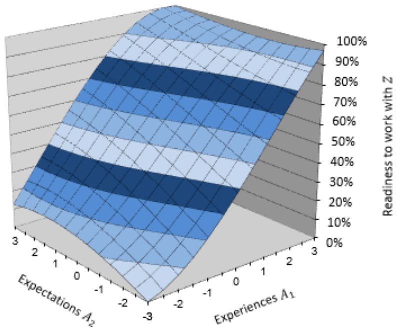
	Performance-related feature (usefulness)	**Relational feature (attitude)**
Android robotic lower-level manager, male participants	a. 	b. 
Android robotic lower-level manager, female participants	c. 	d. 
Humanoid robotic lower-level manager, male participants	e. 	f.  g.
Humanoid robotic lower-level manager, female participants	h. 	i.  j.

Figure H1. Three-Dimensional Response Surfaces for Different Robotic Agents as Lower-Level Managers, Sample Split by Participant Gender

Acknowledgements

Three years of work on a dissertation are short and long at the same time. Short, because one can spend more time on a topic and new and interesting questions come up at every corner. Long, because a lot happens in less than three years and the world changes a lot.

Now, after roughly 5400 hours of work, more than 430 working days in the home office (plus a much smaller number of days working at the university or in the leap in time lab), 2 business trips, almost countless emails, meetings and Zoom calls, and a randomly adopted cat, I am proud to submit my dissertation. None of this would have been possible without a number of people who have had a great impact on my work. It was an exciting time and I am grateful for the support I received along the way.

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