Group Decision and Negotiation (2022) 31:871–912
https://doi.org/10.1007/s10726-022-09792-z

Elaborating Team Roles for Artificial Intelligence-based Teammates in Human-AI Collaboration

Dominik Siemon[1]

Accepted: 20 June 2022 / Published online: 20 July 2022

Abstract
The increasing importance of artificial intelligence (AI) in everyday work also means that new insights into team collaboration must be gained. It is important to research how changes in team composition affect joint work, as previous theories and insights on teams are based on the knowledge of pure human teams. Especially, when AI-based systems act as coequal partners in collaboration scenarios, their role within the team needs to be defined. With a multi-method approach including a quantitative and a qualitative study, we constructed four team roles for AI-based teammates. In our quantitative survey based on existing team role concepts (n = 1.358), we used exploratory and confirmatory factor analysis to construct possible roles that AI-based teammates can fulfill in teams. With nine expert interviews, we discussed and further extended our initially identified team roles, to construct consistent team roles for AI-based teammates. The results show four consistent team roles: the coordinator, creator, perfectionist and doer. The new team roles including their skills and behaviors can help to better design hybrid human-AI teams and to better understand team dynamics and processes.

Keywords Human-AI collaboration · Collaboration · Artificial intelligence · Team roles · Team composition

1 Introduction

The rapid development of artificial intelligence (AI) in recent years leads to an enormous potential for the entire value creation of organizations (Russell and Norvig 2020). High computing power and novel algorithms are used to evaluate large amounts of data, make profitable predictions or recognize patterns (Kaplan and Haenlein 2019). AI is a phenomenon or term that has been already used for a long time (McCarthy et al. 1955) and is seen as a process rather than a technology in its

✉ Dominik Siemon
dominik.siemon@lut.fi

[1] School of Engineering Science, LUT University, Mukkulankatu 19, 15210 Lahti, Finland

own right. Berente et al. (2021) therefore define AI as "the frontier of computational advancements that references human intelligence" (p. 5), which led to several novel AI-based systems and applications, especially recently. AI-based systems subsequently take many forms, for example, as interactive actors with humans. Prominent systems are for example Apple's Siri or Amazon's Alexa, that are assisting users in the private sector, but also employees in organizational processes, for example in IT support (Maedche et al. 2016; Kaplan and Haenlein 2019; Morana et al. 2019). This increased implementation, usage, and the mere presence of such AI-based systems is changing the way we interact and co-exist with technology (Anderson et al. 2018; Kaplan and Haenlein 2019; Seeber et al. 2020; Mirbabaie et al. 2021).

Today, computers are no longer perceived as mere tools, but as interaction and collaboration partners in mutual value creation (Nass and Moon 2000; Seeber et al. 2020; Mirbabaie et al. 2021). This is mainly due to the way they interact and communicate, namely in the most natural way possible. Improvements in methods of natural language processing led to the fact that computers are perceived as human and are therefore treated accordingly (Nass and Moon 2000; Epley et al. 2007; Qiu and Benbasat 2009). Not only language but general behavior and appearance play a decisive role in how we perceive and interact with them. Such AI-based systems become not only more intelligent but also more human-like with characteristics such as personality, autonomy, empathy, and emotion (Nass and Moon 2000; Epley et al. 2007; Qiu and Benbasat 2009; Ahmad et al. 2021). These characteristics distinguish AI-based systems as we define them, which simulate human intelligence with all its facets (personality, autonomy, empathy, and emotion), from past automation systems, which were primarily designed to process tasks in an intelligent and automated way (Berente et al. 2021). We therefore see AI-based systems as systems that reference human intelligence in all its facets, incorporating social behavioral patterns in order to be able to interact in collaborative processes. In this context, it is often said that AI will take over many jobs in the future because of its sheer power to perform tasks faster and more efficiently (Aleksander 2017; Anderson et al. 2018; Schwartz et al. 2019).

However, many researchers argue that "humans and computers have complementary capabilities that can be combined to augment each other" (Dellermann et al. 2019, p. 4). Concepts such as hybrid intelligence, human-AI symbiosis, or human-in-the-loop argue that superior results can be accomplished when combining the capabilities of humans and AI in mutual value generation, by continuously learning from each other and improving each other (Dellermann et al. 2019; Gerber et al. 2020). The main aspect of these concepts is that tasks are performed collectively, and dependent activities are coordinated. If these mutual activities are now used to achieve a common goal, AI-based systems become team members in a collaboration scenario (Siemon et al. 2018; Seeber et al. 2020; Mirbabaie et al. 2021). As a result, the collaboration between humans and AI-based systems arises, which changes the way teams work together. This leads to new workplace configurations where autonomous AI-based systems jointly work within a team, fulfill certain roles and take over interdependent tasks (Bittner et al. 2019; Seeber et al. 2020).

Accordingly, established theories on group phenomena and processes from team, organization, and group research have to be reflected, reconsidered or even completely overthrown (Krämer et al. 2012; Seeber et al. 2020). Although, research has shown that traditional social responses and team dynamics can be applied to human-AI collaboration, as there are "more similarities between human–human and human–machine interactions than differences" (Krämer et al. 2012, p. 233), still many aspects of human-AI collaboration need to be further investigated. In addition to aspects that have recently been researched more frequently, such as trust in AI (Elson et al. 2020; Jessup et al. 2020), forms of reciprocity in human-AI collaboration (Goodman et al. 2016), or anthropomorphism (Qiu and Benbasat 2009; Araujo 2018; Watson 2019), team composition, and in specific, the potential roles of AI-based systems within a team are crucial for future human-AI collaboration.

Research from outside the core of information systems often focuses on certain tasks (Daugherty and Wilson 2018) or even jobs (Morini-Bianzino, 2017) that AI-based systems can or will fulfill in future work scenarios. Nevertheless, this philosophy still limits AI to the perception of a tool or an assistant that is used when humans need help, for example in decision making or when certain jobs need to be done (Maedche et al. 2016). In functioning teams, however, all members meet on an equal footing and each member contributes their knowledge and skills to the team (Belbin 2010; Siemon et al. 2019), taking on a certain role. A team role is a given function, task, or position, based on individual abilities, suitability, and performance that a team member has been assigned to or that has developed over time within a team (van de Water et al. 2008; Belbin 2012; Aritzeta et al. 2016). Researchers argue that taking different roles for the composition of a team into account is a key factor for an efficient performance (Bunderson and Sutcliffe 2002; Belbin 2010). Belbin's construct of team roles is one of the most renowned concepts that is widely used in practice and thoroughly researched, according to which teams work effectively when they consist of a large number of heterogeneous personalities and roles (Belbin 2012). The systematic management of teams is therefore essential to whether they fail or succeed in solving complex tasks and problems. Studies show that although groups can be unbalanced, it is inevitable to fulfill certain characteristics, take on certain tasks, and thus fulfill a certain role to allow effective collaboration (Bunderson and Sutcliffe 2002; van de Water et al. 2008; Belbin 2010; Aritzeta et al. 2016). Completely unbalanced groups, with only one role or the lack of an essential role for the joint work of a certain task, are often doomed to failure (Belbin 2010). The goal is therefore not necessary to achieve perfect and balanced teams, which complement each other in their roles in the best possible way, but mainly to fill essential roles, without which there is no functioning teamwork.

Thus, to be perceived as an equal partner, an AI-based teammate must fulfill a compelling and consistent team role, but one that should not reflect an omnipotent and omniscient partner, rather a teammate who is also limited in its skills and abilities. Otherwise, humans would merely rely on the abilities of the AI-based teammate and eventually exert less effort (Karau and Williams 1993). A functioning team with specific and convincing team roles is therefore preferable in order to reach a hybrid intelligence in which the abilities are combined and exhausted by both, humans and AI-based systems (Dellermann et al. 2019).

However, as of today, current applications of AI, such as virtual assistants or chatbots can be considered as weak AI as opposed to strong AI (Anderson et al. 2018;

Russell and Norvig 2020; Diederich et al. 2022). Weak AI represents intelligent systems that can solve problems, make decisions, generate ideas or contribute in a collaboration scenario, compared to strong AI, which presents AI with an "actual" mind and a so-called "machine consciousness" (Hildt 2019). Nevertheless, AI (in the sense of weak AI), can nowadays be designed to pick up certain behaviors and skills that are normally attributed by humans and thus be used as an equal member in a team. In contrast, due to habitual behavior, character traits, skills, and acquired knowledge, humans are limited in the choice of roles they can take on. AI-based systems, in contrast, are designed by humans and can specifically be equipped with certain skills and behaviors (Anderson et al. 2018), which is why nearly any role can be fulfilled by AI. However, for a team to function it is important that all teammates include their skills and abilities and therefore complement each other, which raises the question which skills and behaviors should be fulfilled by AI-based teammates? Thus, in our research, we address the following research question:

RQ Which set of behavior, including abilities and skills should be fulfilled by AI-based teammates in order to create functioning human-AI teams?

To address this research question, we review extant related studies and artifacts on human-AI collaboration as well as on tasks and roles that are fulfilled by AI-based systems. We furthermore provide theoretical background on teams, management and composition of teams, team roles and social response theory (i.e. computers are social actors paradigm) (Nass and Moon 2000). We then derive our research objective and present our research model, which are possible team roles for human-AI collaboration. We followed a sequential multi-method approach (Venkatesh et al. 2013) similar to Fujimoto (2016) and evaluated this model employing a survey resulting in a data set of 1,358 participants, which we analyzed with exploratory- and confirmatory factor analysis. We identified four desired new team roles for AI-based team members, which we compared to existing team role concepts. With a qualitative study, we interviewed nine experts that regularly compose and supervise teams in practice. With the results of the interviews, we refined and extended our team roles. Our findings not only contribute to team research, but also to human-AI interaction and collaboration. Practitioners can use our results as a starting point for building future human-AI teams and designing effective collaboration scenarios with AI-based systems.

2 Related Work

In 1996, Nass et al. investigated whether computers can be teammates. By relying on the group dynamic literature of human–human interaction, the researchers studied if team affiliation can be created in human–computer interaction. The results show that subjects affiliate the computer as a team member and that "effects of being in a team with a computer are the same as the effects of being in a team with another human" (Nass et al. 1996, p. 669). Although the study does not address explicit team roles, it shows that subjects change their behavior and perceive computers as friendly and cooperative when dependent teamwork exists (Nass et al. 1996). Based on these results, Nass and Moon (2000) examined, in a series of studies, how humans behave towards computers and what social responses result in an interaction with computers. Among other things, they found that people perceived and evaluated different roles such as tutor or evaluator differently. A tutor was perceived as competent and friendly, while an evaluator was perceived as dominant. Even though, the researchers did not focus on any specific team roles, different characteristics, tasks, and behavioral aspects were preferred by the participants, which leads to the assumption that computers should only fulfill certain roles (Nass and Moon 2000). Other concepts take up these aspects and argue that the symbiosis between humans and AI is to be aimed for (Gerber et al. 2020). A joint value creation and a meaningful distribution of tasks, in which the complementary capabilities lead to effective collaboration, is most beneficial. This however means that AI-based teammates should not take over every role within a team but should rather be designed to fulfill certain activities which are most fitting and effective and thus complement the advantages of humans (Dellermann et al. 2019).

In their agenda for future collaboration engineering research, de Vreede and Briggs (2019) discuss the expanding conception of teams. As "artificial agents will become fully functional members of teams" (de Vreede and Briggs 2019, p. 103), they raise the question of which roles automated agents can fulfill and which tasks they can perform. Similar results were obtained in a panel discussion on issues and research opportunities in collaborating with technology-based autonomous agents hold in 2019 (Seeber et al. 2020). Among other things, the researchers mentioned the aspect of designing new human–machine workplace configurations, specifying, in particular, the tasks of the machines and the roles to be assumed. The design of the autonomous technology-based agent with regard to its personality and behavior and the role it plays in the team is a decisive part in this context. "For example, it might be a decision-making tool, an assistant, a peer, or even a manager" (Seeber et al. 2020, p. 10).

Research on the specific tasks, skillsets, and behaviors, however, is fragmented and varies by task and context. For example, Jarrahi (2018) present AI-based systems, that, with their greater computational information processing capacity and analytical capabilities, can extend the humans' cognition in order to address the complexities in decision making. As a result, a definite distribution of roles with specific tasks and skills emerges. Larson (2010) specifically focused on the role of mediators and arbitrators and investigated, how and if AI-based systems can be used to dispute resolution. Besides identifying many unsolved issues, the authors think that possible AI applications that fulfill roles such as a mediator or arbitrator in team constellations are becoming apparent (Larson 2010). Maher and Fisher (2012) developed an AI-based system that takes on the role of an idea evaluator and assesses the novelty, the degree of surprise and unexpectedness of an idea. Strohmann et al. (2018) focus on the role of a creativity moderator or facilitator, which are designed to organize, conduct, and facilitate creativity-intensive processes. Their role is to intervene, moderate and provide input when needed (Strohmann et al. 2018). Hofeditz et al. (2022) developed and investigated a specific form of AI-based teammate;

ELSA, an emotional support agent that was able to strengthen trust among virtual collaborative team members, thus fulfilling a specific role. Elshan and Ebel (2020) present design knowledge (i.e. skillset and abilities) for Timmy, an AI-based teammate that acts as a peer in education scenarios. In addition, there are several other studies that deal with dedicated tasks and roles of AI-based systems in collaboration (Hayashi and Ono 2013; Gnewuch et al. 2017; Mirbabaie et al. 2021).

To process this vast field of research, Bittner et al. (2019) have created a taxonomy to help researchers and designers understand this dynamic field as well as the interrelations of different design options in human-AI collaboration. In order to support the collaboration engineering process and team composition, the taxonomy especially emphasis on the role of AI within teams, which is a central design choice. They identified roles such as the facilitator (e.g. tutors or teachers), the peer (e.g. teammate or sparring partner) and the expert (e.g. analyst or evaluator) that can be taken over by AI-based teammates. However, they call for further research, especially with regard to specific team roles, interaction dynamics, and team composition to test their proposed taxonomy and roles (Bittner et al. 2019).

Overall, it can be said that despite many studies and concepts on tasks and roles of AI-based teammates in future human-AI collaboration scenarios, there is no comprehensive research on which set of behavior and skills should be fulfilled by an AI-based teammate, independent from task and context. This raises the question of whether existing theories serve as a basis or can even be transferred to human-AI constellations (Krämer et al. 2011, 2012) or whether completely new team constellations have to be considered.

3 Theoretical Background

3.1 Human-AI Collaboration

Collaboration can be defined as the joint effort towards a common goal that includes aspects such as team or group formation, productivity, continuity, allocation of responsibility, as well as adaptation and learning (Randrup et al. 2018). Due to the complexity and versatility of collaboration, research on it is interdisciplinary, including disciplines like psychology, economics, organization- and team research (Randrup et al. 2018; Siemon et al. 2019). Through the use of information technology (IT), collaboration is increasingly being carried out digitally, and computer scientists are participating in collaboration research with artifacts, guidelines, and applications for effective team and group work (Briggs 2006; Brown et al. 2010). While IT is traditionally considered as a tool, the increased use of intelligent systems extends the research disciplines of collaboration technology or computer-supported cooperative work by aspects like human–computer collaboration (HCC) or human–machine (or AI) collaboration. Despite many overlaps, HCC substantially distinguishes itself from the research field of human–computer interaction and focuses more on aspects of collaboration instead of focusing on interaction and information presentation theories (Terveen 1995). In the HCC discipline, the research on AI has a major influence since the autonomy and above all the intelligence of IT is brought to the fore.

This leads to the fact that computers are endowed with human-like abilities, which subsequently enables them to act like humans (Maedche et al. 2016; Seeber et al. 2020).

When computers are equipped with human-like capabilities and appearance, the Media Equation Theory comes into play, which states that humans tend to respond to media as if it was another human (Reeves and Nass 1996). Humans show polite, cooperative behavior and even express traits such as aggressiveness or humor (Reeves and Nass 1996; Hoffmann et al. 2009). Nass et al. (1996) showed in several studies that this kind of reaction is automatic and inevitable and occurs more often than people think. Individual's interaction with computers is thus fundamentally social and natural as it is with real humans (Reeves and Nass 1996). Based on this, Nass and Moon (2000) developed the social response theory, which states that people apply social rules and expectations to computers, even though they know that these machines have no feelings, intentions, or human motivations (Nass and Moon 2000). The theory includes interactive and collaborative aspects, which also consider collective performance including phenomena such as reciprocity. In several studies, Nass and Moon (2000) show that, when a computer provides help, favors, or benefits, it triggers the mindless response of a participant, feeling obliged to help the computer. Consequently, social response theory also applies to team constellations in which computers work together with humans on issues, distribute tasks, coordinate actions, and accordingly generate shared value (Nass and Moon 2000). If computers now exhibit human behavior, interact human-like, and look human-like, defined role concepts should also be maintained to ensure a functioning team.

3.2 Teams and Team Composition

A team is defined as a number of individuals that work together to reach a constituted goal (van de Water et al. 2008; Belbin 2012). In a team, individuals (human or non-human) have complementary skills, coordinate, and combine activities in order to generate synergetic effort that leads to joint value creation (Cohen and Bailey 1997; Belbin 2012). In this sense, a team is a group of individuals who work together for different purposes and objectives with different durations and are holistically responsible for a common goal (Aritzeta et al. 2016). Key aspects of teams are the complementary skills of each team member who contribute to the achievement of the goals with their respective skills and the resulting mutual dependencies (Margerison et al. 1986; Belbin 2012; Aritzeta et al. 2016). These differences are diverse and are not only reflected in individual abilities, knowledge, experience, and special skills, but also in social and cognitive characteristics (Aritzeta et al. 2016). In particular, different thought patterns, abilities to make associations and mental leaps and general approaches to problem-solving are different (Saldaña-Ramos et al., 2014; Aritzeta et al. 2016). Social abilities and individual norms, such as the ability to communicate, to deal with conflicts and the attitude to share own thoughts with a group or to initially think and work independently are very different (Saldaña-Ramos et al. 2014; Katzenbach and Smith 2015; Aritzeta et al. 2016). If these differences appear in teams, one speaks of diversity (Bunderson and Sutcliffe

2002; Bouncken 2004). Diversity is defined as the differences between individuals in relation to an attribute that makes one person different from another (Horwitz and Horwitz 2007; Chae et al. 2015). When teams consist of members with different knowledge and skills, especially their overall performance can be improved, since the process of exploration and exploitation requires a high degree of diversity (Bunderson and Sutcliffe 2002; Horwitz and Horwitz 2007). Furthermore, studies show that diversity is important for developing new innovations, creating new business practices, and exploring new products and services (Bouncken 2004; Ames and Runco 2005). However, the effectiveness of teams depends on many aspects, such as the task to be solved, the boundary conditions such as the time the team works together, and the relevance and influence of the decisions (Cohen and Bailey 1997; Bunderson and Sutcliffe 2002; Belbin 2012; Katzenbach and Smith 2015). It is therefore of great importance to systematically compose teams in order to address a task in the best possible way (Jackson 1991; Belbin 2010; Aritzeta et al. 2016). When assembling teams that need to work together in an interdisciplinary manner to solve complex problems, it is therefore necessary to explicitly determine which different social categories should be covered and how great the diversity should be (Jackson 1991; Higgs et al. 2005; Mello and Ruckes 2006; Belbin 2010).

The composition of a team refers to the overall mix of attributes between the team members and is based on the characteristics and skills of the individuals who make up the team (Higgs et al. 2005; Mello and Ruckes 2006). It considers the characteristics of the team members and how the individual contributions can be combined in the best possible way to achieve the goal and improve team performance. Team composition studies have focused on aggregated member characteristics, diversity, and team size as categories related to team composition (Higgs et al. 2005; Mello and Ruckes 2006; Belbin 2010). Thus, the way a team is configured has a strong influence on the team processes and the results the team achieves (Senior 1997; Higgs et al. 2005; Belbin 2010). Composing teams with their different members is therefore a complex undertaking, that however, primarily influences the success or failure of a team (Belbin 2010). In order to collate these different aspects and individual characteristics, researchers have developed so-called team role models, which are intended to provide practical support for team composition and team management (Benne and Sheats 1948; Margerison et al. 1986; van de Water et al. 2008; Belbin 2012).

3.3 Team Roles

A team role is the label given to a function or position that an individual has been assigned within a team or that has developed in the course of team dynamics (van de Water et al. 2008; Belbin 2012). In general, a role describes the rights and duties of its owner (Belbin 2012). The other members of the team have certain expectations of this role and assumptions about what the role holder will or should do. One of the best-known and most widely used team role concept was developed by Belbin in 1981. It is primarily used by decision-makers and managers that are responsible for the management of teams and their composition (Belbin 2012). A team role, as

Table 1 Belbin's team roles (Belbin 2012)

Category	Role	Description
Action-oriented	Shaper	Challenges the team to improve
	Implementer	Puts ideas into action
	Completer Finisher	Ensures thorough, timely completion
People-oriented	Coordinator	Acts as a chairperson
	Team Worker	Encourages cooperation
	Resource Investigator	Explores outside opportunities
Though-oriented	Plant	Presents new ideas and approaches
	Monitor-Evaluator	Analyzes the options
	Specialist	Provides specialized skills

defined by Belbin (2012), is a set of behaviors that form a cluster, which is shaped by the individual's personality, mental abilities, current values and motivations, field constraints, experience, and role learning (van de Water et al. 2008; Belbin 2012). Individuals develop differently through the influence of various factors that affect each other (van de Water et al. 2008; Turner 2010; Belbin 2012). This creates certain characteristics of role behavior in teams, which according to Belbin (2012) consists of four dimensions: feeling, willpower, thinking, and decisiveness. Belbin (2012) analyzed the results of teams of his courses and identified eight different team roles that resulted from the behavior patterns of the members. In 1981 he summarized these in his team role framework and later added another role resulting in overall nine team roles (Belbin 2012). Each role has different expressions of the four dimensions and can in turn be divided into three main categories, action-oriented roles, people-oriented roles, and though-oriented roles (Belbin 2010). Table 1 provides an overview of Belbin's team roles including a description for each role.

Shortly after the publication of his work, researchers began questioning Belbin's team roles (Furnham et al. 1993; Fisher et al. 1996). In particular, they challenged the validity and reliability of Belbin's approach and independently tested the psychometric properties of the instruments (Furnham et al. 1993). Belbin argues that the team role inventory is not a psychometric tool, but rather a support for team management practices (Belbin 1993). Other studies examined Belbin's team roles, often based on the inventory in its original form, and found, that there are only five role constructs instead of eight or nine (Fisher et al. 1996). Again, Belbin argued that his team roles concept is not a psychometric tool, which cannot necessarily be determined by factor analysis and should include qualitative assessments (Belbin 2012). Therefore, in order to obtain better results of the Belbin individual report, observations of external persons (so-called observer assessments) are used to determine suitable team roles (Belbin 2012).

In addition to this established role concept, Margerison et al. (1986) developed the so-called Margerison-McCann Team Management Profile, which describes similar roles concepts. However, the construct does not contain explicit team roles, but rather information about a person's work preferences, which can then be used to better assign the respective tasks in a team (Margerison et al. 1986). The concept

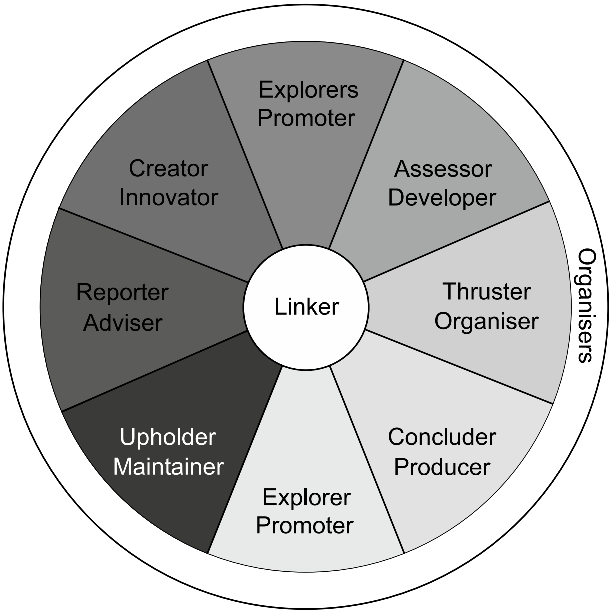

Fig. 1 Team management wheel (Margerison et al. 1986)

was developed in the 1980s and led to the establishment of the Institute of Team Management Studies at the University of Queensland, which continued to develop the concept. The basis for the application of the Team Management System is a standardized survey with 60 questions (so-called Team Management Index), which assumes that each team is divided into eight types of work (Margerison et al. 1986). These types are promoting, developing, organizing, producing, inspecting, maintaining, advising, and innovating. The working methods can then be assigned to people, bringing together work preferences and creating concrete roles that each person in a team would like to take on according to their profile and can perform preferentially (Margerison et al. 1986). Margerison et al. (1986) (Margerison et al. 1986) also constructed superordinate categories, which are, the explorers, the organizers, the controllers, and the advisers, which have eight sectors that describe preferences and behavioral characteristics, which they also refer to as team roles. The center of the wheel also contains a role called the Linker (Margerison et al. 1986). Figure 1 shows their Team Management Wheel.

Similar to Belbin (2012) (Belbin 2012), Margerison et al. (1986) state that their Team Management Wheel is “a practical model which can be used in a variety of management development applications” (Margerison et al. 1986, p. 9).

In 1948, Benne and Sheats released a paper on the functional roles of group members that can be classified into three groups consisting of overall 27 individual roles. Group task roles encompass 12 roles that “are related to the task which the group is deciding to undertake or has undertaken” (Benne and Sheats 1948, p. 42). Group building and maintenance roles consist of seven roles that mainly work towards the functioning of the group. The third category cover individual roles, which are eight

Table 2 Benne and Sheats (1948) team roles

Class	Role
Group task roles	Initiator-contributor, Information seeker, Opinion seeker, Information giver, Opinion giver, Elaborator, Coordinator, Orienter, Evaluator-critic, Energizer, Procedural technician, Recorder
Group building and maintenance	Encourager, Harmonizer, Compromiser, Gate-keeper and expediter, Standard setter or ego, Group-observer and commentator, Follower
Individual roles	Aggressor, Blocker, Recognition-seeker, Self-confessor, Playboy, Dominator, Help-seeker, Special interest pleader

roles that focus on individual goals and often hinder the overall team performance (Benne and Sheats 1948). Table 2 provides an overview of the roles.

Benne and Sheats (1948) also argue that there is no optimal group and thus no perfect composition and that not all roles are relevant or necessary for a group to function. Rather, their objective was to create an overview with their identified roles and support the training of group membership roles, which "requires the identification and analysis of various member roles actually enacted in group processes" (Benne and Sheats 1948, p. 49). It is also worth noting that the individual roles that tend to conflict with or disrupt the team are identified roles that are not necessarily desired or wanted (Benne and Sheats 1948).

A related concept is the Myers-Briggs Type Indicator, which provides a broader view of individual characteristics and properties (Myers 1962). The indicator primarily allows statements to be made about the different individual psychological preferences in the way individuals perceive the world and make decisions (Quenk 2009). Although it provides far-reaching insights into individual character traits and, above all, behavior, the concept is not primarily used for team management (Pittenger 2005). Other related concepts are the STAR roles model concept (Kates and Galbraith 2010) or the ten management positions by Mintzberg (Mintzberg 1989), that however mainly focus on manager and mentor roles.

These role concepts have substantial overlaps in their definitions or their descriptions of the skills, characteristics, and behaviors.

4 Methodology

Human characteristics and knowledge are shaped over years, making them more suitable for certain roles and less so for others (Cohen and Bailey 1997; van de Water et al. 2008). Usually, people can fulfill more than one team role that matches their skills and behaviors (Belbin 2012). As knowledge, as well as behavior changes over time, fitting team roles might shift as well. Belbin (2012) developed a survey of questions for self-assessment and additional assessment by expert observers, called Self-Perception Inventory, in order to determine the most suitable team role profiles. A similar instrument is the Team Management Systems, developed by Margerison et al. (1986) (Margerison et al. 1986). These instruments serve as self-assessment tools to best classify individuals and thus enable team composition (Margerison et al. 1986; Belbin 2012).

If individuals know their roles, Belbin (2012), as well as Margerison et al. (1986) argue that they better understand their strengths and weaknesses, which leads to more effective communication and overall teamwork. However, an AI-based teammate can explicitly be designed and equipped with knowledge, skills, and behaviors (Anderson et al. 2018; Jarrahi 2018; Siemon et al. 2018; Mirbabaie et al. 2021). It can be designed in such a way that it can best fulfill specific roles.

In our research, we investigate which characteristics, behavior patterns and thus roles such a system should take on in human-AI teams. To determine these possible characteristics and to construct possible team roles for AI-based team members, we developed a questionnaire based on existing role descriptions, including characteristics, skills, and behaviors of team role concepts by Belbin (2012), Margerison et al. (1986), and Benne and Sheats (1948). As theoretical terms are constructs, which cannot be directly observed or experienced and in order to transform them into a form that can be empirically recorded and examined, operationalization is necessary (Shaughnessy et al. 2000; Bryman 2016). To operationalize the existing team roles, we used the following available material on team roles, which we have also compared with current public information from Belbin's consulting firm[1] and the TMS International Inc.,[2] and expanded it if necessary:

1. Benne and Sheats (1948). Functional Roles of Group Members. *Journal of Social Issues*.
2. Margerison et al. (1986). The Margerison-McCann Team Management Resource – Theory and Applications. *International Journal of Manpower*.
3. Belbin (2012). *Team roles at work*. Routledge.

We explicitly did not rely on Belbin's Self-Perception Inventory, as it was developed for self-assessment purposes and is legally protected and any use or modification is prohibited. We excluded the nine individual roles of Benne and Sheats (1948) because they follow "individual needs which are irrelevant to the group task and which are non-oriented or negatively oriented to group building" (Benne and Sheats 1948, p. 45). We then analyzed the different role descriptions and concepts in order to form set of descriptions, skills and behaviors. In doing so, similarities between the role descriptions of the different role concepts were grouped and subsequently merged accordingly. An example of this process with two questions can be find in Table 11 in the Appendix. This resulted in a set of unique descriptions, which were then used to construct a questionnaire (see Tables 11 and 13). In this process, the descriptions were merely reworded and put into question form, which did not entail any change in content. Table 13 furthermore shows the questions and their origin. To address our research question, we followed a sequential multi-method approach and conducted two studies, which build on each other. Venkatesh et al.

[1] https://www.belbin.com/.

[2] https://www.teammanagementsystems.com/.

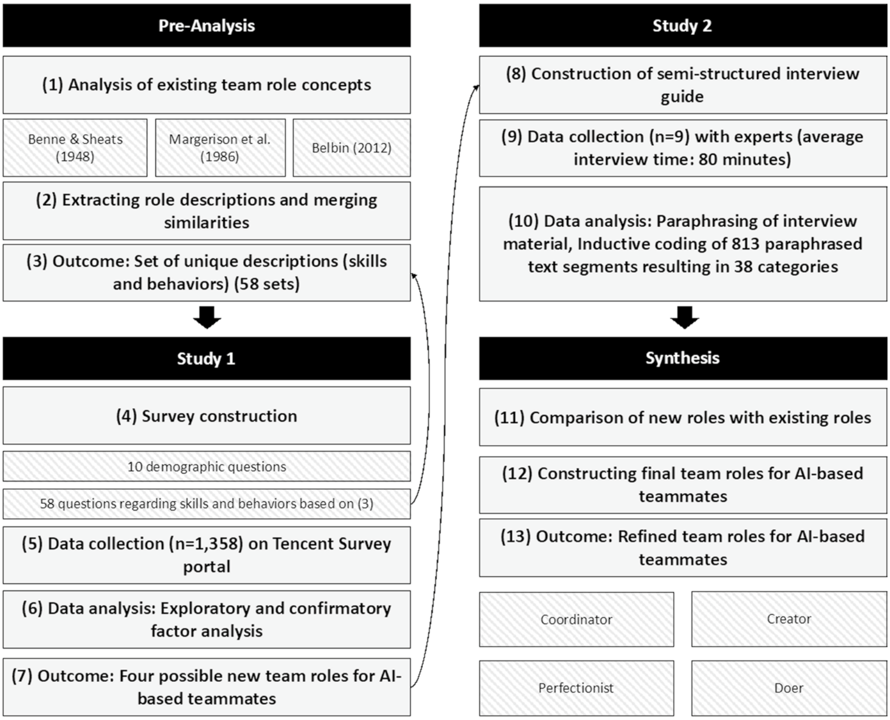

Fig. 2 Research process

(2013) describe this as sequentially in which “findings from a qualitative (or a quantitative) study will theoretically and/or empirically inform a later quantitative (or a qualitative) study” (p. 38). In our approach, the first study aims to identify possible team roles for AI-based team members and follows a quantitative approach. In a second study, the identified team roles are then discussed with nine experts in order to extend, modify or even completely discard them. Figure 2 provides an overview of the research process.

4.1 Study 1

The objective of the first study is to find out which set of behavior, including abilities, skills as well as rights and duties within a team could or should be fulfilled by AI to create functioning human-AI teams.

To address this, we have designed a questionnaire in which participants should base their thoughts on the description of the capabilities and express their attitude and perception toward an AI-based teammate, by imagining a scenario where they are working in a team with an AI-based teammate. For this, we have constructed 58 questions in total, which contain characteristics, abilities, and behavior, for example, “an AI-based team member might develop new and fundamental ideas” or “an

AI-based team member might stimulate discussions in difficult situations to provoke new perspectives" (see Table 13 in the Appendix). Each question should be answered on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree). All items considering characteristics, abilities, and behavior of AI-based team members of the constructed survey can be found in the Appendix (see Table 13).

The questionnaire starts by briefly describing the development and application background of AI technology, and comprehensively introduces the concept of an AI-based teammate (see Table 12 in the Appendix). This was necessary because the perception of current AI-based systems is still limited due to currently existing services such as Amazon's Alexa or Apple's Siri, which are not yet without flaws and overall still serve as assistants rather than co-equal partners (Siemon et al. 2018; Seeber et al. 2019, 2020; Mirbabaie et al. 2021). It was important to place the participants in a scenario where AI is used free of technological hurdles and limiting perceptions and is seen as an equal partner in joint value creation (see Table 12 in the Appendix).

Including demographic questions (e.g., gender, age, and occupation) and open questions, the questionnaire consists of overall 68 questions. The survey was constructed using English measures, which were independently translated into Chinese by three native speakers (forward translation), jointly discussed (panel) and subsequently back-translated to check for linguistic equivalence of the initial measures. The successful equivalence check led to the use of the translated measures as the final instrument in Chinese. Our questionnaire was translated into Chinese mostly for practical reasons with the aim of distributing it through a Chinese survey portal (Tencent Survey portal) to get the required number of participants to conduct a reliable factor analysis.

With our survey, we followed an inductive approach by developing new team roles for AI-based teammates and assume that the observable relationships between different indicators can be explained by the assumption of latent variables (Shaughnessy et al. 2000; Bryman 2016). With an explorative factor analysis (EFA) the observations of these indicators are used to draw conclusions about a few underlying latent variables, e.g. factors, which are then used to construct possible team roles similar to the approach by Fujimoto (2016). Subsequently, the existing factor structure is analyzed with confirmatory factor analysis (CFA) in order to test whether the data fits our hypothesized factors (Rummel 1988; Mair 2018). Finally, new roles for AI-based team members were defined on the existing factors and its descriptions and compared to existing team role concepts.

4.1.1 Data collection

Our survey was distributed via the Tencent Survey portal, between November 2019 and January 2020.

In total, data was collected from 2.582 participants, whereas, after data cleansing, a data set of 1,358 was used (52% recall rate). On average, participation in the survey took twelve minutes and 35 s. Data cleansing was performed as a precondition for the data analysis (Osborne 2013), to search, identify, and correct input errors and potentially unpredictable inputs (Raithel 2008). In order to control error and identify

Table 3 Rotated component matrix

Item	Factor			
	1	2	3	4
AITM1	0.784			
AITM2	0.743			
AITM3	0.727			
AITM4		0.746		
AITM5		0.742		
AITM6		0.716		
AITM7			0.831	
AITM8			0.759	
AITM9			0.629	
AITM10				0.774
AITM11				0.748
AITM12				0.654

Extraction method: Principal component analysis.

Rotation method: Varimax with Kaiser normalization.

Rotation converged in 5 iterations.

outliers, data quality was checked through visual validity (Raithel 2008; Bryman 2016).

Overall, 25 participants are under 18, 740 are between 18 and 24, 126 are between 25 and 34, 231 between 35 and 44, 182 between 45 and 55 and 54 over 55. 713 participants are female, 645 are male, whereas nobody answered diverse or chose to not answer. Almost half (45%) of the sample are students (in colleges and universities), and the other half are employed (55%).

4.1.2 Results

Measure of sampling adequacy (MSA) was used to test whether the sample data is suitable for conducting EFA. The MSA-value of each item is on the diagonal of the anti-image-correlation matrix. The MSA-value of each item is on the diagonal of the anti-image-correlation matrix and the MSA-value of the items is between 0.722 and 0.959 (Rummel 1988; Mair 2018). An examination of the Kaiser–Meyer–Olkin measure of sampling adequacy suggested that the sample was factorable with 0.80 (with $p < 0.05$), which is above the commonly recommended value of 0.60 (Rummel 1988; Mair 2018). Furthermore, we computed Bartlett's test of sphericity, which was significant with $\chi 2$ (1358) = 2243.52, df = 66 and $p < 0.05$ and Cronbach's alpha with $\alpha = 0.77$. After splitting the sample into two equal parts (random), 58 questions (see Table 13 in the Appendix) describing characteristics, skills, and behavior of an AI-based teammate were factor analyzed using principal component analysis followed by varimax rotation method with Kaiser normalization (Rummel 1988; Mair 2018). The analysis yielded four

Table 4 Questions and roles

Item	Factor	Description (e.g. question) *An AI-based teammate …*
AITM1	1	*… might be good at convincing team members to take action*
AITM2	1	*… might take over the leadership of a team if necessary*
AITM3	1	*… might establish useful contacts*
AITM4	2	*… might be good at finding many possible solutions for new situations*
AITM5	2	*… might conduct research, in order to develop something new based on it*
AITM6	2	*… might always be looking for new ideas and developments*
AITM7	3	*… might be particularly good at completing tasks in detail*
AITM8	3	*… might go into great detail when solving a task*
AITM9	3	*… might rather be a perfectionist when it comes to solving tasks*
AITM10	4	*… might push for concrete actions so that no time is wasted and can separate the important from the unimportant*
AITM11	4	*… might primarily be interested in finding practical solutions that work*
AITM12	4	*… might be good at completing tasks properly*

factors explaining a total of 60.614% of the variance for the entire set of variables. Table 3 shows the rotated component matrix with its extracted factors and items.

The measurements of EFA are all within the common threshold, and a total of four factors were extracted. Each factor contains three items, and 12 items in total remained which can be seen in Table 4.

We continue with CFA to validate the roles in terms of indicator reliability, factor reliability (i.e. composite reliability), convergence validity and discriminant validity (Homburg and Giering 1998; Bryman 2016; Mair 2018). Indicator reliability is used to measure the reliability for each observed variable and represents a ratio between the variance explained by the factor to which a single variable belongs and the total variance of this variable (Rummel 1988; Bryman 2016). Factor reliability is required to state how well a factor is measured by all the indicators, which are assigned to it. Convergent validity refers to the degree of consistency of measurement errors and is reported as the average variance extracted (AVE). The examination of indicator reliability, factor reliability and convergent validity is summarized in Table 5 below.

Item AITM9 has a deficiency in indicator reliability, with 0.396, which is slightly lower than the minimum threshold for 0.4, but is still acceptable (Rummel 1988; Homburg and Giering 1998).

In order to determine whether the different indicators are unrelated, we measure discriminant validity with inter-correlations between factors, which indicate low and very low correlations between each factor (see Table 6) (Rummel 1988; Raithel 2008). Furthermore, the AVE score of each construct is greater than the squared inter-correlation coefficients (see Table 7), whereas discriminant validity is provided.

After validating the extracted factors, we assess content validity and nomological validity, by discussing the identified factors in terms of content and comparing them with existing role concepts (Rummel 1988; Bryman 2016). In particular, we check

Table 5 Indicator reliability, factor reliability and AVE

Item	Factor	Factor loading	Indicator reliability	Factor reliability	Convergent validity (AVE)
AITM1	1	0.784	0.615	0.796	0.565
AITM2		0.743	0.552		
AITM3		0.727	0.529		
AITM4	2	0.746	0.557	0.779	0.540
AITM5		0.742	0.551		
AITM6		0.716	0.513		
AITM7	3	0.831	0.691	0.786	0.554
AITM8		0.759	0.576		
AITM9		0.629	0.396		
AITM10	4	0.774	0.599	0.770	0.529
AITM11		0.748	0.560		
AITM12		0.654	0.428		
Common threshold		*> 0.4*	*≥ 0.4*	*≥ 0.6*	*≥ 0.5*

Table 6 Inter-correlations between factors

	Factor 1	Factor 2	Factor 3	Factor 4
Factor 1	1			
Factor 2	0.446**	1		
Factor 3	0.251**	0.326**	1	
Factor 4	0.193**	0.304**	0.302**	1

**Correlation is significant at the 0.01 level

Table 7 Discriminant validity (comparison of AVE with squared inter-correlations)

	Factor 1	Factor 2	Factor 3	Factor 4
Factor 1	0.565			
Factor 2	0.199**	0.540		
Factor 3	0.063**	0.106**	0.554	
Factor 4	0.037**	0.092**	0.091**	0.529

**Correlation is significant at the 0.01 level

whether bipolar roles exist, whether roles are very close to each other in terms of content, or whether roles are inconsistent in themselves.

4.1.3 Discussion

The first factor represents a team role, which we call the *coordinator*, as this role is both able to take the lead and persuade other team members, but is also able to make relevant connections. Alternative terms would be the boss, organizer or leader, due to their persuasive and directive abilities. The role has no bipolar capabilities and is therefore inherently consistent. In Belbin's team concept, the role is comparable to the co-ordinator, resource-investigator, and shaper (Belbin 2012). In Margerison-McCann's Team Management Wheel, there are overlaps with the roles of thruster-organizer, explorer-promoter, upholder-maintainer (Margerison et al. 1986). Comparable roles of Benne and Sheats is coordinator or initiator-contributor (Benne and Sheats 1948). All of these roles also have several similarities.

The second factor represents a team role that we refer to as the *creator*. Other terms would be the innovator, explorer, or ideator. This role primarily reflects creative skills, such as finding many possible solutions or searching for new ideas and developments. However, this role is also characterized by its ability to research in order to develop new things based on this. These aspects are not bipolar and do not show inconsistencies, which is why the role can be seen as coherent. Comparable roles according to Belbin (2012) are the plant, resource-investigator. Similar roles according to Margerison et al. (1986) are the creator-innovator, assessor-developer, explorer-promoter, reporter-adviser. Benne and Sheats (1948) defined roles like the initiator-contributor, information-giver, elaborator that show similarities.

The third factor describes a team role, which we refer to as the *perfectionist*. Other possible names would be the detail-oriented or stickler for order. This role is characterized above all by its detailed and orderly work, up to perfectionist execution of certain tasks. All aspects and abilities of this role are consistent within themselves and do not exhibit contradictory abilities. Comparable roles to Belbin (2012) include the completer-finisher and specialist. Roles from the concept of Margerison et al. (1986) are the controller-inspector, upholder-maintainer, reporter-adviser. Benne and Sheats (1948) defined a similar role with the elaborator.

The fourth factor describes a team role that we call the *doer*. Other names would be the implementer or shaper. This role is mainly characterized by its implementing activities and finding practical solutions. Also driving the group forward in a short time and being able to distinguish relevant things from irrelevant things characterizes this role. All the abilities and aspects do not contradict each other and are consistent within themselves. Belbin (2012) defined similar roles with the implementer, co-ordinator or shaper. Margerison et al. (1986) show similar capabilities with the assessor-developer or thruster-organiser, while Benne and Sheats (1948) defined comparable roles with evaluator-critic, energizer, orienter, or procedural technician.

Overall, all roles are clearly distinguishable from each other in terms of content and there is no substantial overlap between the individual roles. Table 8 presents the team roles, their description, and the similar role concepts of Belbin (2012), Margerison et al. (1986) as well as Benne and Sheats (1948).

4.2 Study 2

In order to discuss, confirm, reject, extend or adapt the identified team roles, we conducted qualitative interviews with experts who frequently work in teams, compose

Table 8 AI-based team roles compared to existing role concepts

Role	Description	Similar role concepts
Coordinator	*Is good at convincing team members to take action*	<u>Belbin</u>: Co-ordinator, Resource-Investigator, Shaper
	Can take over the leadership of a team if necessary	<u>Margerison-McCann</u>: Thruster-Organiser, Explorer-Promoter, Upholder-Maintainer
	Can establish useful contacts	<u>Benne and Sheats</u>: Coordinator, Initiator-Contributor
Creator	*Is good at finding many possible solutions for new situations*	<u>Belbin</u>: Plant, Resource-Investigator
	Conducts research, in order to develop something new based on it	<u>Margerison-McCann</u>: Creator-Innovator, Assessor-Developer, Explorer-Promoter, Reporter-Adviser
	Is always looking for new ideas and developments	<u>Benne and Sheats</u>: Initiator-contributor, Information-Giver, Elaborator
Perfectionist	*Is particularly good at completing tasks in detail*	<u>Belbin</u>: Completer-Finisher, Specialist
	Goes into great detail when solving a task	<u>Margerison-McCann</u>: Controller-Inspector, Upholder-Maintainer, Reporter-Adviser
	Is rather perfectionist when it comes to solving tasks	<u>Benne and Sheats</u>: Elaborator
Doer	*Pushes for concrete actions so that no time is wasted and can separate the important from the unimportant*	<u>Belbin</u>: Implementer, Co-ordinator, Shaper
	Is primarily interested in finding practical solutions that work	<u>Margerison-McCann</u>: Assessor-Developer, Thruster-Organiser,
	Is good at completing tasks properly	<u>Benne and Sheats</u>: Evaluator-Critic, Energizer, Orienter, Procedural technician

them or regularly work with AI and thus have corresponding expertise in at least one of these areas.

The interviews were conducted with the support of a semi-structured interview guide (see Appendix), which is advantageous when the goal of the interviews is to make specific statements about certain aspects but also allows for exploratory input (Mayring 2014; Bryman 2016). Interviews that follow a guide are based on open-ended questions to which the interviewee can give an honest answer based on his/her experience and expertise (Mayring 2014; Bryman 2016). The guide helps orient the interviewer, ensuring that all critical aspects of the research question are included. Furthermore, queries and deviations are possible (Mayring 2014). The creation of the interview guide was based on the identified team roles and on the 58 defined questions describing characteristics, abilities, and behaviors of AI-based teammates. The creation process was done in several iterative steps and involved collecting, reviewing, sorting, and subsuming individual questions (Helfferich 2011). The interview guide was then reviewed by four independent researchers and possible changes were discussed and adopted. The final version of the interview guide consists of 28 questions, which in turn were divided into four segments. Each segment starts with a short introduction and one or two introductory questions. The interview guide can be found in the Appendix.

4.2.1 Data collection and data analysis

To ensure that the qualitative interviews provide adequate basis for an analysis, it is necessary to select suitable experts to interview. Since the term expert is often overused (Mayring 2014; Bryman 2016) and justified by every day- and common-sense knowledge, specific criteria such as expertise and experience should be specified. To select our experts for the interviews, we specified precise criteria, such as having more than 5 years of practical experience in the field of AI and/or teamwork and composition of teams.

Identification of suitable experts was conducted via company websites and professional social networks such as LinkedIn and Xing. Besides, personal contacts were used and various established companies in areas relevant to this work were contacted directly. After the identification of suitable experts, we directly contacted them, explaining our objectives and asking them for possible interview time slots. In total, 21 experts were contacted, and nine experts were interviewed (twelve declined our request). We planned a second round of interviews if data saturation did not occur. After the analysis of the data, however, data saturation occurred, so that no second round was conducted. Data saturation was noted as only few new codes were generated after the sixth interview and, most importantly, no new codes were generated during the last interview (Fusch and Ness 2015).

The interviewees are all male, German, and between 34 and 58 years old and work in different companies. An overview of our interview panel can be found in Table 9.

The interviews were conducted in January, February and March 2021 and took on average 80 min (minimum 63 min, maximum 95 min). The recorded interviews were transcribed and coded using the qualitative data analysis software MaxQDA

Table 9 Interview panel

ID	Job title and organization	Age	Expertise
EX1	Senior consultant and project manager (engineering company)	38	His expertise is based on ten years of practical experience as a project manager with team responsibility in a medium-sized company
EX2	Solution architect and IT innovation manager (large software and energy company)	34	He has been professionally involved in the areas of machine learning and digital assistants for six years. Furthermore, he is a lecturer in these areas at two universities in Europe
EX3	Managing director (medium-sized software company)	58	He has been the managing director of a medium-sized company since 2010 and has also worked as a project manager for five years
EX4	Project leader (software company for intelligent solutions)	34	His experience is based on two years of practical experience as a project manager with team responsibility and working in the field of AI in a medium-sized company
EX5	Team leader reliability design (multinational engineering and technology company)	47	He has been working as a team leader for more than five years. In doing so, he acts as both a lateral and disciplinary manager
EX6	Research associate (institute of communications engineering at a German university of technology)	39	He works as a research associate and conducts research in the areas of deep learning, convolutional neural networks, generative adversarial networks and image compression
EX7	Assistant professor (institute for computer science at a German university)	39	He has been working in the field of AI for several years and is primarily involved in research on adaptive autonomous machines
EX8	Project leader and software architect (large German software company)	35	He has team leadership experience, due to his position as project manager, and AI know-how. Furthermore, he deals with the embedding and integration of humans in the digital world and the development of socio-cyber-physical production systems
EX9	Research group leader (institute of computer science at a German university of applied sciences)	41	His expertise is based on leading and composing teams and in the field of AI in which he conducts research

(version 2020). The codes are formed inductively on the material, which ensures that the analysis is conducted as closely as possible to the text resulting in a realistic picture of the facts (Mayring 2014). For a better understanding and overview, the answers of the interview partner are compared as a paraphrase of the formed code. Paraphrasing the answers is necessary to reduce the amount of text to be analyzed to a necessary minimum. This makes it easier to conduct and understand the analysis. Overall, we coded 38 categories and assigned 813 text segments (paraphrased) to the code system. The categories are then used to make cross-expert statements about a particular aspect. This preserves the quantitative interpretative approach and makes the various expert opinions on a particular aspect comparable so that general statements can be made about the four roles of AI-based team members. This process resulted in several insights considering whether AI enriches work in teams, as well as the extent to which the identified team roles are valid or have to be extended.

4.2.2 Results and discussion

The initial findings from the interviews show that the majority of the experts still see current AI technology merely as a tool. EX5 emphasis this thoughts by stating that, “I always think to myself, that’s still way too far away. I know the AI, what is feasible and I know how you have to train AI so that it can do something”. In their initial thoughts, the experts mostly assign time-intensive assisting skills to the AI-based team member. This is mainly due to the bias exerted by the current capabilities of AI-based systems, their susceptibility to errors, and limited functions. However, after the interviewer pointed out to them that they should not constrain themselves to the current AI-based systems, but rather think more freely and detachedly from current technologies, the experts were guided to think more freely.

This perception is partly reflected in the responses regarding the first role, the coordinator. In order to be able to assume leadership over a human team, a certain degree of emotional and social intelligence is required, which is still viewed very skeptically by the interviewees (“Regarding the social abilities of an AI, the emotional component, I claim is not programmable, certain memorized phrases yes” stated by EX1). However, the experts stated that the coordinator will be able to coordinate and manage a team very well, but the leadership of humans can only be served to a limited extent, due to the relevance of emotional and social intelligence. Furthermore, the experts agree that the coordinator will have difficulties motivating other participants, as this, again, requires emotional and social intelligence. In addition, the coordinator’s ability to discuss is seen as a challenge, as some experts believe that the coordinator can only discuss well as long as it focuses on facts, not on emotional discussions. However, the arguments of the coordinator will themselves be very well thought out and sound. In this context, the experts emphasized that the coordinator’s discussion behavior will be expressed as neutral, fact-based, and unemotional (“I think an AI can discuss very well, in the sense of, it can prove well facts why this and that is so or why it is good or bad. I think an AI can discuss very well in this case.” stated by EX4). Overall, the experts emphasize the emotional and social intelligence that the coordinator must possess to fulfill its role. In order to be an accepted role and to be seen as a co-equal team member by the human participants, the coordinator must therefore be able to lead his team through social and emotional intelligence, to motivate them and to discuss factually but also on an emotional level.

Concerning the second role, the creator, the experts emphasize above all its ability to create something new, in order to be able to be a functioning team role. Experts state, that the creator has the possibility of accessing all the information and playing out a wide variety of scenarios in a short time (EX9 states “If we take this theoretical approach, an AI can be more creative due to the fact that it has no performance degradation.”), but also state that its creativity will be different from that of humans. Thus, the ability to uncover previously unknown patterns is a major strength of this role. Again, they mention, that the creation of novel thoughts might be more factual and fact-based than that of humans since the emotional component is missing. However, the experts mention this approach as very positive overall since the creator’s skills are thus a perfect basis for problem-solving and the creator can thus find rational solutions to given problems. The experts would consequently, to fulfill the expectations of the human team members towards this role, add the ability of problem-solving. Furthermore, they state that the creator can form new patterns and associations that may be overlooked by human team members.

The experts’ impression of the third role, the perfectionist, is largely positive. The perfectionist works with great care on operational, repetitive tasks in a comprehensive and thorough way (EX9 states in this context that “especially when it comes to logical and technical problems or when it comes to evaluating technical or logical thinking, an AI helps”). The perfectionist’s way of working is described in more detail by the experts and is seen as a co-equal team member who finds an optimal solution to previously described problems depending on objective parameters. The experts argue that the perfectionist works carefully and independently of the task type. This makes the perfectionist particularly useful for repetitive tasks, or tasks requiring great diligence, as it will neither be bored nor demotivated. The expectations of human team members are therefore very clear for this team role. The experts affirm that other team members consequently count on this role when it comes to specifying relevant details of an idea, not forgetting relevant aspects, or completing work down to the last detail.

The experts agree on the fourth role, the doer, who works according to the guiding principle of "getting things done” and can improve the efficiency of the team (EX8 states in this context that an AI-based teammate has “a lot of capacity, doesn’t really feel time pressure and works quite effective and efficient”). The only criticism voiced by the experts lies in the statement that the doer must be interested in finding practical solutions since an AI does not have a natural interest. However, the experts argue that the doer must have a basic understanding of what practical means in order to find a practical solution. This is not necessarily given, as, on the contrary, an AI usually tries to find rather the optimal solution, which does not necessarily have to be the most practical solution. Consequently, the doer must put fact-based work and finding an optimal solution behind finding solutions quickly and practically. EX2 states that an AI-based teammate “tries to find the fact-based solution and not necessarily what is practical for us”. Thus, the experts emphasize the doer’s ability to prioritize tasks above all. Furthermore, the doer must be given an understanding of the importance and a framework for evaluation. Overall, the experts emphasize the ability to prioritize, to distinguish unimportant from important, and to defer from optimal solutions to minimum viable solutions to represent a functioning team role and to fulfill the expectations of the other team members.

Across roles, the experts highlight emotional and social capabilities in particular as being important for all team roles. These aspects include the social and emotional intelligence of the AI-based team members and their behavior. Usually, the experts described any role as mostly rational, neutral and unemotional, which is not always what is needed. A broader emotional range and different social capabilities are needed. An AI-based team member does not have a natural social aptitude but can be taught, according to most experts. Consequently, teamwork with an AI-based team member can only work if this social and emotional intelligence is learned.

Furthermore, the experts highlight the ability of analytical thinking, especially for the perfectionist, and the ability of multitasking for every role. The knowledge contributed by an AI-based team member is also consistently emphasized by the experts, as the data basis of an AI enables the retrieval of diverse information. The experts primarily attribute these capabilities to the perfectionist.

The contribution that an AI-based team member offers to decision-making is also perceived as consistently positive. In this regard, an AI-based team member can act as an expert in a field and rationally simplify deciding. This is seen especially in the role of the doer. An AI-based team member can also be used in conflict resolution, as it can address conflicts uninfluenced, especially through rational evaluation. The AI-based team member will treat all conflict parties equally and could point out possible solutions. Here, however, the experts again mention the aspect of emotional and social intelligence, which is important for addressing the conflicting parties. The impact on time management when an AI-based team member takes the lead is also consistently rated positively by the experts. This AI-based team member is able to optimize the various time dependencies so that work can be carried out efficiently in terms of time. The experts see these capabilities in the role of the coordinator.

Furthermore, the experts address the ability to assess the capabilities of human team members and accordingly the assignment of tasks based on this assessment by an AI-based team member as a possible ability. An AI-based team member will be able to evaluate all individuals objectively and without bias based on their strengths and weaknesses. However, again, social and emotional intelligence is important when assigning tasks to human teammates. The experts assign this ability to the role of the coordinator.

Besides, the experts mention that the structuring of results by an AI-based team member will be better and faster. An important point here is the understanding of the structure since a good structure for an AI-based team member will not necessarily be a good structure for humans. These are the skills the experts see in the perfectionist.

Overall, experts agree that it is important for the roles to be internally consistent and not to take on other tasks that fall outside their role model. Expectations of AI-based team members very much influence the behavior of human team members and determine whether a team works or not. If an AI-based team member breaks out of their role and takes on tasks and behaviors and demonstrates ability not normally

Table 10 Revised AI-based team roles

Role	Description
Coordinator	Is good at convincing and motivating team members to take action
	Can take over the leadership of a team if necessary
	Is good at assigning tasks to other team members
	Is good at discussing and arguing with other team members
	Can capture emotions and social dynamics within the team
	Is good at solving conflicts
Creator	Is good at finding many and new possible solutions for situations
	Conducts research, to develop something new based on it
	Is always looking for new ideas and developments
	Is good at uncovering novel patterns and form new associations
	Is good at innovative problem-solving
	Is good at contributing expert knowledge to a complex task
Perfectionist	Is good at completing tasks in detail
	Goes into great detail when solving a task
	Is rather a perfectionist when it comes to solving tasks
	Is good at finding optimal solutions to previously described problems depending on objective parameters
	Is good at analytical thinking and structuring
	Is good at validating if no aspects are missing
Doer	Pushes for concrete actions so that no time is wasted and can separate the important from the unimportant
	Is good at finding practical solutions that work
	Is good at completing tasks properly
	Is good at prioritizing and making decisions
	Is good at distinguishing the unimportant from important

associated with the role, they can disrupt the team dynamic. Especially when AI-based team members are too powerful, human team members tend to sit back and rest on the AI-based team member's skills.

5 Discussion and implications

The goal of our research is to investigate what behaviors, including skills, abilities, and rights and responsibilities within a team, should be fulfilled by AI-based teammates to create functioning human-AI teams. In doing so, we identified relevant literature on team roles and analyzed existing role concepts. Based on these role concepts, a questionnaire was designed and placed in the context of AI-based team members. Using 1,358 participants, interrelated factors were examined that were identified as new team roles. These four roles were discussed and expanded with the help of nine experts. With the help of the experts, we were able to expand the four team roles, ultimately resulting in the following team roles presented in Table 10.

The experts fortified the four identified team roles but also expanded them to include specific skills to construct consistent team roles. In doing so, they drew on their experience in team composition, reinforcing, among other things, the point that other team members have certain expectations of a particular role. If a role exhibits certain behaviors or showcases its skills, other skills and tasks are expected of it. These tasks and behaviors must be internally consistent so that the dynamic in the team is not destroyed. Consequently, a bipolar role that exhibits inconsistent capabilities can disrupt expectations and disrupt collaboration. Also, AI-based team members should not take roles that are too powerful.

Our findings come with a variety of implications that contribute to both theory and practice. Our team roles contribute to the understanding of human-AI collaboration by naming specific skills and behaviors that should be adopted by AI in future human-AI teams. Besides, our results show that certain skills are preferred in AI-based team members, such as analytical thinking, coordination, and other assisting tasks. Our findings also contribute to basic theories of team composition or traditional team role concepts by showing that AI-based team roles have similarities to traditional role concepts (see Table 8). Our identified team roles have several similarities to existing team role concepts, which in turn contributes to the research about team roles in general. However, our identified AI-based team roles also include certain skills and behavioral aspects that are usually not ascribed to the nature of AI and thus even more relevant. Emotional and social intelligence in particular are relevant for some roles (e.g., coordinator and doer), but also creative thinking and acting, are emphasized in this context. The ability of the doer to find rather practical solutions instead of finding optimal solutions indicates a skill that is rather against the nature of AI. In other words, abilities that are untypical for AI-based systems. In addition, abilities rather associated with AI-based systems, such as analytical thinking, information processing, or content structuring are aspects that were reinforced by our two studies.

Our findings are also in line with the approaches of hybrid intelligence or human-AI symbiosis, as they emphasize the complementary strengths of AI and argue that AI, even if partially possible, should not have as many abilities as possible, but should take on a consistent role. Only in this way, human team members can and will bring their value to the collaboration and the shared potential between humans and AI can be fully realized.

Furthermore, our constructed team roles represent a contribution to practice when it comes to implementing AI-based team members with equal rights. Designers can decide which role is needed in a team and consequently map it as a consistent role and implement corresponding skills and behaviors.

6 Conclusion and outlook

Functioning teams are made up of different members who have distinct skills and exhibit diverse behaviors (van de Water et al. 2008). For a team to function, it is not necessary to cover all existing team roles or to combine as many different team roles as possible. Rather, it is important that all actors fulfill their roles, as their skills and behaviors are not only necessary for the functioning of the team, but also entail certain expectations from other team members (Belbin 2012). Other team members have certain expectations of this role and assumptions about what the role holder will or should do. These expectations and assumptions consequently also prevail in human-AI teams in which humans work on an equal footing with AI-based team members (van de Water et al. 2008).

Therefore, in order to design functioning human-AI teams, it is important to determine what behaviors, including skills, abilities, and rights and responsibilities within a team, should be performed by AI-based teammates to create functioning human-AI teams. Using a multi-method research approach, we were able to identify four different team roles, which we validated and expanded with a total of nine experts.

However, our study also has several limitations. Even though the multi-method approach combines both the strengths of quantitative and qualitative research, the narrow samples, in particular, depict a limitation. The participants of the quantitative study represent only a specific target group who do not necessarily have many years of experience in teamwork. Cultural and national habits also play a role, which hinder the generalization of the results without further ado. The selection of our experts is also limited not only by the small number but also by demographic data. All experts are male and belong to one nationality (German). In further studies, the diversity of the experts needs to be increased in order to create transferable findings.

Further research, especially experimental research is needed to examine the individual aspects of the team roles on collaboration, perception and, above all, their acceptance. However, this depends heavily on how the AI-based systems work and is hardly feasible at this stage. Researchers could draw on proven research methods, such as the Wizard-of-Oz experiment, which has proven particularly useful in simulating AI-based systems (Riek 2012). In this context, it is also important to capture the team roles of the human participants and to investigate what effect it has when a complementary AI-based team role joins the team or a team role that is similar to the human team member.

Through our two studies, we were able to lay a foundation for research in team roles in human-AI collaboration and define team roles to be adopted by AI-based systems. As teams will be increasingly composed as hybrid human-AI constellations in the future (Larson 2010; Seeber et al. 2019, 2020; Mirbabaie et al. 2021), our AI-based team roles represent a fundamental insight to design functioning future hybrid teams.

Appendix

See Tables 11, 12, 13.

Table 11 Analysis of role descriptions (examples)

Merged description	Source	Descriptions (excerpts)
(1) Primarily interested in finding practical solutions. Solutions that really work	Belbin (2012)	*"Turns ideas into practical actions" (p. 22)*
	Margerison (1986)	*"Their whole interest is in developing an innovation to the point where it can work" (p. 12–13)*
	Benne and Sheats (1948)	*"Thus, he may evaluate or question the "practicality", the "logic", the "facts" or the "procedure"" (p. 44)*
	Teammanagementsystems.com	*"Organizes and implements"; "Enjoys prototype or project work"*
	Belbin.com	*"Needed to plan a workable strategy and carry it out as efficiently as possible "*
(10) A perfectionist when it comes to solving tasks	Belbin (2012)	*"Perfectionism" (p. 56)*
	Margerison (1986)	*"…are people who enjoy doing detailed work" (p. 13)*
	Teammanagementsystems.com	*"Detail-oriented"*
	Belbin.com	*"Most effectively used at the end of tasks to polish and scrutinise the work for errors, subjecting it to the highest standards of quality control."*

Table 12 Survey introduction text

Brief description of the development and application of AI technology
Artificial intelligence is a term that has existed for a long time and is associated with different technologies, methods and processes or is also referred to as technological progress. Increased computing power, as well as access to and the presence of large amounts of data in combination with novel methods (machine learning) makes applications of artificial intelligence possible today. Present examples are interactive systems like Apple's Siri, Amazon's Alexa or other chatbots or voice assistants
Although such existing systems are still flawed and in many ways far from being on par with human intelligence, technological progress continues and such systems are getting better and better. This is getting to a point where artificial intelligence is reaching a point where it can no longer be distinguished from natural intelligence
It is important that when answering this questionnaire, that you do not base your thoughts on current applications of artificial intelligence with their flaws and characteristics, but rather think of an artificial intelligence as flawless, on par and without current boundaries. The following scenario should help you to better imagine these thoughts
Scenario
Imagine that you are working in a team together with human participants and participants that are systems based on artificial intelligence. Those AI-based teammates are equal to you in your team constellation. They are not assistants neither are they support systems, but co-equal partners in your teamwork. Your team consists of several participants who take on different roles. A team role is the name for a function or position that has been assigned to a person within a team or that has developed in the course of team dynamics. A team role includes the rights and responsibilities of its holder, and other members of the team have certain expectations of that role and assumptions about what the role holder will or should do. One example is someone who is referred to as the coordinator. A person that takes on tasks related to team and task coordination for example
Your human team members have taken on certain roles based on their teamwork experience, skills, and mindset, which are characterized by behaviors and taking on certain tasks. In this scenario you don't know yet what roles your human teammates will take. Everyone has their specific skills and behavior that they will provide to the teamwork
However, since artificial intelligence is developed and designed by humans, the question now is which set of behaviors, including abilities and skills should be fulfilled by AI-based teammates in order to create functioning human-AI teams?
Remember, your artificial team members are co-equal to the human team members
Feel your way into this scenario and answer the following questions

Segment 1 General (What is your daily work routine like? What tasks and activities do you perform?)

1. How do you assess the meaningfulness of the 4 roles found? (see table below[3])
2. If you were working in or putting together a group and one group member's job was taken over by an AI, what tasks would you have the AI take over?
3. How does their daily work and previous experience relate to working in groups?
4. How does their day-to-day work and previous experience relate to working with AI?
5. How do you feel about working with an AI as a team member?

[3] Table with AI-based team roles (compared to Table 8).

Table 13 58 questions about AI-based teammates derived from Belbin (2012), Margerison et al. (1986), Benne and Sheats (1948)

ID	Item	Source	Role
1	An AI-based teammate might primarily be interested in finding practical solutions. Solutions that really work	Belbin	Implementer
		Margerison	Assessor-Developer, Thruster Organisers
		Benne und Sheats	Evaluator-critic
2	An AI-based teammate might push for concrete actions to ensure that no time is wasted in meetings and to separate the important from the unimportant	Belbin	Co-ordinator
		Margerison	Thruster Organisers
		Benne und Sheats	Energizer, orienter
3	An AI-based teammate might be good at completing tasks thoroughly	Belbin	Shaper, Implementer
		Margerison	Thruster-Organisers
		Benne und Sheats	Procedural technician
4	An AI-based teammate might be able to discover and apply new alternatives	Belbin	Plant, Specialist
		Margerison	Creator-Innovator
		Benne und Sheats	Initiator-contributor
5	An AI-based teammate might challenge and encourage team members	Belbin	Shaper
		Margerison	-
		Benne und Sheats	Energizer
6	An AI-based teammate might show alternatives	Belbin	Plant, Specialist
		Margerison	Creator-Innovator, Explorer Promoter
		Benne und Sheats	Initiator-contributor
7	An AI-based teammate might provide arguments to invalidate unsuitable proposals	Belbin	Shaper, Monitor Evaluator
		Margerison	Upholder-Maintainer
		Benne und Sheats	Information Giver, evaluator-critic
8	An AI-based teammate might contribute expertise to complex tasks	Belbin	Specialist
		Margerison	Reporter-Adviser, Assessor-Developer
		Benne und Sheats	Information Giver, Elaborator

Table 13 (continued)

ID	Item	Source	Role
9	An AI-based teammate might create action plans which then lead to actions	Belbin	Co-ordinator
		Margerison	Thruster-Organiser
		Benne und Sheats	Coordinator, initiator-contributor
10	An AI-based teammate might rather be a perfectionist when it comes to solving tasks	Belbin	Completer-Finisher, Specialist
		Margerison	Controller-Inspector, Upholder-Maintainers
		Benne und Sheats	-
11	An AI-based teammate might show objective options for action in difficult situations	Belbin	Monitor-Evaluator, Specialist
		Margerison	Reporter-Advisers
		Benne und Sheats	Information-Giver, Elaborator
12	An AI-based teammate might particularly be good at completing tasks in detail	Belbin	Completer-Finisher, Specialist
		Margerison	Controller-Inspector, Reporter-Adviser
		Benne und Sheats	Elaborator
13	An AI-based teammate might capture and work on all important issues in a project	Belbin	Teamworker, Implementer
		Margerison	Thruster-Organiser
		Benne und Sheats	-
14	An AI-based teammate might assess the importance of subtasks in any situation and create a good schedule	Belbin	Coordinator
		Margerison	Thruster-Organiser
		Benne und Sheats	Coordinator, Orienter
15	An AI-based teammate might develop good ideas and bring them into the teamwork if it helps everyone	Belbin	Plant, Resource Investigator
		Margerison	Creator-Innovator, Explorer-Promoter
		Benne und Sheats	Initiator-Contributor, Opinion Giver
16	An AI-based teammate might hardly structure the research results	Belbin	Plant, Specialist
		Margerison	Creator-Innovator, Explorer-Promoter

Table 13 (continued)

ID	Item	Source	Role
		Benne und Sheats	Initiator-Contributor
17	An AI-based teammate might support the solution of a task with expert knowledge	Belbin	Specialist
		Margerison	Reporter-Adviser, Assessor-Developer
		Benne und Sheats	Information Giver
18	An AI-based teammate might contribute to the progress of a project under time pressure	Belbin	Shaper, Completer-Finisher
		Margerison	Thruster-Organiser
		Benne und Sheats	-
19	An AI-based teammate might protect the team from inaccuracies and from forgetting things	Belbin	Monitor-Evaluator
		Margerison	Upholder-Maintainer, Controller-Inspector
		Benne und Sheats	Recorder, evaluator-critic
20	An AI-based teammate might create good connections between people	Belbin	Resource-Investigator, Teamworker
		Margerison	Explorer-Promoter, Thruster-Organiser
		Benne und Sheats	Coordinator
21	An AI-based teammate might develop new and fundamental ideas	Belbin	Plant
		Margerison	Creator-Innovator
		Benne und Sheats	Initiator-Contributor
22	An AI-based teammate might be good at finding many possible solutions for new situations	Belbin	Plant, Resource-Investigator
		Margerison	Creator-Innovators, Assessor-Developer
		Benne und Sheats	Initiator-Contributor
23	An AI-based teammate might go into great detail when solving a task	Belbin	Completer-Finisher, Specialist
		Margerison	Controller-Inspector, Reporter-Adviser
		Benne und Sheats	Elaborator
24	It might be difficult for an AI-based teammate to keep the overall goal in mind. It might rather consider the task to be done	Belbin	Specialist, Plant

Table 13 (continued)

ID	Item	Source	Role
		Margerison	Explorer-Promoter, Creator-Innovator
		Benne und Sheats	-
25	An AI-based teammate might not work well if appointments are not well structured and not well managed	Belbin	Implementer, Teamworker
		Margerison	Upholder-Maintainer
		Benne und Sheats	-
26	An AI-based teammate might take over the leadership of a team if necessary	Belbin	Co-ordinator
		Margerison	Thruster-Organiser
		Benne und Sheats	Coordinator
27	The weakness of an AI-based teammate might be hold back by potential problems	Belbin	Implementer, Teamworker
		Margerison	Concluder-Producer
		Benne und Sheats	-
28	An AI-based teammate might always be looking for new ideas and developments	Belbin	Plant, Resource-Investigator
		Margerison	Creator-Innovator, Explorer-Promoter
		Benne und Sheats	Initiator-contributor
29	An AI-based teammate might research in order to develop something new on this basis	Belbin	Resource-Investigator
		Margerison	Reporter-Adviser, Assessor-Developer
		Benne und Sheats	Information-giver, Elaborator
30	An AI-based teammate might make an important contribution to the decision-making process, as it can assess it well	Belbin	Monitor-Evaluator, Co-ordinator
		Margerison	Reporter-Adviser, Controller-Inspector
		Benne und Sheats	Evaluator-Critic
31	An AI-based teammate might join the group and waits for a task to be assigned to it to be completed	Belbin	Implementer, Teamworker
		Margerison	Concluder-Producer

Table 13 (continued)

ID	Item	Source	Role
		Benne und Sheats	Procedural-Technician
32	It might be difficult for an AI-based teammate to start if the goals are not yet clearly defined	Belbin	Implementer, Teamworker
		Margerison	Concluder-Producer, Upholder-Maintainer
		Benne und Sheats	Orienter
33	An AI-based teammate might have a strong influence on decision-making processes	Belbin	Monitor-Evaluator, Co-ordinator
		Margerison	Reporter-Adviser, Controller-Inspector
		Benne und Sheats	Evaluator-Critic, Orienter
34	An AI-based teammate might work so carefully that there is a risk that the progress of the project will be disrupted	Belbin	Completer-Finisher, Specialist
		Margerison	Upholder-Maintainer, Controller-Inspector
		Benne und Sheats	Information-seeker, opinion-seeker
35	An AI-based teammate might support a team very well in finding solutions with its broad spectrum of knowledge	Belbin	Teamworker
		Margerison	Reporter-Adviser
		Benne und Sheats	Information giver, Elaborator
36	An AI-based teammate might also work in a new and unknown project team in a goal-oriented manner	Belbin	Teamworker, Resource Investigator
		Margerison	Explorer-Promoter
		Benne und Sheats	-
37	An AI-based teammate might be able to discuss against the opinion of others or defend the position of a minority	Belbin	Shaper, Monitor Evaluator
		Margerison	Upholder-Maintainer
		Benne und Sheats	Evaluator-Critic, Opinion-Giver
38	An AI-based teammate might work best when it focuses on only one task	Belbin	Implementer, Specialist
		Margerison	Concluder-Producer, Controller-Inspector

Table 13 (continued)

ID	Item	Source	Role
		Benne und Sheats	Procedural-technician
39	An AI-based teammate might guide team members without pushing them in one direction	Belbin	Co-ordinator, Teamworker
		Margerison	Explorer-Promoter
		Benne und Sheats	Coordinator, Orienter
40	An AI-based teammate might judge which person works well in a team	Belbin	Monitor-Evaluator, Co-Ordinator
		Margerison	Thruster-Organiser
		Benne und Sheats	Evaluator-Critic, Orienter
41	An AI-based teammate might be good at bringing in new ideas	Belbin	Plant, Resource Investigator
		Margerison	Creator-Innovator, Explorer-Promoter
		Benne und Sheats	Initiator-Contributor, Opinion Giver
42	An AI-based teammate might provide reasons for alternative approaches without losing sight of the actual goal	Belbin	Resource-Investigator
		Margerison	Explorer-Promoter, Reporter-Adviser
		Benne und Sheats	Initiator-contributor, Elaborator
43	An AI-based teammate might have the problem that it is often impatient with those who negatively influence progress	Belbin	Shaper
		Margerison	Thruster-Organiser
		Benne und Sheats	-
44	An AI-based teammate might establish useful contacts outside of the own team	Belbin	Resource-Investigator
		Margerison	Explorer-Promoter
		Benne und Sheats	-
45	An AI-based teammate might be good at convincing team members of an action to be taken	Belbin	Co-ordinator, Shaper
		Margerison	Explorer-Promoter, Upholder-Maintainer
		Benne und Sheats	Coordinator, initiator-contributor

Table 13 (continued)

ID	Item	Source	Role
46	An AI-based teammate might have the problem of delegating tasks even when others would be better suited to do so	Belbin	Completer-Finisher
		Margerison	-
		Benne und Sheats	-
47	An AI-based teammate might get along well in teams	Belbin	Teamworker, Resource-Investogator
		Margerison	Explorer-Promoter
		Benne und Sheats	-
48	The weakness of an AI-based teammate might be that it cannot develop its own opinion	Belbin	Implementer, Teamworker
		Margerison	Concluder-producer
		Benne und Sheats	Opinion-Seeker
49	An AI-based teammate might stimulate discussions in difficult situations to provoke new perspectives and start the solution process	Belbin	Shaper, Monitor-Evaluator
		Margerison	Thruster-Organiser, Explorer-Promoter
		Benne und Sheats	Evaluator-Critic, Energizer, Orienter
50	The weakness of an AI-based teammate might be that it is not able to assess the ideas of the team members correctly and would simply agree with them	Belbin	Implementer, Teamworker
		Margerison	Concluder-Producer
		Benne und Sheats	Opinion-Seeker
51	An AI-based teammate might find it difficult to take command quickly	Belbin	Plant, Implementer, Specialist
		Margerison	Concluder-Producer, Reporter-Adviser
		Benne und Sheats	-
52	An AI-based teammate might be particularly good at thinking "outside the box"	Belbin	Plant, Shaper
		Margerison	Creator-Innovator
		Benne und Sheats	Initiator-contributor
53	An AI-based teammate might only be analytical and has no intuition	Belbin	Monitor-Evaluator,Completer-Finisher

Table 13 (continued)

ID	Item	Source	Role
		Margerison	Controller-Inspector, Reporter-Adviser
		Benne und Sheats	Information-Giver, Evaluator-Critic
54	An AI-based teammate might be good at working in a team with people and might also work in the background if it leads to valuable results	Belbin	Monitor-Evaluator, Specialist
		Margerison	Upholder-Maintainer, Reporter-Adviser, Controller-Inspector
		Benne und Sheats	-
55	The weakness of an AI-based teammate might be that it runs the risk of giving too much input when it has a new idea	Belbin	Plant, Resource-Investigator
		Margerison	Creator-Innovator, Reporter-Adviser
		Benne und Sheats	Initiator-Contributor
56	An AI-based teammate might quickly assess what the next steps are	Belbin	Co-ordinatorm Monitor-Evaluator
		Margerison	Thruster-Organiser
		Benne und Sheats	Orienter, Coordinator
57	An AI-based teammate might get to know its colleagues better and thus strengthen the human–machine relationship	Belbin	Resource-Investigator, Teamworker
		Margerison	Explorer-Promoter, Upholder-Maintainer
		Benne und Sheats	-
58	An AI-based teammate might quickly assess the strengths of team members and assign appropriate tasks accordingly	Belbin	Co-ordinator
		Margerison	Thruster-Organiser
		Benne und Sheats	Coordinator

Interview guide

Segment 2 AI Social abilities and creator(How do you feel about an AI as a collaborator (human-wise)?)

6. What is your opinion about the creativity of an AI especially compared to humans?
7. What is your opinion about an AI team member's ability to form an own opinion?
8. What is your opinion about an AI team member's assessment and appropriate assignment of individuals?
9. How valuable do you consider ideas contributed by an AI team member?
10. What is your opinion about the discussion skills of an AI team member?
11. What is your opinion about the discussion behavior of an AI team member?
12. What is your opinion about the social skills of an AI team member?

Segment 3 AI leader and coordinator (How do you feel about an AI as a leader?)

13. What is your opinion about the motivational potential of an AI team member?
14. What is your opinion about the leadership potential of an AI team member?
15. What is your opinion about the conflict resolution potential of an AI team member?
16. What is your opinion about the impact on time management when leadership is provided by an AI team member?
17. What is your opinion about an AI team member's ability to create plans?
18. What is your opinion about an AI team member's ability to evaluate the importance of tasks and scheduling?
19. What is your opinion about an AI team member's ability to structure deliverables?

Segment 4 AI Implementer, doer and perfectionist (How do you feel about an AI as an implementer?)

20. How would you evaluate solutions to problems found by an AI?
21. What is your opinion about an AI team member's ability to think analytically?
22. What is your opinion about an AI team member's ability to work in a team?
23. What is your opinion about the multitasking ability of an AI team member?
24. What is your opinion about the diligence of an AI team member's completion of a task?
25. What is your opinion about the interest of an AI in finding practical solutions?
26. What is your opinion about an AI team member's ability to contribute expert knowledge to a complex task?
27. What is your opinion about the impact of time pressure on the way an AI team member works?
28. What is your opinion about the contribution of an AI team member to decision making?

Acknowledgements This project would not have been possible without the help of Ruobing, who helped me distribute the questionnaire and translated it into Chinese with her colleagues, and Stephen for his help in conducting the interviews.

Funding Open Access funding provided by LUT University (previously Lappeenranta University of Technology (LUT)).

References

Ahmad R, Siemon D, Robra-Bissantz S (2021) Communicating with machines: conversational agents with personality and the role of extraversion. in: Proceedings of the 54th Hawaii international conference on system sciences, p 4043

Aleksander I (2017) Partners of humans: a realistic assessment of the role of robots in the foreseeable future. J Inf Technol 32(1):1–9

Ames M, Runco MA (2005) Predicting entrepreneurship from ideation and divergent thinking. Creat Innov Manag 14(3):311–315

Anderson J, Rainie L, Luchsinger A (2018) Artificial intelligence and the future of humans. Pew Research Center

Araujo T (2018) Living up to the Chatbot Hype: the influence of anthropomorphic design cues and communicative agency framing on conversational agent and company perceptions. Comput Hum Behav 85:183–189

Aritzeta A, Senior B, Swailes S (2016) Team role preference and cognitive styles: a convergent validity study. Small Group Research. https://doi.org/10.1177/1046496404273742

Belbin RM (1993) A reply to the belbin team-role self-perception inventory by furnham, steele and pendleton. J Occup Organ Psychol 66(3):259–260

Belbin RM (2010) Management teams: why they succeed or fail. Routledge

Belbin RM (2012) Team roles at work. Routledge

Benne KD, Sheats P (1948) Functional roles of group members. J Soc Issues 4(2):41–49

Berente N, Gu B, Recker J, Santhanam R (2021) Managing artificial intelligence. MIS Q 45:1433–1450

Bittner EAC, Oeste-Reiß S, Leimeister JM (2019) Where is the bot in our team? Toward a taxonomy of design option combinations for conversational agents in collaborative workmaui, Hawaii, USA

Bouncken RB (2004) Cultural diversity in entrepreneurial teams: findings of new ventures in Germany. Creat Innov Manag 13(4):240–253

Briggs RO (2006) On theory-driven design and deployment of collaboration systems. Int J Hum Comput Stud 64(7):573–582

Brown SA, Dennis AR, Venkatesh V (2010) Predicting collaboration technology use: integrating technology adoption and collaboration research. J Manag Inf Syst 27(2):9–54

Bryman A (2016) Social research methods. Oxford University Press, New York

Bunderson JS, Sutcliffe KM (2002) Comparing alternative conceptualizations of functional diversity in management teams: process and performance effects. Acad Manag J 45(5):875–893

Chae SW, Seo YW, Lee KC (2015) Task difficulty and team diversity on team creativity: multi-agent simulation approach. Comput Hum Behav 42:83–92

Cohen SG, Bailey DE (1997) What makes teams work: group effectiveness research from the shop floor to the executive suite. J Manag 23(3):239–290

Daugherty PR, Wilson HJ (2018) Human+ machine: reimagining work in the age of AI, Harvard Business Press.

Dellermann D, Ebel P, Söllner M, Leimeister JM (2019) Hybrid intelligence. Bus Inf Syst Eng 61(5):1–7

Diederich S, Brendel A, Morana S, Kolbe L (2022) On the design of and interaction with conversational agents: an organizing and assessing review of human-computer interaction research. J Assoc Inf Syst

Elshan, E. and P. Ebel. (2020). Let's Team Up: Designing Conversational Agents as Teammates. In: ICIS 2020 Proceedings. retrieved: https://aisel.aisnet.org/icis2020/digital_learning_env/digital_learning_env/2 [Accessed:

Elson J, Derrick D, Ligon G (2020) Trusting a humanoid robot : exploring personality and trusting effects in a human-robot partnership. http://scholarspace.manoa.hawaii.edu/handle/10125/63806. Accessed: 16 March 2020

Epley N, Waytz A, Cacioppo JT (2007) On seeing human: a three-factor theory of anthropomorphism. Psychol Rev 114(4):864

Fisher SG, Macrosson W, Sharp G (1996) Further evidence concerning the belbin team role self-perception inventory. Personnel review

Fujimoto M (2016) Team roles and hierarchic system in group discussion. Group Decis Negot 25(3):585–608

Furnham A, Steele H, Pendleton D (1993) A psychometric assessment of the belbin team-role self-perception inventory. J Occup Organ Psychol 66(3):245–257

Fusch PI, Ness LR (2015) Are we there yet? Data saturation in qualitative research. Qual Rep 20(9):1408

Gerber A, Derckx P, Döppner DA, Schoder D (2020) Conceptualization of the human-machine symbiosis – a literature review. Accessed: 16 March 2020

Gnewuch U, Morana S, Maedche A (2017) Towards designing cooperative and social conversational agents for customer service. In: ICIS 2017 Proceedings. retrieved: https://aisel.aisnet.org/icis2017/HCI/Presentations/1. Accessed

Goodman T, Miller ME, Rusnock CF, Bindewald J (2016) Timing within human-agent interaction and its effects on team performance and human behaviour. In: 2016 IEEE international multi-disciplinary conference on cognitive methods in situation awareness and decision support (CogSIMA), pp.35–41

Hayashi Y, Ono K (2013) Embodied conversational agents as peer collaborators: effects of multiplicity and modality. In: 2013 IEEE RO-MAN, pp120–125

Helfferich C (2011) Die Qualität Qualitativer Daten. Springer

Higgs M, Plewnia K, Ploch J (2005) Influence of team composition and task complexity on team performance. Team Performance Manag Int J

Hildt E (2019) Artificial intelligence: does consciousness matter? Front Psychol 10:1535

Hofeditz L, Harbring M, Mirbabaie M, Stieglitz S (2022). Working with ELSA – how an emotional support agent builds trust in virtual teams retrieved: http://hdl.handle.net/10125/79380. Accessed: 30 May 2022

Hoffmann L, Krämer NC, Lam-chi A, Kopp S (2009) Media equation revisited: do users show polite reactions towards an embodied agent? In: Ruttkay Z, Kipp M, Nijholt A, Vilhjálmsson HH (eds) Intelligent virtual agents. Springer, Lecture Notes in Computer Science, Berlin, Heidelberg, pp 159–165

Homburg C, Giering A (1998). Konzeptualisierung Und Operationalisierung Komplexer Konstrukte: Ein Leitfaden Für Die Marketingforschung.

Horwitz SK, Horwitz IB (2007) The effects of team diversity on team outcomes: a meta-analytic review of team demography. J Manag 33(6):987–1015

Jackson SE (1991) Team composition in organizational settings: issues in managing an increasingly diverse work force. Group process and productivity. Sage, Thousands Oaks, Ca, pp 138–173

Jarrahi MH (2018) Artificial intelligence and the future of work: human-AI symbiosis in organizational decision making. Bus Horiz 61(4):577–586

Jessup S, Gibson A, Capiola A, Alarcon G, Borders M (2020) Investigating the effect of trust manipulations on affect over time in human-human versus human-robot interactions retrieved: http://scholarspace.manoa.hawaii.edu/handle/10125/63807. Accessed: 16 March 2020

Kaplan A, Haenlein M (2019) Siri, siri, in my hand: who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. Bus Horiz 62(1):15–25

Karau SJ, Williams KD (1993) Social loafing: a meta-analytic review and theoretical integration. J Pers Soc Psychol 65(4):681–706

Kates A, Galbraith JR (2010) Designing your organization: using the STAR model to solve 5 critical design challenges. Wiley

Katzenbach JR, Smith DK (2015) The wisdom of teams: creating the high-performance organization, Harvard Business Review Press.

Krämer NC, Eimler S, von der Pütten A, Payr S (2011) Theory of companions: what can theoretical models contribute to applications and understanding of human-robot interaction? Appl Artif Intell 25(6):474–502
Krämer NC, von der Pütten A, Eimler S (2012) Human-agent and human-robot interaction theory: similarities to and differences from human-human interaction. In: Zacarias M, de Oliveira JV (eds) Human-Computer Interaction: The Agency Perspective, Studies in Computational Intelligence. Springer, Berlin, pp 215–240
Larson DA (2010) Artificial intelligence: robots, avatars and the demise of the human mediator. Social Science Research Network, Rochester, NY
Maedche A, Morana S, Schacht S, Werth D, Krumeich J (2016) Advanced user assistance systems. Bus Inf Syst Eng 58(5):367–370
Maher ML, Fisher DH (2012) Using AI to evaluate creative designs. In: DS 73–1 Proceedings of the 2nd international conference on design creativity Volume 1,
Mair P (2018) Modern psychometrics with R. Springer
Margerison C, McCann D, Davies R (1986) The Margerison-McCann team management resource — theory and applications. Int J Manpow 7(2):2–32
Mayring P (2014) Qualitative content analysis: theoretical foundation, basic procedures and software solution.
McCarthy J, Minsky ML, Rochester N, Shannon CE (1955) A proposal for the Dartmouth summer research project on artificial intelligence. AI Mag 27(4):12
Mello AS, Ruckes ME (2006) Team Composition. J Bus 79(3):1019–1039
Mintzberg H (1989) Mintzberg on management: inside our strange world of organizations. Simon and Schuster
Mirbabaie M, Stieglitz S, Brünker F, Hofeditz L, Ross B, Frick NRJ (2021) Understanding collaboration with virtual assistants – the role of social identity and the extended self. Bus Inf Syst Eng 63(1):21–37
Morana S, Kroenung J, Maedche A, Schacht S (2019) Designing process guidance systems. J Assoc Inf Syst, 20(5). retrieved: https://aisel.aisnet.org/jais/vol20/iss5/6 [Accessed:
Morini-Bianzino HJW, Daugherty PR, Nicola (2017) The jobs that artificial intelligence will create. MIT Sloan Manag Rev. Retrieved: https://sloanreview.mit.edu/article/will-ai-create-as-many-jobs-as-it-eliminates/ [Accessed: 17 August 2020]
Myers IB (1962) The Myers-Briggs type indicator: Manual
Nass C, Fogg BJ, Moon Y (1996) Can computers be teammates? Int J Hum Comput Stud 45(6):669–678
Nass C, Moon Y (2000) Machines and mindlessness: social responses to computers. J Soc Issues 56(1):81–103
Osborne JW (2013) Best practices in data cleaning: a complete guide to everything you need to do before and after collecting your data, Sage.
Pittenger DJ (2005) Cautionary comments regarding the myers-briggs type indicator. Consult Psychol J Pract Res 57(3):210
Qiu L, Benbasat I (2009) Evaluating anthropomorphic product recommendation agents: a social relationship perspective to designing information systems. J Manag Inf Syst 25(4):145–182
Quenk NL (2009) Essentials of Myers-Briggs Type indicator assessment. John Wiley & Sons
Raithel J (2008) Quantitative Forschung. Springer
Randrup N, Druckenmiller D, Briggs RO (2018) Toward a philosophy of collaboration. Int J e-Collab (IJeC) 14(2):19–36
Reeves B, Nass CI (1996) The media equation: how people treat computers, television, and new media like real people and places. Cambridge University Press
Riek LD (2012) Wizard of Oz studies in Hri: a systematic review and new reporting guidelines. J Hum-Robot Interaction 1(1):119–136
Rummel RJ (1988) Applied factor analysis, Northwestern University Press.
Russell SJ, Norvig P (2020) Artificial intelligence: a modern approach. Pearson Education Limited, Malaysia
Saldaña-Ramos J, Sanz-Esteban A, García J, Amescua A (2014) Skills and abilities for working in a global software development team: a competence model. J Softw Evol Process 26(3):329–338
Schwartz J, Hagel J III, Wooll M, Monahan K (2019) Reframing the future of work. MIT Sloan Manag Rev 60(3):1–6

Seeber I, Bittner E, Briggs RO, de Vreede T, de Vreede G-J, Elkins A, Maier R, Merz AB, Oeste-Reiß S, Randrup N, Schwabe G, Söllner M (2019) Machines as teammates: a research agenda on AI in team collaboration. Inf Manag 103174.

Seeber I, Waizenegger L, Seidel S, Morana S, Benbasat I, Lowry PB (2020) Collaborating with technology-based autonomous agents. Internet Res.

Senior B (1997) Team roles and team performance: is there 'really' a link? J Occup Organ Psychol 70(3):241–258

Shaughnessy JJ, Zechmeister EB, Zechmeister JS (2000) Research methods in psychology. McGraw-Hill

Siemon D, Becker F, Eckardt L, Robra-Bissantz S (2019) One for all and all for one - towards a framework for collaboration support systems. Educ Inf Technol 1–25

Siemon D, Strohmann T, Robra-Bissantz S (2018) The virtual collaborator - a definition and research agenda. Int J e-Collab (IJeC) 14(4):24–43

Strohmann T, Fischer S, Siemon D, Brachten F, Lattemann C, Robra-Bissantz S, Stieglitz S (2018) Virtual moderation assistance: creating design guidelines for virtual assistants supporting creative workshops. In: Proceedings of the 22nd pacific asia conference on information systems, Yokohama

Terveen LG (1995) Overview of human-computer collaboration. Knowl-Based Syst 8(2):67–81

Turner JC (2010) Social categorization and the self-concept: a social cognitive theory of group behavior

Venkatesh V, Brown SA, Bala S (2013) Bridging the qualitative-quantitative divide: guidelines for conducting mixed methods research in information systems. MIS Quart 21–54

de Vreede G-J, Briggs RO (2019) A program of collaboration engineering research and practice: contributions, insights, and future directions. J Manag Inf Syst 36(1):74–119

van de Water H, Ahaus K, Rozier R (2008) Team roles, team balance and performance. J Manag Dev 27(5):499–512

Watson D (2019) The rhetoric and reality of anthropomorphism in artificial intelligence. Mind Mach 29(3):417–440