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When AI joins the Team: A Literature Review on Intragroup Processes and their Effect on Team Performance in Team-AI Collaboration

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WHEN AI JOINS THE TEAM: A LITERATURE REVIEW ON INTRAGROUP PROCESSES AND THEIR EFFECT ON TEAM PERFORMANCE IN TEAM–AI COLLABORATION

Research Paper

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Abstract

Although systems based on artificial intelligence can collaborate with humans on various complex tasks, little is known about how AI systems can successfully collaborate with human teams (team–AI collaboration). Team performance research states that team composition and intragroup processes are important predictors of team performance. However, it remains unclear how intragroup processes differ in team–AI collaboration from processes in human teams and how these differences affect team performance. To answer these questions, we synthesize evidence from 18 empirical articles. The results indicate that intragroup processes like communication and coordination are less effective in team–AI collaboration. Moreover, empirical findings are conflicting on whether team cognition and trust are higher in team–AI collaboration compared to human teams. Likewise, the results on team performance differences between team–AI collaboration and human teams are inconsistent. With this article, we offer a foundation for future research on team–AI collaboration.

Keywords: Team–AI Collaboration, Artificial Intelligence, Team Performance, Intragroup Processes

1 Introduction

Advances in machine learning enable systems based on artificial intelligence (AI) to collaborate with humans on complex tasks like situation assessment, planning, and decision making. AI offers the potential to improve performance by objectified, faster, and more accurate task execution (Shen et al., 2019), while humans provide complementary capabilities like context knowledge (Hemmer et al., 2021). Human–AI collaboration can reap the benefits of both, AI systems and humans. Research has already shown that humans collaborating with AI can outperform both, the individual human as well as the individual AI (Wu et al., 2022; Hemmer et al., 2021). Whether high performance is achieved depends on a multitude of factors like trust, acceptance, or attitudes towards AI (Jussupow et al., 2020; Shin, 2021). Similarly, the decision augmentation literature in IS currently tries to establish an understanding of the challenges that are associated with successful AI-aided decision making (Fügener et al., 2022). These include the effect of AI characteristics like opacity on incorporating AI advice into judgments and uncertainty (Lebovitz et al., 2022), cognitive processes, such as metacognitive strategies to monitor and control reasoning processes (Jussupow et al., 2021), as well as outcomes like achieving fairness through augmentation (Teodorescu et al., 2021).

However, current research in information systems (IS) focuses mainly on individuals collaborating with AI. The social nature and the high level of complexity of teamwork due to socio-emotional influences, coordination, and communication costs (Bales, 1950) limit the generalizability of findings from the individual level to the team level. Yet, research in IS has neglected how human teams can effectively collaborate with AI systems. IS research is only starting to acknowledge team–AI collaboration, as illustrated by the international research initiative of Seeber et al. (2020) who developed a research agenda for exploring AI systems as teammates. Currently, aspects of team–AI collaboration are mainly addressed through the concept of human–autonomy teaming in the human factors literature (Lyons et al., 2021; O'Neill et al., 2022; Flathmann et al., 2021; Baker et al., 2021). However, this concept does not selectively refer to a team of humans collaborating with AI systems, but to "one or more humans collaborating with one or more AI systems" (McNeese et al., 2018, p. 263). Therefore, research on human–autonomy teaming mainly focuses on one human collaborating with one AI system, as noted by a recent literature review (O'Neill et al., 2022). In fact, there is only a small body of literature investigating the effect of intragroup processes on team performance in team–AI collaboration. Therefore, very little is known about how AI systems affect intragroup processes and team performance.

Filling this gap is particularly crucial since organizations often use teams when dynamic and complex objectives need to be addressed. If AI joins such teams in the future, it is necessary to understand the mechanisms of team–AI collaboration and how they affect team performance. Team performance research in social psychology and management science has generated rich theories and findings on whether and under what conditions working in teams yields a group-specific surplus in performance (Schulz-Hardt and Mojzisch, 2012; Jehn and Mannix, 2001). Therefore, human–autonomy teaming is often approached by leveraging principles of human teaming (Flathmann et al., 2021; Baker et al., 2021; Lyons et al., 2021). Yet, the introduction of AI as a teammate might challenge the traditional assumptions of team performance theories as they behave differently than human team members and, thus, are likely to change intragroup processes. Therefore, it is questionable whether findings on human collaboration can be transferred to team–AI collaboration without any changes. Still, team performance literature offers several starting points to investigate team–AI collaboration. For instance, it was already shown that composition and intragroup processes are relevant predictors of team performance (Schulz-Hardt et al., 2006; Webber, 1974; Hussain et al., 2022). These considerations can be captured in the following research questions:

RQ1: *Are there differences in team performance between team–AI collaboration and human teams?*

RQ2: *How do intragroup processes differ in team–AI collaboration from intragroup processes in human teams?*

To answer our research questions, we conducted a systematic cross-sectional literature review that focuses on empirical literature on team–AI collaboration. The contributions of this article are threefold: First, we contribute to the literature on human–autonomy teaming and human–AI collaboration in IS by introducing a clear conceptualization of team–AI collaboration and summarizing the current state of research on intragroup processes. In doing so, we expand the scope of current research on human–AI collaboration in IS to a team level. Second, we contribute to the literature on team performance by comparing team performance in team–AI collaboration with team performance in human teams as well as identifying the underlying differences in intragroup processes. Third, we contribute to practice and the current discussion on how AI might shape the future of work by identifying factors that facilitate or inhibit team performance when working with AI.

2 Conceptual Background

2.1 Artificial intelligence as an autonomous team member

AI is a vast field with many practical applications and active research topics. Taking the complex and dynamic nature of AI into account, it can be conceptualized as the frontier of computational advancements that mimics human intelligence in addressing ever more complex decision making problems (Berente et al., 2021). Machine learning algorithms can be trained on unstructured training data like images, text, or audio and have revolutionized the extent to which systems can learn. Currently, these algorithms are trained on task-specific data to fulfill a target task, such as speech recognition or image classification (Seeber et al., 2020). They are proficient in their specific task but lack generalized awareness regarding the world beyond their design, which is why AI is currently often referred to as weak or narrow (Collins et al., 2021; Schneider et al., 2021). However, they offset their scope-related limitations by outperforming humans in many of their assigned tasks. Popular examples are diagnosing cancer based on CT images (Shen et al., 2019) and playing complex games, such as Go (Silver et al., 2018). Generative and context-aware AI systems, like OpenAI's ChatGPT, have gained widespread popularity in recent times due to their ability to generate human-like text responses to natural language prompts by leveraging large language models.

The ability of AI systems to learn and act autonomously triggers a growing body of literature discussing the shift from AI systems as tools to AI systems as team members (e.g., Lyons et al., 2021). AI systems as autonomous team members fundamentally challenge the perspective on human–AI collaboration. AI systems' advanced capabilities can be captured in the differentiation between automation and autonomy. In this context, automation can be defined as "technology that requires human intervention or control" and autonomy can be defined as "technology capable of working alongside humans as teammate, carrying out the essential taskwork and teamwork functions of a human teammate" (McNeese et al., 2018, p. 263). Especially with AI research and development continuously advancing, AI systems become more and more agentic and independent of user interference (Russell, 2019). Baird and Maruping (2021) consider systems designed to make autonomous decisions as agentic. On the contrary, traditional IS literature conceptualizes systems as tools used by humans (Baird and Maruping, 2021). However, the capabilities of AI systems challenge traditional assumptions about user system interactions, such as a unilateral relationship, ignorance of the environment, functional transparency of the underlying reasoning, and users' awareness of interacting with an artifact (Schuetz and Venkatesh, 2020). Thus, in this paper, we view AI systems from a socio-technical perspective, focusing on the ability to participate in collaborative work with several humans. That means that success depends on technical and social factors and their dynamic interplay (Sarker et al., 2019).

2.2 Team–AI collaboration

Traditionally, a team is defined as two or more people who interact dynamically, interdependently, and adaptively toward a common and valued goal/objective/mission, who have each been assigned specific roles or functions to perform, and who have a limited life-span membership (Salas et al., 1992). Teamwork often includes several subgoals that lead to the team's main goal. Due to the narrow focus of AI systems, they can address an individual subgoal within the hierarchical goal decomposition of a team's activity (Schneider et al., 2021; Miller et al., 2020). Moreover, teams are characterized by complementary skills of each teammate that contribute to achieving a certain goal (Furnham et al., 1993; van de Water et al., 2008). As Siemon (2022, p. 877) states: "These differences are diverse and are not only reflected in individual abilities, knowledge, experience, and special skills, but also in social and cognitive characteristics". Likewise, humans provide complementary capabilities like social skills, emotional skills, broader context knowledge as well as interdisciplinary knowledge (Hemmer et al., 2021). However, research indicates that AI-based team members not only need to demonstrate task-specific skills but also social skills (Bittner et al., 2019; van Diggelen et al., 2019). For instance, AI systems must demonstrate altruism, benevolence, interdependence, emotion, communication, and synchronicity to be perceived as team members (Wynne and Lyons, 2018; Lyons and Wynne, 2021).

There is a variety of different terms referring to humans collaborating with an AI system, like human–AI interaction (HAI), human–AI collaboration, and human–autonomy teaming (HAT). Since there is no clear conceptual distinction, they are often used interchangeably. Meanwhile, there is a vast amount of literature on HAI, but in recent years HAT is becoming more and more prevalent. Lyons et al. (2021) suggest that the terminological shift from HAI to HAT might be due to the significant advances in machine learning. O'Neill et al. (2022, p. 907) conceptualize a HAT as "a team including an AI agent which is seen as performing a unique role in the team". Further, Larson and DeChurch (2020) argue that the AI agent must offer a unique contribution to the team's performance. McNeese et al. (2018, p. 263) define HAT as "a team between one or more humans and one or more AI agents, who take on independent and unique roles and pursue a common goal or complete a task”. Similarly, collaboration refers to the “joint effort towards a goal that includes aspects such as team formation, productivity, continuity, allocation of responsibilities and success” (Siemon, 2022, p. 876).

In essence, all these conceptualizations focus on the capabilities of AI to function as a team member. However, much of the extant research implicitly assumes one human who collaborates with one AI system (Lyons et al., 2021; O'Neill et al., 2022), while aspects of teams collaborating with AI remain neglected. The differentiation is not trivial, as the social nature of a team adds a new level of complexity. For instance, team performance literature has shown that successful teamwork depends on a variety of motivational, cognitive, and social factors that sets teams apart from individuals (for an overview Schulz-Hardt and Brodbeck, 2014). As outlined in the next section, intragroup processes are often responsible for facilitating or hindering team performance (e.g., Schulz-Hardt and Mojzisch, 2012). Yet, to our knowledge, there is no precise conceptualization of a team of humans working with an AI system as well as other constellations of human–AI teams. This entails a risk of construct confusion and thus can lead to a lack of specificity in the object of studies. This lack of conceptual clarity can have a negative impact on building a cohesive body of scientific literature on team–AI collaboration. Moreover, the characteristics and dynamics of intragroup processes cannot be addressed precisely.

Therefore, we introduce the concept of *team–AI collaboration* to describe *a set of two or more humans who interact with an AI system dynamically, interdependently, and adaptively toward a common and valued goal/object/mission, and who have each been assigned specific roles or functions* (based on a team definition proposed by Salas et al. (1992)). This definition emphasizes the goal-oriented and collaborative nature of teams while accounting for the composition of several humans interacting with one AI system. Consequently, our definition is more specific than the one of HAT, which refers to one or more humans collaborating with one or more AI systems. Thus, HAT, as defined by McNeese et al. (2018) becomes an umbrella term for different compositions of AI systems and humans in a collaborative setting. Analog to the conceptualization of team–AI collaboration, we suggest the following taxonomy, which is illustrated in Figure 1: *human–AI collaboration* refers to one human collaborating with one AI system. *Human–multi–AI collaboration* refers to a set of two or more AI systems that interact with one human. The term *team–multi–AI collaboration* refers to a set of two or more humans interacting with a set of two or more AI systems.

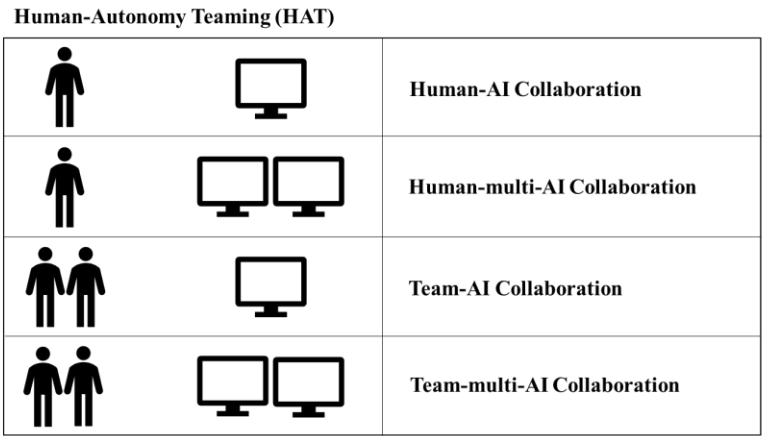

Figure 1. Taxonomy of human–autonomy teaming with the specification of four different HATs.

2.3 Intragroup processes as antecedents of a successful team–AI collaboration

Team performance can be conceptualized as the extent to which a team accomplishes its goals (Jong et al., 2016). These goals can range from efficiency (time, cost, and resources), and effectiveness (capability to achieve a desired outcome, accuracy) to psychological variables like team satisfaction (Campion et al., 1996). Accordingly, team performance measures can differ depending on the requirements of a certain task. The overall rationale for combining humans and AI systems is that they may facilitate better performance relative to humans alone or AI systems alone, particularly in situations of high uncertainty (Cummings, 2014; Lyons et al., 2021). Research has shown that this can lead to better performance (Dellermann et al., 2019; Wu et al., 2022).

Team performance research has a long history of studying whether and under which conditions working in teams yields a team-specific surplus in performance compared to individuals (e.g., Schulz-Hardt and Mojzisch, 2012). Focal antecedents to team performance are intragroup processes, which refer to behaviors and experiences of team members within a team, such as conflicts or cooperation (e.g., Diehl and Stroebe, 1987; Mathieu et al., 2008). They can be categorized into taskwork and teamwork. Taskwork describes functions that individual team members must perform to accomplish the team's goal, while teamwork describes the interaction between team members (McIntyre and Salas, 1995). These intragroup processes can either facilitate (process gain) or hinder (process loss) team performance by enabling or constraining member interactions, contributing to teamwork effectiveness (Mathieu et al., 2008; Paulus and Yang, 2000; Diehl and Stroebe, 1987; Latané et al., 1979).

The most known model on team performance is the input, mediators, and outcome model (IMO-model), which was reviewed by Ilgen et al. (2005) and updated by Mathieu et al. (2008). The IMO-model includes three main factors. First, input factors like resources, team composition, task, characteristics of the team members, etc. Accordingly, the characteristics of AI systems could also be considered as input factors. Second, these input factors influence intragroup processes, which mediate the relationship between inputs and outputs. Accordingly, input factors describe the characteristics of the individuals, the team, and the context. The mediators summarize intragroup processes like coordination, communication, and interaction that transform team inputs into outcomes. Mediators also include emerging states like cognitive, emotional, and motivational aspects. Third, outcomes like team performance are the product of input factors and intragroup processes and can be evaluated from different perspectives (Mathieu et al., 2008). Therefore, the IMO-model describes different antecedents, intragroup processes, and outcomes. We selected this model because it allows the explorative comparison of intragroup processes and outcomes of different compositions (e.g., human vs. team–AI collaboration), which is at the core of our research question.

Previous literature reviews on human–autonomy teaming did not selectively refer to team–AI collaboration and mainly included articles focusing on one human with one AI system. Moreover, they did not focus on analyzing the effect of team composition (team–AI collaboration vs. human teams) on intragroup processes and team performance. Therefore, it remains unclear how performance and intragroup processes differ between team–AI collaboration and human teams (Lyons et al., 2021; O'Neill et al., 2022). While research on intragroup processes is rooted in research on human teams, intragroup processes might also be relevant for explaining differences in performance in human–AI collaboration. However, existing articles are predominantly limited to individuals collaborating with AI systems (Lyons et al., 2021; O'Neill et al., 2022). Accordingly, it remains an open question how AI systems as autonomous team member affect intragroup processes in team–AI collaboration and how these intragroup processes differ from intragroup processes in human teams. Moreover, it is unclear how these differences in intragroup processes affect team performance in human teams compared to team–AI collaboration.

3 Method

We conducted a systematic and cross-sectional literature review to not only include papers from information systems, but also related fields like computer science, cognitive science, psychology, and human factors. Our search approach followed the guidelines by Webster and Watson (2002) focusing on peer-reviewed journals and conference proceedings. The search was conducted in September 2022 and was restricted to articles written in English and published between 2012 and 2022 to ensure that the contemporary definition of AI is met. We first conducted a keyword search on Google Scholar and EBSCO with the following keywords in the title or abstract: *(group OR team) AND (AI OR "artificial intelligence" OR autonomy OR "deep learning" OR "machine learning") AND (collaboration OR* *teaming OR "team-AI interaction"*). The database search on Google Scholar with this search string based on the title yielded 16 articles, and the EBSCO search based on the abstract or title returned 890 articles. We selected all databases in the EBSCO search and were connected to the VPN of the University of Mannheim.

Since the goal is to identify literature on intragroup processes in team–AI collaboration, we only included studies that provide empirical results (in contrast to conceptual frameworks), include at least two humans and one AI system in a collaborative setting, and focus on intragroup processes (e.g., interaction, communication, emotion, motivation). Furthermore, we excluded studies that involve robots since the embodiment and physical presence has confounding effects (Reig et al., 2019). The titles and abstracts of the 16 articles from Google Scholar were screened. Based on the inclusion criteria, 12 articles were excluded (two on robots, two nonempirical articles, two focusing on individuals, three duplicates of a not peer-reviewed master's thesis, and three not focusing on intragroup processes), resulting in a list of only four articles. To identify further articles, we continued our search in EBSCO based on the abstract or title resulting in 890 articles. Duplicates were removed, and the titles and abstracts of the 890 articles from the EBSCO search were also screened based on the inclusion criteria resulting in a list of 56 articles. These 56 articles were assessed in more detail by a full-text screening. Another 38 articles were excluded based on the full-text screening. The excluded literature is divided into 9 articles that focus on robots, 8 exclusively theoretical articles, 14 focusing on individuals, and 7 that focus on software development, resulting in a final sample of 18 articles that were also consistent with the Google Scholar search and a forward and backward search based on the article of McNeese et al. (2021a). Only two articles returned from IS outlets. Most articles were published in human factors (50%) or cognitive science (22.2%) related outlets. Figure 2 provides an overview of the literature selection process, the number of included and excluded articles as well as inclusion criteria from the EBSCO search. Each article of the final list went through a classification process, where applied methods (design, operationalization of AI, experimental task) and research focus (independent variable, dependent variable, and main results) were dummy coded resulting in a detailed concept matrix following these categories: article, outlet, independent variables, dependent variables, best performing HAT and operationalization of performance. The coding scheme was created inductively and iteratively.

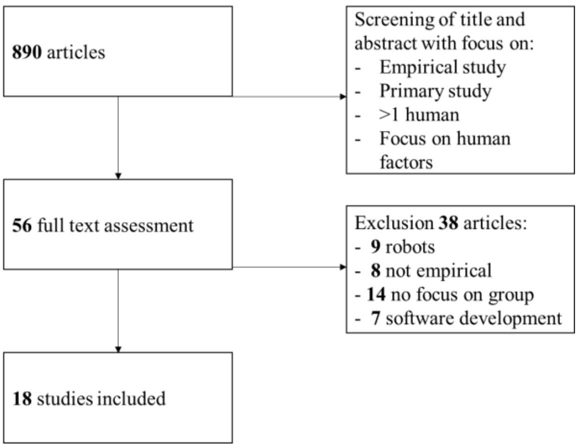

Figure 2. *Literature selection and number of included and excluded articles based on inclusion criteria from the EBSCO search.*

Most studies of the final sample follow an experimental design (88.8%). The AI system was mostly conceptualized as Wizard of Oz (WOZ) (38.9%). WOZ refers to a setting where participants interact with a system that is described as autonomous, but which is, in fact, operated by a human. Another operationalization of the AI system was the ACT-R cognitive modeling architecture (33.3%), which consists of modules for language analysis, language generation, dialog modeling, situation modeling, and agent-environment interaction. The most common experimental manipulations were team composition (61.1%), different training of the participants before the experimental task (11.1%), and the effect of disruptive events like technical failures (11.1%). On average, 1.5 intragroup processes were investigated per article. Team performance was measured in 77.8% of the articles as the dependent variable. Other prevalent dependent variables were team communication/coordination (55.6%), team cognition (50.1%), and trust (22.2%). Team cognition is used as an umbrella term for processes like team situation awareness and mental models. Most included articles (88.8%) utilize experimental settings in simulation scenarios, wherein team members and the AI system are assigned specific roles with the goal of completing a mission. The scenario that was predominantly utilized (61.1%) involved a simulated remotely piloted aircraft (RPAS) as an experimental task. The RPAS task involved three interdependent roles: the navigator plans the mission route, the pilot controls the RPAS, and the photographer takes photos of color-coded strategic target waypoints. Communication is crucial among team members, with the navigator sending waypoint information to the pilot, who negotiates the altitude with the photographer. The photographer adjusts camera settings and sends feedback to the team. Two studies used the NeoCITIES task, where three players with different roles (Hazmat, police officers, and firefighters) work together to complete emergency tasks. They have specific resources to handle events that happen over time in a fictional college town. The remaining studies used comparable mission scenarios. One study simulated a group decision, and one used a correlative study design (see the appendix for an overview of the included literature).

4 Results

In the subsequent section, we describe the key findings of our literature review, starting with the results regarding the best-performing constellation of human–AI teams, followed by the underlying intragroup processes, and finally, a conceptual model based on the IMO-model that integrates these findings.

4.1 Best performing team

More than half of the included articles use team composition as the main manipulation. Team performance is often measured with a composite of mission variables, including the rate at which targets are successfully photographed, the time individuals spend in alarm and warning states, the rate at which critical waypoints are acquired, and the number of missed targets or recovery from failures. Four articles compare human teams (three humans) to teams collaborating with AI (two humans and one AI system) and expert teams (two humans and one expert human). These studies report that expert teams performed better than regular human teams, which performed similarly to teams collaborating with AI (Demir et al., 2019; McNeese et al., 2018; Demir et al., 2017; Myers et al., 2019).

However, the results regarding the comparison between teams collaborating with AI and human teams are conflicting. On the one hand, several studies reveal that teams collaborating with AI perform similarly to human teams (Demir et al., 2018; Myers et al., 2019). On the other hand, a number of studies report performance differences between teams collaborating with AI and human teams (Fügener et al., 2021; Demir et al., 2018; McNeese et al., 2021c; Flathmann et al., 2021; Schelble et al., 2022). Specifically, including an AI team member can result in weaker performance (Fügener et al., 2021; Demir et al., 2018) as teams collaborating with AI process targets less efficiently than human teams (McNeese et al., 2018). In contrast, other studies suggest that including an AI team member can result in higher performance (McNeese et al., 2021c; Schelble et al., 2022). For instance, human teams perform as well as teams collaborating with AI objectively (measured with a composition score of mission variables), but the subjective (perceived) performance in team–AI collaboration is higher than in human teams, while human–multi–AI teams performed objectively better than human teams (Schelble et al., 2022). Generally, the most desired AI characteristic are instrumental skills to achieve high performance (Zhang et al., 2021).

In sum, there are differences in team performance between different compositions of teams. The findings on the comparison between team–AI collaboration and human teams remain inconclusive.

4.2 Underlying intragroup processes

The IMO-model of team performance suggests that intragroup processes mediate the relationship between input (composition) and output (performance). Therefore, we analyzed the literature with a focus on intragroup processes that might explain the conflicting results on team performance. Especially we focus on how these intragroup processes differ between team–AI collaboration and human teams. Our analysis revealed that the literature on team–AI collaboration mainly considered the intragroup processes of communication, coordination, trust, and team cognition. These are positively related to team performance but differ notably between team–AI collaboration and human teams. Subsequently, these factors, their interaction, and the effect of training will be described.

4.2.1 Communication, coordination, and trust

Communication and coordination are positively related to team performance (e.g., Demir et al., 2021; Demir et al., 2016), but human teams differ in their communicative and coordinative behavior from teams collaborating with AI. Communication is defined as the transmission of information within as well as across teams (Baker et al., 2021). Team coordination is generally defined as “orchestrating the sequence and timing of interdependent actions” (Marks et al., 2001, p. 363).

Generally, teams collaborating with AI exchange less information, engage less in nonverbal coordination, and engage in lower levels of task planning (Musick et al., 2021; Demir et al., 2018, 2017). For instance, Demir et al. (2019) find that the relationship between composition and team performance is mediated by coordination behavior that was lower in teams collaborating with AI than in expert teams, which in turn leads to lower levels of team performance. In comparison, human teams show unstable coordination patterns, which are also not beneficial for team performance (Demir et al., 2019). Additionally, the diminishing performance of the teams collaborating with AI is associated with behavioral passiveness due to a lack of planning, while human teams are more active in task planning (Demir et al., 2018). The authors conclude that the AI system did not show enough adaptive behavior, which was evident in the human teams. Surprisingly, even if human team members followed the optimal communication behavior when communicating with an AI team member, they were still not able to improve their performance. The authors explained this contra-intuitive result by the lack of human-like behavior of the AI system (Demir et al., 2016). However, this seems to be essential since people expected the AI system to act like a human team member, such as providing support or exchanging information proactively (Zhang et al., 2021). In sum, these findings indicate lower levels of communication and coordination in teams collaborating with AI compared to human teams.

However, some articles suggest a more complex relationship indicating that coordination and communication behavior in team–AI collaboration is affected by prior experience, attitudes (Zhang et al., 2021), AI systems capabilities, and time spent collaborating with AI. For instance, McNeese et al. (2021b) find that human teams did not continue to enhance their coordination over time, while teams collaborating with AI were able to improve steadily. In addition, the human teams had more team conflicts, which negatively impacted team performance. Van Wissen et al. (2012) find that successful interactions with other team members (humans and AI alike) seem to be more important than offered incentives when choosing a team. Moreover, success from previous interactions with other team members (AI and human alike) was identified as the most significant factor affecting the decision whether to defect from an existing team. No significant difference is reported with respect to the rate of defection from AI-led teams compared to the defection from human-led teams (van Wissen et al., 2012).

4.2.2 Team cognition

Different aspects of team cognitions constitute further prominently studied aspects of intragroup processes. Zhang et al. (2021) find that team cognition is one of the most important aspects of teamwork. Team cognition is cognitive activity at the team level, often leading to a team mental model (Cooke et al., 2013; Fiore et al., 2010; Cannon-Bowers et al., 1990). Hence, mental models can be seen as an emergent property of team cognition as the team members develop a shared understanding and mental representations of knowledge about the team's environment and tasks (Cannon-Bowers et al., 1990; Demir et al., 2016; McNeese and Cooke, 2016). Team situation awareness can be defined as, "the degree to which every team member possesses the situation awareness required for his or her responsibilities" (Endsley and Robertson, 2000, p. 303).

The findings regarding team cognition are inconsistent as well. Some articles suggest similar levels of team situation awareness (Demir et al., 2019; McNeese et al., 2018; Demir et al., 2017) and mental models (Schelble et al., 2022) in team–AI collaboration compared to human teams. However, the majority of articles indicate differences in team cognition between team–AI collaboration and human teams (McNeese et al., 2021c; Schelble et al., 2022; Musick et al., 2021). For instance, McNeese et al. (2021c) find that perceived team cognition was highest in human-only teams, with teams collaborating with AI and human–multi–AI teams reporting perceived team cognition 58% below the human teams. Nevertheless, this article finds that team performance and team situation awareness were lowest in human teams, yet teams collaborating with AI are similar in the iterative development of team cognition (McNeese et al., 2021c). Correspondingly, Musick et al. (2021) find that multi–AI HATs rarely demonstrate team cognition. On the other hand, Schelble et al. (2022) find that team cognition was higher in teams collaborating with AI. One way to improve mental models in team–AI collaboration are task-related explanations by the AI system (Schadd et al., 2022).

4.2.3 Interaction of intragroup processes and the effect of training

Moreover, some articles investigate the dynamic interplay of these intragroup processes. Since teams collaborating with AI were different in their action-related communication and explicitly shared goals, the development of team cognition was affected (McNeese et al., 2021c). Moreover, Demir et al. (2019) find that the relationship between composition and team performance was mediated by the coordination behavior, which was lower in teams collaborating with AI than in expert teams, leading to lower levels of team situation awareness. Further, the higher levels of team conflict in human teams also affected team situation awareness (McNeese et al., 2021b). Adding to the complexity, two studies have revealed that training can improve communication and coordination (Johnson et al., 2021; Johnson et al., 2020; Demir et al., 2019b). For instance, Johnson et al. (2020) find that teams who received coordination training communicated more information, though this effect appeared to diminish over time. However, in all training conditions, teams requested information equally, with a reduction over time. It was observed that teams who received coordination training were more likely to overcome failures attributed to the AI systems. Moreover, communication and coordination are connected to the development of trust. Trust is associated with higher team performance (Demir et al., 2021; McNeese et al., 2021a). For example, Johnson et al. (2021) find that specific trainings improved team performance, the overall communication behavior as well as trust in the AI system. Schelble et al. (2022), find that trust was higher in teams collaborating with AI compared to human teams, but decreased with the addition of more AI teammates. Moreover, McNeese et al. (2021a) find that trust in teammates (human and AI alike) positively affects team performance.

4.3 Integrative model

Overall, our findings suggest that including an AI system as a team member can affect intragroup processes. Therefore, we reconceptualized the IMO-model of team performance based on the current state of research on intragroup processes in team–AI collaboration. This reconceptualization summarizes our approach and findings. Since we focus on the effect of composition, namely how teams collaborating with AI differ in their intragroup processes and team performance from human teams, we conceptualized composition as an input factor. The composition of the team affects intragroup processes, which mediate the relationship between input (composition) and outcome (team performance). The prominent intragroup processes, that have been considered by team–AI collaboration literature are trust, team cognition, communication, and coordination. Therefore, we conceptualize these intragroup processes as mediators. These mediators positively affect team performance. We also specify their relationship: communication and coordination are closely related, and communication has a positive effect on the development of team cognition and trust in team–AI collaboration. Moreover, coordination has a positive effect on trust. Furthermore, the literature suggests a positive relationship between these intragroup processes and team performance. Figure 3 illustrates the reconceptualized IMO-model based on the results of this literature review on team–AI collaboration (team–multi–AI is not included because it was not investigated in the reviewed literature). The model visualizes the effect of the different HAT compositions on intragroup processes, their so far investigated relationships, and their effect on team performance.

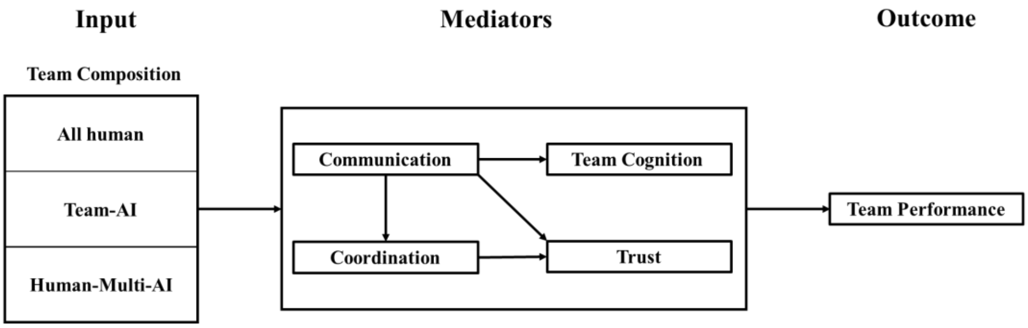

Figure 3. Reconceptualized IMO-model based on our results on differences in intragroup processes and team performance in team–AI collaboration compared to human collaboration.

5 Discussion

Our results indicate that teams collaborating with AI differ in performance and intragroup processes (communication, coordination, trust and team cognition) from human teams, but the findings remain inconclusive. Moreover, the relationship between intragroup processes and performance in team–AI collaboration is complex. Adding to that complexity, we also see that these intragroup processes are interrelated e.g., communication affects the development of team cognition and trust. In the following, we discuss the main findings, outline the contributions of this literature review, followed by implications for future research, and a conclusion.

5.1 Discussion of the findings on communication and coordination

One of our main findings is that communication and coordination behavior is less apparent in team–AI collaboration compared to human teams. This can be explained by a lack of human-like behavior and the low communicative and coordinative capabilities of the AI system. At the same time, the expectation of humans to collaborate with AI might have reduced their own communication and coordination behavior in the sense of a self-fulfilling prophecy. That denotes that the expectation of collaborating with an AI system with low communicative and coordinative capabilities impairs participants' own communication and coordination. However, the included literature did not clearly differentiate between communication with the AI system and communication between the human team members, which would have offered more insight into this possible explanation. Moreover, it was not clearly differentiated between coordination and communication, which were mainly used synonymously. This can be regarded as problematic since coordination always requires a form of communication, but the opposite is not necessarily true. Therefore, our literature review does not offer selective results on communication and coordination. Generally, the experimental setting offered limited room for communication and coordination since there was no face-to-face interaction. Future research should clearly distinguish between communication and coordination. In a similar vein, future research will have to identify how AI participation affects different forms of communication (e.g., verbal, nonverbal, paraverbal) and communication contents (e.g., information exchange, formal and informal communication) in more detail. Equally, different forms of coordination behavior in team–AI collaboration need to be investigated in more detail. Finally, there are several aspects that indicate a more complex relationship between communication, coordination, and team performance in team–AI collaboration. Communication and coordination in team–AI collaboration can be improved by training and prior collaboration experience. Both are affected by attitudes, AI systems capabilities, and time spent collaborating with AI. Future research will have to further improve our understanding of these factors and their relationship with communication and coordination in team–AI collaboration.

5.2 Discussion of the findings on team cognition and trust

The results regarding team cognition and trust remain more inconsistent than the results regarding communication and coordination. One article finds that trust was higher in teams–collaborating with AI (Schelble et al., 2022), while another article shows that trust in team members is (human and AI alike) positively related to team performance (McNeese et al., 2021a). Moreover, most articles report differences in team cognition between team–AI collaboration and human teams. The articles that report similar levels of team situation awareness measured the construct with the total number of successful completed roadblocks. On this basis, it does not offer insights into cognitive processes of the team members, which are the core of team situation awareness. Instead, the total number of successfully completed roadblocks is rather an outcome measure, which can be seen as confounded with team performance. Apart from that, the lower levels of communication and coordination behavior suggest lower team cognition as communication improves team cognition. In fact, human teams tend to show higher levels of team cognition (when excluding the results that measured team situation awareness with the number of successfully completed roadblocks). However, future research should further enhance our understanding of the development of team cognition in team–AI collaboration, since there is also a study that finds higher levels of team cognition in team–AI collaboration. Currently, there is no sufficient empirical evidence for a conclusive statement.

5.3 Discussion of the findings on team performance

Furthermore, to our surprise, a careful analysis of the literature reveals that there are often no significant differences in team performance in team–AI collaborations to human teams, even though including AI systems as teammates change the communication and coordination behavior of human teams. Moreover, the results regarding team performance differences between human teams and team–AI collaboration remain inconsistent in that it is not clear which composition performs better. Our approach has been to explain performance differences through variations in the underlying intragroup processes. However, there are also alternative explanations grounded in the methodologies of the analyzed literature, which can be divided into three main categories: First, the operationalization of the AI system. Second, the operationalization of team performance, and third the experimental task and setting. One explanation is that the operationalization of AI systems affects team performance. Some studies use actual systems, while others use a WOZ approach. These differences in the operationalization of AI systems are likely to be confounded with functional skills affecting performance. However, this article did not focus on the effect of different capabilities of AI systems on intragroup processes. Future research will have to further improve our understanding of the effect of the capabilities of AI systems on intragroup processes. Furthermore, the operationalization of team performance also might have masked differences in team performance between human teams and teams collaborating with AI. Team performance was mostly measured with a composition score of mission variables. These mission variables were mainly quantitative in nature (failure recovery, time spent in warning and alarm states, number of missed targets, rate of good photographs, and number of points aggregated). It remains unclear whether the same result pattern would be replicated with a different measurement of team performance e.g., focusing more on the quality of the output of collaboration. Finally, the experimental task in the simulation scenarios might have affected these results. One specific characteristic of these experimental settings is that they are relatively low in complexity, meaning that they have a clearly defined initial state as well as clearly defined and limited roles, goals, and possibilities for action. Therefore, future research needs to investigate team–AI collaboration in settings that require dynamic communication, like hidden profiles (Schulz-Hardt and Mojzisch, 2012).

5.4 Contribution to theory and practice

We attempt to contribute to the existing literature on human–autonomy teaming and human–AI collaboration by addressing several research gaps. Our first contribution is providing a clear conceptualization of team–AI collaboration as well as other compositions of HATs. Through providing conceptual clarity, we establish a foundation for future research in the relatively neglected field of team–AI collaboration. Furthermore, we contribute to the literature on human–AI collaboration in IS by summarizing the current state of research on team–AI collaboration. Hence, we shift the focus in the current discussion on human–AI collaboration in IS research from the individual to the team level. Especially, the decision augmentation literature in IS currently tries to establish an understanding of the challenges related to successful AI-aided decision making (Jussupow et al., 2021; Fügener et al., 2022; Lebovitz et al., 2022). While challenges connected to an autonomous intelligent teammate are also discussed in the augmentation automation problem in IS, we barely notice any research that focuses on other aspects of team–AI collaboration (O'Neill et al., 2022; Seeber et al., 2020). Further, our results regarding communication hold important implications for the group decision making process, which is strongly dependent on information exchange and reasoning (Schulz-Hardt and Mojzisch, 2012). Decision augmentation research in IS should focus on how AI systems affect team decision making outcomes and processes. This is particularly important since team–AI collaboration to support strategic organizational and clinical decision making is getting more and more important in practice. Second, we contribute to team performance literature by summarizing the state of research on how intragroup processes affect team performance in team–AI collaboration and how intragroup processes of teams collaborating with AI differ from those in human teams.

Finally, we contribute to practice by summarizing success factors like team cognition, trust, communication, and coordination to effectively integrate AI with human teams. Additionally, our findings suggest that it is important for professionals to be trained in effectively working with AI systems and to be informed about their capabilities and limitations, to enhance team performance. Similarly, our results hold important implications for the software development and the development of AI-based team members. Our results convey the notion that AI-based team members should have high skill levels in their role-related task but should also be able to participate in the teamwork process through communication and coordination activities.

5.5 Limitations and directions for future research

We have already outlined some limitations of our literature review above. However, there are some aspects that we will further elaborate on, which should be addressed by future research. For instance, another limitation of our literature review is its explorative nature. We did not focus on specific intragroup processes in detail, but rather provided an overview. Our inconsistent results suggest that a more in detail investigation of every single process will be necessary to explain collaboration outcomes. Moreover, the sample of included articles is highly specific, since most studies incorporate a similar simulation scenario, predominantly using student samples. This limits the generalizability to other tasks, settings, and demographics. Future research should investigate intragroup processes in a more naturalistic setting, e.g., that allows face-to-face interaction. Additionally, most articles conceptualize team–AI collaboration as two humans collaborating with one AI system. Therefore, future research will have to compare larger team sizes collaborating with AI to investigate the incremental value of more than two humans (Fügener et al., 2021). Further, intragroup processes are conceptualized as mediators within the IMO-model of team performance (Hackman, 1987), but we could not find studies formally reporting mediation analyses (which is consistent with the findings of O'Neill et al., 2022). Future research should examine the relationship between composition (input factors) with intragroup processes as mediators and team performance as an outcome in an integrative model. These limitations must be considered when interpreting the results of our literature review. Some intragroup processes are not directly linked to team composition or team performance. Additionally, several intragroup processes that affect performance in human teaming, that have not yet been investigated in the context of team–AI collaboration. For instance, different aspects of motivation, cognitions, attitudes, relationships etc.

5.6 Conclusion

The aim of this literature review is to gain insights into team performance differences between human teams and teams collaborating with AI as well as the underlying differences in intragroup processes based on the IMO-model of team performance. In conclusion, our literature review can be considered as the starting point of a new research stream in IS focusing on intragroup processes in team–AI collaboration. Overall, our findings suggest that including an AI system as a team member affects intragroup processes. Yet, it remains unclear if these changes benefit or harm the team performance. One important implication of this result is that theories and principles of human teaming cannot be readily transferred to team–AI collaboration. Rather it seems that the specific characteristics of the AI systems and their effect on intragroup processes constitute boundaries of the IMO-model. Future, research will have to take our results up to further investigate the specific characteristics of team–AI collaboration to improve our understanding.

Appendix – Reviewed literature

Article	I	M	O	Best performing	Task
Demir et al. (2018)	Comp	Comm/Coord	TP	All hum > Team-AI (AI=WOZ)	RPAS
McNeese et al. (2021c)	Comp	Team cog, TSA	TP	AI only > HAA =HHA>All hum	NeoCITIES
Schelble et al. (2022)	Comp	Team cog, Trust	TP	HAA>HHH	NeoCITIES
Fügener et al. (2021)	Team size	Exp AI char	TP	Smaller teams	Simulation
McNeese et al. (2018)	Comp	Comm/Coord, TSA	TP, TSA	Expert>All hum=Team–AI*	RPAS
Demir et al. (2017)	Comp	Comm/Coord, TSA	TP	Expert>All hum = Team–AI*	RPAS
Demir et al. (2019a)	Comp	Comm/Coord, TSA	TP	Expert>All hum = Team–AI*	RPAS
Myers et al. (2019)	Comp	-	TP	Expert>All hum = Team–AI*	RPAS
Demir et al. (2016)	Comp	Comm/Coord	TP	Not reported	RPAS
Demir et al. (2021)	Fail	Comm/Coord, Trust	TP	-	RPAS
Johnson et al. (2021)	Fail, Training	Comm/Coord, Trust	TP	-	RPAS
McNeese et al. (2021a)	Fail	Trust	TP	-	RPAS
Johnson et al. (2020)	Training	Comm/Coord	TP	-	RPAS
McNeese et al. (2021b)	Comp	TSA, Coord	-	-	RPAS
van Wissen et al. (2012)	Comp	Fairness, Defection	-	-	Colored Trails
Musick et al. (2021)	Comp	Comm/Coord, Team cog	-	-	Escape island
Zhang et al. (2021)	Exp, Attitude	Willingness to cooperate		-	Correlative study
Schadd et al. (2022)	Expl	Mental model	TP	-	Blanket search task

Table 1. Order criterion: starting with articles that give information on the best performing team. RPAS: simulated remotely-piloted aircraft system, TSA: team situation awareness, HAA: team composed of one human and two AI systems, HHA: team composed of one human and two AI systems, Comp: composition, Fail: Failure type, Comm/Coord: Communication/coordination, Expl: explainability, Exp: experience

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