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The Influence of Knowledge Sharing on Team Effectiveness in Human-Agent Teams: The Moderating Role of Team Coordination

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Master in Human Resources Management and Organizational Consulting

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Abstract in Portuguese

A crescente importância da tecnologia e a rápida integração da Inteligência Artificial (IA) nas equipas organizacionais transformaram a colaboração tradicional, dando origem às Equipas Humano-Agente (HATs), nas quais os agentes de IA funcionam como membros ativos da equipa. Nas equipas tradicionais, compostas apenas por humanos, a partilha de conhecimento e a coordenação entre os membros da equipa são fatores críticos para a sua eficácia; contudo, a investigação sobre a dinâmica destes processos em HATs permanece limitada. Este estudo investiga a influência dos comportamentos de partilha de conhecimento (doação e recolha de conhecimento) na eficácia das equipas em HATs, com foco no papel moderador dos mecanismos de coordenação da equipa (coordenação implícita e explícita). O estudo foi realizado numa amostra de 29 equipas. Foi utilizada uma metodologia de inquérito para captar as perceções dos membros humanos das equipas e dos líderes aquando da colaboração com agentes de IA, sendo os dados analisados ao nível da equipa. Os resultados revelam que a doação de conhecimento entre membros humanos e agentes de IA está positivamente relacionada com o desempenho da equipa quando apoiada por elevados níveis de coordenação explícita. Em contraste, a coordenação implícita não apresentou efeitos de interação significativos na relação entre os comportamentos de partilha de conhecimento e o desempenho da equipa. Estes resultados salientam o papel crítico da comunicação estruturada nas HATs e oferecem implicações teóricas e práticas para a conceção de processos de partilha de conhecimento e coordenação na colaboração humano-IA. O estudo contribui para o avanço da compreensão da dinâmica das HATs, informando as estratégias organizacionais para a integração da IA nas equipas e destacando os principais desafios para o desenho das HATs do futuro.

Palavras-chave: Equipas humano-agente, Inteligência Artificial, Eficácia da equipa, Partilha de conhecimento, Coordenação explícita, Coordenação implícita

Códigos de Classificação JEL:
O15 – Recursos Humanos
D23 – Comportamento Organizacional

Abstract in English

The growing importance of technology and the rapid integration of Artificial Intelligence (AI) into organisational teams have transformed traditional collaboration, giving rise to Human-agent Teams (HATs) in which AI agents function as active teammates. In traditional human-only teams, knowledge sharing and team coordination is a critical driver of team effectiveness. Research on the dynamics of these processes in HATs remains limited. This study investigates the influence of knowledge sharing behaviours (knowledge donating and collecting) on team effectiveness in HATs, with a focus on the moderating role of team coordination mechanisms (implicit and explicit coordination) in a sample of 29 teams. A survey methodology was employed to capture human team members' and leaders' perceptions when collaborating with AI agents and data were analysed at the team level. The findings reveal that knowledge donating between human and AI team members is positively related to team performance when supported by high levels of explicit coordination. In contrast, implicit coordination showed no significant interaction effects on the relationship between knowledge sharing behaviours and team performance. These results highlight the critical role of structured communication in HATs and offer theoretical and practical implications for designing knowledge sharing and coordination frameworks in human-AI collaboration. The study contributes to advancing the understanding of HAT dynamics, informing organisational strategies for integrating AI into teams, and highlighting key challenges for designing future HATs.

Keywords: Human-agent teams, Artificial Intelligence, Team effectiveness, Knowledge sharing, Explicit coordination, Implicit coordination

JEL Classification codes:
O15 – Human Resources
D23 – Organisational Behaviour

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Glossary of acronyms

AA	Artificial Agent; Autonomous Agent
AI	Artificial Intelligence
H	Hypothesis
HAT	Human-Agent Team; Human-Agent Teaming
IMO	Input-Mediator-Output
IPO	Input-Process-Output
TMS	Transactive Memory System

1. Introduction

“Our future competitiveness depends on AI adoption in our daily businesses, and Europe must up its game and show the way to responsible use of AI. That is AI that enhances human capabilities, improves productivity, and serves society.” (Ursula von der Leyen, as cited in Whiting, 2024)

The growing significance of technology in our environment today is a given. This statement by Ursula von der Leyen, the President of the European Commission, during the 2024 World Economic Forum Annual Meeting in Davos underscores this fact (Whiting, 2024). With the continuous evolution of machine learning and Artificial Intelligence (AI), the interconnected roles of intelligent agents are becoming essential components of our daily life (Iftikhar et al., 2024). As organisations increasingly incorporate AI into their operations and teams, unique challenges arise in fostering effective collaboration. AI is rapidly transforming the landscape of modern work environments by fundamentally changing how organisations structure teams and collaborate. AI has transitioned from being a mere tool to becoming an active teammate, resulting in the rise of human-AI teams or human-agent teams (HATs) (Flathmann et al., 2021; Iftikhar et al., 2024; Schelble et al., 2022). HATs are teams that consist of one or more humans and one or more agents (Flathmann et al., 2021), in which AI performs diverse roles including decision-making, augmentation, and task automation (Iftikhar et al., 2024). This evolution is driven by AI's capacity to enhance human performance, optimise decision-making, and improve the efficiency of processes (Schmutz et al., 2024). In general, AI represents a set of information and communication technologies developed to mimic human cognitive processes, with the aim of improving job performance, boosting operational efficiency, and driving economic growth (Arakpogun et al., 2021).

As AI integration in workplaces expands, its influence on team effectiveness grows. Team effectiveness comprises of tangible outputs (e.g., productivity and quality), which are also referred to as performance, and the influences on team members on an individual (e.g., attitudes and behaviours) and team level (e.g., cohesion and satisfaction) (Mathieu & Gilson, 2012). The shift from traditional human-only teams to HATs has made AI’s influence on team structure, processes, and effectiveness relevant. Therefore, understanding how AI team members affect team effectiveness becomes critical. The unique nature of HATs introduces new requirements for knowledge sharing, team coordination, and performance measurement, presenting an urgent need to reassess traditional team models to address these new structures (Iftikhar et al., 2024). Unlike human-only teams, HATs require careful consideration of how human and AI teammates interact, communicate, and coordinate to achieve shared objectives. Organisations must ensure that human-AI collaboration is productive, ethical, and aligned with business goals.

The evolution of HATs challenges established models of team effectiveness and creates a pressing need for new approaches to understand collaboration in human-AI contexts.

Traditional models of team effectiveness, such as the Input-Process-Output (IPO) model by McGarth (1964) and the “Big Five” of teamwork by Salas et al. (2005), explain which factors are relevant for making teams perform well. These traditional models have been extensively tested in human-only teams, where implicit coordination and shared mental models often play a crucial role in fostering collaboration. Shared mental models are pre-existing cognitive frameworks that team members develop over time and help to interpret tasks and how the team operates (Rico et al., 2019). These models have been validated in human-only teams, where members rely on established shared mental models to guide their understanding of the task, anticipate each other’s actions, and coordinate implicitly. However, integrating AI into teams introduces significant challenges for knowledge sharing and coordination because AI agents typically lack the shared cognitive frameworks and anticipatory abilities that are fundamental to human teamwork (Marques-Quinteiro et al., 2013; Rico et al., 2019; Schmutz et al., 2024).

Especially, when performing dynamic and complex tasks, effective coordination is essential for team performance. Team coordination can occur through explicit or implicit processes (Marques-Quinteiro et al., 2013). Implicit coordination refers to an unspoken, mutually understood process that allows team members to work together seamlessly by anticipating future task demands and the needs of others, without requiring explicit communication. Explicit coordination is a process in which team members communicate directly to share plans, clarify responsibilities, and gather necessary information to perform tasks (Rico et al., 2019). These coordination mechanisms allow team members to operate efficiently in changing environments, especially during complex, high-stakes tasks (Hagemann & Kluge, 2017). However, AI relies on explicit instructions to function within team settings. Thus, explicit coordination becomes especially crucial in HATs to ensure that AI agents receive the information they need to operate effectively (Seeber et al., 2020). Nevertheless, exploring how teams can develop forms of implicit coordination with AI over time, potentially through improved interfaces and adaptive learning systems, could offer valuable insights into the evolution of human-AI collaboration (Georganta et al., 2024).

Cognitive processes like knowledge sharing are often facilitated by shared mental models and implicit coordination, allowing for fluid, non-verbal communication. Knowledge sharing is essential for enhancing team effectiveness, particularly in emerging context and plays a critical role in achieving, maintaining, and improving team performance (Yoo et al., 2022). It describes the exchange of task-relevant information and know-how that aids in problem-solving, implementing procedures, and reinforcing idea development within teams (Cummings, 2004; Pulakos et al., 2003). The concept of knowledge sharing involves distinct behaviours, namely knowledge donating (proactively sharing one's knowledge) and knowledge collecting (seeking knowledge from others) (de Vries et al., 2006). These behaviours are influenced by how individuals perceive others' readiness to exchange knowledge, impacting the dynamics of knowledge sharing (Wang & Noe, 2010). In traditional human teams, effective knowledge sharing is associated with better decision-making, problem-solving, and higher innovation rates, as members can draw from each other’s expertise to respond adaptively to complex situations (Mesmer-Magnus & DeChurch, 2009). In HATs, this process currently is particularly complex because AI agents rely on explicit knowledge, or structured inputs provided by human teammates. Unlike humans, who can infer meaning from non-verbal cues or incomplete information, AI requires clear, unambiguous data to operate effectively (Seeber et al., 2020). This reliance on structured information means that traditional knowledge-sharing processes in HATs may require formalisation, with human team members needing to adapt their communication to meet the AI’s processing requirements.

As AI systems gain relevance in team tasks, the question arises as to how well traditional models of team effectiveness apply to HAT. Despite the growing presence of AI in team settings, there is limited research on how human team members would perceive the knowledge sharing, coordination, and team effectiveness dynamics in HATs. While studies have examined AI as a tool or assistant, fewer have explored its role as a teammate (Schmutz et al., 2024). This study aims to address this gap by focusing on the following central question:

> *What is the impact of knowledge sharing (knowledge donating and collecting) between human and AI team members on team effectiveness in traditional teams as well as in HATs, and how do team coordination mechanisms (explicit and implicit coordination) moderate this relationship?*

The role of explicit coordination becomes especially crucial in ensuring that AI systems receive the information they need to function optimally. Meanwhile, exploring how teams might develop forms of implicit coordination with AI systems over time will provide insights into the future evolution of human-AI collaboration (Georganta et al., 2024).

This study employs a structured, quantitative research design, using a survey to investigate the perceptions and attitudes of human team members and leaders toward collaborating with non-human teammates. Previous studies also measured perceptions, such as perceived team performance or perceived team cohesion (e.g., Schelble et al., 2022), instead of conducting real case experiments. As AI systems are integrated into teams as active teammates, human members’ perspectives on these key factors are critical for better understanding HAT functioning. This work addresses the gap in research regarding knowledge sharing and its influence on team effectiveness within HATs from a team-level perspective. It also examines if explicit and implicit coordination mechanisms moderate this relationship. These findings will inform strategies for organisations to support effective knowledge sharing and coordination in HATs and provide valuable insights for future research directions. Although traditional models of team effectiveness provide a foundation, they may need to be adapted to HAT settings. The urgency to explore this area is particularly important given that AI integration in teams is not a distant possibility but a present reality in many industries.

2. Literature Review

Teamwork is central to organisational success, as it enables companies to coordinate complex tasks, foster innovation, and adapt to changing demands (Salas et al., 2015). Team effectiveness, classified as the ability to achieve collective goals, is influenced by several factors, including communication, leadership, and coordination (Marques-Quinteiro et al., 2013). As tasks become progressively complex, organisations rely on teams to solve problems and achieve higher levels of performance (Kozlowski & Ilgen, 2006). Traditionally, models like the “Big Five” in teamwork (Salas et al., 2005) emphasised the importance of trust, communication, and coordination among human team members.

However, the introduction of AI systems as teammates fundamentally transforms how teams operate. AI has evolved from being a tool used by teams to becoming an active team member, resulting in HATs, where humans and AI collaborate toward a shared goal (Schmutz et al., 2024). These teams are not only prevalent in high-stakes environments, including autonomous driving and healthcare, but are becoming common across industries (Seeber et al., 2020). AI agents with high levels of autonomy enhance performance, reduce human workload and increase task efficiency by making decisions independently. This allows human teammates to redirect their attention toward higher-level strategic decisions and tasks (Georganta et al., 2024; Schmutz et al., 2024). However, these benefits are coupled with new challenges in coordination and communication, as AI lacks the innate ability to engage in human-like, implicit coordination, adaptation, and situational awareness (Demir et al., 2019; Grimm et al., 2018; Klein et al., 2004; Schneider et al., 2021).

New forms of teams, as for instance HATs, disrupt the existing team functioning and poses new challenges for researchers, organisations, team members, and leaders. Not only does AI affect team dynamics, but also requires leaders to adapt their behaviours, and new strategies for effective team collaboration need to be determined (Georganta et al., 2024; Larson & DeChurch, 2020; Schmutz et al., 2024). What is considered as predictors for team performance in traditional teams (e.g. Hackman, 1987; Salas et al., 2005; Shiflett, 1979) needs to be verified for human-AI collaborative settings. The following chapters define the concept of HATs as a new form of teams, as well as the study variables knowledge sharing, team coordination, and team performance. Furthermore, their relationships are elaborated and the hypotheses introduced to state the relevance of the study.

2.1 Human-Agent Teams

The introduction of AI into teams fundamentally changes how humans behave (Demir & Cooke, 2014). The following chapter defines HATs, why they are relevant, and how they have been studied.

In the past, technology and AI systems have been seen as a mere tool to support human team members in their tasks. In contrast, according to the teammate view, technology is viewed as an active, social entity that functions as a co-equal member of the team rather than as a tool that restricts or enhances human behaviours (Larson & DeChurch, 2020). This perspective has been broadened by recent research in human-computer interaction, which focuses on developing technologies that enable productive human-AI collaboration by supporting human functions as well as assuming team roles or responsibilities (Ajoudani et al., 2018; Breazeal et al., 2005; Groom & Nass, 2007).

Human-AI teams, human-agent teams, or human-autonomy teams (HATs) are teams that consist of at least one team member that is human and one that is AI. Those teams share traditional team requirements, such as shared goals and interdependence among team members. Nevertheless, they require additional consideration of the AI team member's characteristics to clearly distinguish it from an assistance tool (Cuevas et al., 2007; Flathmann et al., 2021; O'Neill et al., 2022). DeCostanza et al. (2018) made a useful distinction between "technology" and "agent" in team contexts. An agent, whether robotic or AI-based, takes on a distinct role within the team and directly improves team performance, whereas technology refers to devices, software, or systems used to foster team processes. This transition from technology as a tool to technology as an agent has changed team dynamics significantly (DeCostanza et al., 2018).

To be considered as a teammate, the AI must hold a certain level of decision-making autonomy, possess a clearly defined and distinct role within the team, and its tasks and outcomes must be interdependent with those of the human team members (Flathmann et al., 2021; O'Neill et al., 2022). While HATs maintain these basic team functions, they differ from traditional human teams in several ways. Factors like transparency, reliability, and the autonomy level of AI become crucial predictors of team performance, as these dimensions influence how effectively AI is integrated into the team's operations. Moreover, despite the technical differences, HATs still rely on human-team dynamics, for example trust development, which is essential for the team's cohesion and overall performance. This trust becomes even more critical as AI technology advances, and teams develop methods to increase transparency and ensure reliable AI contributions (Flathmann et al., 2021).

These teams rely on an information flow in both directions and exhibit team-like behaviours, including coordination, collaboration, joint planning, replanning, goal reprioritisation, and task reallocation to successfully achieve their objectives (Cuevas et al., 2007). Effective HATs involve a complex interplay of capabilities, such as shared goals and roles, shared mental models, collaboration in problem-solving, adaptability, team situation awareness, and others. Furthermore, a range of factors influence how human team members perceive AI teammates, including the AI's predictability, directability, and shared understanding (Klein et al., 2004).

O'Neill et al. (2022) defined HATs as (1) teams in which autonomous agents (AAs) are identified as a distinct team member by their human teammates, (2) the agents perform a distinct and interdependent role within the team, and (3) teams that comprise of at least one human and one AA. When using the terms "AI", "agent", "AA", and "HATs", the present work refers to the definitions based on O'Neill et al. (2022).

Additionally, the rise of AI and robotics introduces new challenges in distinguishing human-robot teams from HATs. Robots, as embodied agents, resemble human characteristics physically, while AI may be disembodied and still function as a teammate. AI encompasses technologies that perform tasks requiring human-like intelligence, including decision-making or language translation (Larson & DeChurch, 2020). These shifts highlight that HATs will face unprecedented challenges as AI systems take on increasingly complex roles (Chakraborti et al., 2017; Talamadupula et al., 2014).

Endsley (2023) defined key areas that are necessary for HATs to perform successfully and need further research advances. This includes how AI systems should be designed according to their decision biases, trust levels, effective communication strategies and team processes, team situation awareness, as well as team coordination (Endsley, 2023). These factors highlight that collaboration and coordination are just as important for HATs as they are for human-only teams despite the challenges that need to be considered when introducing AI as a team member to a team.

The advancement of AI agents, particularly through deep learning technologies, has significantly expanded their capabilities and interactions with humans (Oh et al., 2018). Research has shown that AI teammates can enhance team performance in the areas of data science and computer security (Mahaini et al., 2019; Wang et al., 2019). However, team performance often differs based on whether the AI is perceived as a tool or as a legitimate team member. Recent studies have highlighted that the most critical factor shaping human perceptions of AI teammates is the AI's skill level. Humans are more receptive and positive towards AI team members when they believe the AI possesses high-level, relevant skills (Zhang et al., 2021). Negative experiences with early or faulty AI systems often contribute to scepticism about AI's abilities, making it crucial for AI teammates to demonstrate a high degree of autonomy to fulfil their role on the team (McNeese et al., 2018).

A key consideration in HATs is finding the right balance between AI autonomy and human control. While AI needs to exhibit a minimum threshold of autonomy to function as a true team member (Flathmann et al., 2021; O'Neill et al., 2022), there are concerns about AI potentially overshadowing or replacing human roles if its autonomy becomes too high (Jarrahi, 2018). Effective human-AI collaboration depends on achieving a balance between the rapid decision-making capabilities of AI and the intuitive judgment of human team members. This balance must consider not only the AI's capabilities but also the comfort levels and receptiveness of human teammates to the AI's role and decision-making autonomy. Clear understanding among all team members, both human and AI, regarding each other's capabilities is essential for successful teamwork (Kerstholt et al., 2018).

The concept of HATs is not new and has been studied before. Although HATs are critical for organisational scholars, much of the research on technology as a team member originates from fields like "human-computer interaction" (p. 10), rather than organisational behaviour (Larson & DeChurch, 2020).

Nevertheless, in the past years, studies investigated HATs in terms of shared mental models and shared cognition (e.g., Andrews et al., 2023; Demir et al., 2020; Schelble et al., 2022), trust (e.g., Georganta & Ulfert, 2024; Schelble et al., 2022; Ulfert & Georganta, 2020; Wildman et al., 2024), coordination (e.g., Demir et al., 2017; Demir et al., 2019; Talamadupula et al., 2014), situation awareness (e.g., Endsley, 2023), and team effectiveness and performance (e.g., Demir et al., 2019; Schelble et al., 2022). Findings suggest that shared mental models and cognition enable team members to anticipate the needs of others which is crucial for effective interaction in HATs, as seen in studies by Andrews et al. (2023) and Demir et al. (2020). However, AI's limited capability to adapt to unspoken cues makes creating shared cognition challenging. This requires explicit strategies for enhancing these mental models in HATs. Trust was found to be another foundational element for HAT effectiveness, particularly in fostering cooperation and information sharing. Research shows that higher trust levels between human and AI members correlate with improved team performance, as trust facilitates smoother workflows and more cohesive team dynamics (Georganta & Ulfert, 2024; Schelble et al., 2022). Moreover, studies have demonstrated that coordination strategies are vital for ensuring that both human and AI members align on tasks. Studies by Demir et al. (2019) and Talamadupula et al. (2014) revealed that structured coordination approaches, including explicit task assignments (Demir et al., 2019) and cognitive tools like mental modelling and plan recognition (Talamadupula et al., 2014), augment HAT performance. These approaches support AI agents in anticipating and aligning with human teammates, thereby compensating for their limited implicit understanding.

In addition to performance predictors like trust and shared cognition, knowledge sharing and team coordination are essential to team performance in human-only teams (e.g., Marques-Quinteiro et al., 2013; Mesmer-Magnus & DeChurch, 2009; Rico et al., 2019). While these factors have received limited attention in the context of HATs, existing research have suggested that they may significantly influence collaborative dynamics in these settings. Effective knowledge sharing ensures that both human and AI team members are fully utilising available information, which enhances decision-making and prevents information silos (Mesmer-Magnus & DeChurch, 2009). Furthermore, team coordination is crucial for synchronising actions, especially in evolving environments where AI and human tasks are interdependent (Georganta et al., 2024). Without proper coordination, inefficiencies and miscommunications can significantly hinder team effectiveness (Schelble et al., 2022). Building on these considerations, the next sections define the central constructs examined in this study and outline the hypotheses that guide the empirical investigation.

2.2 Team Effectiveness in Human-Agent Teams

In organisational settings, team effectiveness remains a critical construct and has been a cornerstone of organisational research (e.g., Marks et al., 2001; Mathieu et al., 2008, 2019; Mathieu & Gilson, 2012). As organisations place greater reliance on teams to manage complex tasks, understanding the factors that drive team effectiveness has become vital, particularly in light of the integration of AI into these environments. This section will explore the evolution of team effectiveness models, differentiate between team effectiveness and team performance, and discuss recent adaptations of these models for HATs.

Team effectiveness refers to how well a team achieves its objectives, meets the needs of its members, and supports individual growth and development (Cohen & Bailey, 1997; Mathieu et al., 2008; Yoo et al., 2022). However, there is no universally accepted definition of team effectiveness. Traditionally, team effectiveness was assessed by two main factors: Team performance, measured in terms of quantity and quality; and team members' affective responses, including satisfaction, viability (willingness to work as a team), and commitment (McGarth, 1964). The two components have been further delineated intro three levels of team effectiveness (Cohen & Bailey, 1997; Hackman, 1987). Hackman (1987) described team effectiveness through three primary criteria: (a) Team performance as evaluated by external stakeholders, (b) the degree to which the team meets the needs of its members, and (c) viability or the team members' willingness to continue working together. Cohen and Bailey (1997) classified effectiveness into three overarching domains: (a) Performance, encompassing efficiency, quality, responsiveness, customer satisfaction, productivity, and innovation; (b) attitudes, including member satisfaction, trust, and commitment; and (c) behaviours, referring to absenteeism, safety issues, and turnover. Over the past decade, the criteria for assessing team effectiveness have broadened beyond traditional indicators of performance quality and quantity. Emerging dimensions emphasise strategic decision-making, accumulation and management of knowledge, creativity, and customer relations, among others (Mathieu et al., 2008).

Due to the broad nature of the earlier frameworks, Mathieu and Gilson (2012) refined the characterisation of team effectiveness into two main types: Tangible outputs, which refer to the products resulting from team interactions; and influences on team members. This approach aligns with the perspective of Mathieu et al. (2000), who defined team outcomes as “results and by-products of team activity that are valued by one or more constituencies” (p. 273). In their work, Mathieu and Gilson (2012) also drew a distinction between related constructs: Team outcomes and team member actions. They clarified that behaviours are actions aimed at achieving goals, while outcomes are the actual results or consequences of these behaviours. They include process improvements, cognitive task performance, and learning behaviours.

Tangible outputs can be measured by productivity, quality, and efficiency. Team members’ reactions are further divided into team-level and individual-level outcomes. At the team level, reactions include emergent states encompassing shared cognitive, affective, and motivational states. At the individual level, outcomes include attitudes, behaviours, reactions, and personal development. Individual outcomes refer to experiences that differ from individual to individual. Team activities can significantly impact individual members' affective states, motivation, and work attitudes, which influence their satisfaction with the team, willingness to continue working within it, and commitment to team goals (Mathieu & Gilson, 2012). This perspective underscores that team functioning affect individual and collective outcomes, including satisfaction and growth, which contribute to sustained team viability.

While often used interchangeably, team effectiveness and team performance are distinct concepts. Team performance refers to the tangible outputs a team produces, for example the completion of tasks, the generation of ideas, or the delivery of high-quality products (Cohen & Bailey, 1997; Yoo et al., 2022). It encompasses factors such as productivity, quality of work, customer satisfaction, and competitiveness. This construct refers to how well the team accomplishes its goals and meets the expectations of those who evaluate its output (Hackman, 1987). In contrast, team effectiveness is often categorised into three distinct dimensions: Growth experience, team satisfaction, and team performance. It comprises not only performance but also the team’s internal processes, including member satisfaction and individual growth. For instance, a team may perform well in the short term by achieving its goals, but if its members are dissatisfied or not learning and growing, the team cannot be considered fully effective (Yoo et al., 2022). Team satisfaction, for example, is more subjective, focusing on how team members perceive their participation within the team. It reflects whether team members feel that their personal needs such as psychological safety, mutual respect, and role clarity are being met (Cohen & Bailey, 1997). Satisfaction within teams often contributes to lower turnover rates, higher engagement, and better overall mental well-being. Growth experience refers to the learning and development opportunities that team members gain from their involvement in the team. This dimension emphasises the long-term benefits of teamwork, particularly in fast-changing environments where continuous learning is important for sustainable organisational success. Unlike learning behaviours (i.e., how team members share knowledge or solve problems), growth experience is about whether individuals feel they are developing professionally and personally as a result of their work in the team (Katz-Navon et al., 2016). Thus, team effectiveness is a broad concept that encompasses both the team's performance and the internal experiences of its members. Team performance, in contrast, is just one component of overall team effectiveness, which focuses on the external outcomes of teamwork, including efficiency, productivity, and quality.

In the context of HATs, understanding this distinction is critical. AI systems may contribute to high team performance by improving workload efficiency (Fan et al., 2010; Fan & Yen, 2011), though this does not necessarily result in team satisfaction. In the present work, the variable team effectiveness follows the definition of Mathieu and Gilson (2012), by not only investigating the tangible outputs of the team but also focusing on the influences on team members, namely team satisfaction and viability.

The following section examines frameworks related to team effectiveness and their evolution. Traditionally, team effectiveness models focused on linear frameworks, emphasising individual contributions and predefined processes (Shiflett, 1979). These early models, for instance Shiflett's general model of small group productivity, highlights factors like resources, task demands, and the alignment of team members' abilities. Subsequent research introduced additional comprehensive models, like the IPO framework proposed first by McGarth (1964) and further developed by Hackman and Morris (1975). This framework considers inputs, processes, and outcomes as integral to understanding team effectiveness. The IPO model suggests that team inputs (e.g., resources, member skills, and task design) interact with team processes (e.g., communication, decision-making, and conflict resolution) to produce effective outcomes (Hackman, 1983, 1987; Hackman & Morris, 1975; McGarth, 1964). The IPO framework was further elaborated to the IMO model, when Marks et al. (2001) and Ilgen et al. (2005) highlighted that many factors mediating the relationship between outcomes and inputs are not strictly behavioural but include shared emotions and thoughts. The IMO model explicitly calls on researchers to specify their theoretical frameworks by investigating the mediating mechanisms that link input variables and team outcomes (O'Neill et al., 2022). Consequently, the term "mediating mechanisms" (M) has replaced "processes" in IMO models. Salas et al. (2005) expanded on this framework by introducing five core components ("Big Five") related to teamwork: Adaptability, mutual performance monitoring, team leadership, team orientation, and backup behaviour. They underlined that these elements collectively foster coordination and team resilience in complex environments.

Traditional models often emphasise stable, co-located teams with clear hierarchies and task divisions (Hagemann & Kluge, 2017). They focus on interpersonal skills, leadership, and communication to drive effectiveness. While these models have contributed to the understanding of team dynamics, it is not entirely clear to what extent they are suitable to address the complexities of modern team structures, where members may belong to multiple teams, work asynchronously, or collaborate with AAs as team members. Advances in technology and globalisation have challenged these frameworks, as modern teams increasingly work virtually, only temporal, or within multi-team systems, where members coordinate across multiple, dispersed teams (Turner et al., 2020). Virtual teams, in particular, present unique challenges and opportunities for team effectiveness, as members rely on technology-enabled communication and need higher levels of trust and knowledge sharing to maintain performance. These teams depend on members' willingness to share expertise and coordinate through technology, which promotes knowledge integration and collective performance (Alsharo et al., 2017; Maynard et al., 2012; Turner et al., 2020). The effective use of transactive memory systems (TMS), which are shared systems for sharing and capturing knowledge (Lewis et al., 2005); and preparation activities, such as strategy and role clarification, helps virtual teams overcome spatial and temporal barriers and maintain alignment with team goals (Marques-Quinteiro et al., 2013; Maynard et al., 2012; Mesmer-Magnus & DeChurch, 2009).

HATs bring an additional layer of complexity. They differ from human-only teams in that they require explicit coordination structures to manage interactions between humans and AI agents, who may not naturally adapt to unspoken team norms (Schelble et al., 2022; Seeber et al., 2020). In HATs, the stability of coordination patterns is crucial for team performance, as AI systems must adjust to human behaviours flexibly yet predictably. Consequently, modern models of team effectiveness in HATs must account for how AI teammates process tasks and communicate. This often requires that AI agents be trained to anticipate human needs and align their actions within a broader team framework (Demir et al., 2019). Furthermore, higher levels of agent autonomy improve performance, reduce human workload and promote task efficiency (Johnson et al., 2012; O'Neill et al., 2022; Wright & Kaber, 2005). Overall, while traditional models provide a valuable foundation, modern frameworks must adapt to address the complexities of virtual, multi-team, and human-AI integrated team settings. These adaptations are necessary for managing coordination, communication, and knowledge sharing in shifting environments.

2.3 Knowledge Sharing in Human-Agent Teams

Knowledge plays a critical role as an organisational resource that offers a sustained competitive advantage in dynamic and competitive environments (e.g., Davenport & Prusak, 1998). Achieving a competitive advantage requires more than simply hiring or training employees with the desired knowledge, skills, and competencies (Wang & Noe, 2010). Companies therefore need to focus on effectively transferring knowledge from experts to new employees and ensure that existing knowledge resources are fully utilised (Davenport & Prusak, 1998; Hinds et al., 2001). This can be done through sharing knowledge among team members and teams and enables organisations to leverage and maximise their intellectual assets (Cabrera & Cabrera, 2005; Damodaran & Olphert, 2000; Davenport & Prusak, 1998). Through the exchange of knowledge, employees help to promote innovation, apply knowledge, and improve the organisation's competitive advantage (Wang & Noe, 2010). In the subsequent section, the concept of knowledge sharing is described by highlighting its definitions and theories, the role in teams, as well as how it has been studied.

To understand the concept of knowledge sharing, it is important to first establish a clear definition of knowledge. Scholars have long debated the distinction between knowledge and information, with some emphasising fundamental differences. Information is understood as stream of messages, whereas knowledge is constructed from information and justified by personal beliefs (Nonaka, 2009). Furthermore, knowledge encompasses practical expertise or know-how, making it more comprehensive than information alone (Kogut & Zander, 1992). In the field of management information systems, the term knowledge is often used to highlight the added value and distinctiveness of knowledge management systems as opposed to conventional information systems (Alavi & Leidner, 2001). However, various researchers argued that the distinction between knowledge and information holds limited practical relevance in the context of knowledge sharing. Therefore, the terms are often used interchangeably (Bartol & Srivastava, 2002; Huber, 1991). Following this view, Wang and Noe (2010) defined knowledge as "information processed by individuals, including ideas, facts, expertise, and judgments relevant to individual, team, and organizational performance" (p. 117).

Knowledge is commonly classified into two primary forms: Tacit and explicit (Nonaka & von Krogh, 2009; Olan et al., 2022). Tacit knowledge is the personal, experience-based knowledge individuals acquire over time, which becomes an unconscious part of their understanding and actions (Göksel & Aydintan, 2017). Organisations highly encourage the sharing of tacit knowledge because it generates new insights that improve business processes and strategies (Olan et al., 2022). In contrast, explicit knowledge is formalised, codified knowledge that can be easily captured and stored in documents, reports, and processes, and shared through information systems within an organisation (Nonaka, 1994). Both tacit and explicit knowledge play crucial roles in fostering effective knowledge sharing within organisations. Tacit knowledge provides depth and context, enriching understanding, while explicit knowledge enables the broad dissemination of information across the organisation (Nonaka & von Krogh, 2009).

Knowledge sharing refers to the exchange of task and organisationally relevant information, know-how, and experiences among individuals to support each other and collaborate in solving problems, implementing procedures, or developing new ideas (Cummings, 2004; Lin, 2007a; Lin, 2007b; Pulakos et al., 2003). This process can occur through a range of communication methods, including written correspondence, face-to-face interactions, or by documenting, capturing, and organising knowledge for collective use (Cummings, 2004; Pulakos et al., 2003). When sharing knowledge individuals exchange tacit and explicit knowledge, allowing them to collaboratively generate new knowledge (van den Hooff & Ridder, 2004). Furthermore, this process takes place at individual and organisational levels. At the individual level, it involves employees engaging with colleagues to assist them in completing tasks more efficiently, or quickly. At the organisational level, knowledge sharing encompasses capturing, structuring, reusing, and transmitting knowledge that is experience-based and available within the organisation, ensuring it is accessible to others across the business (Lin, 2007b). Research has consistently highlighted the importance of knowledge sharing, showing that it plays a critical role in enhancing innovation performance and minimising learning efforts (Calantone et al., 2002).

The concept of knowledge sharing involves specific behaviours and attitudes. Regarding the attitude or intention, van den Hooff et al. (2004) differentiated between willingness and eagerness to share knowledge. Willingness implies readiness to share under the condition of reciprocal sharing, whereas eagerness reflects a proactive desire to share, driven by passion and personal motivation (de Vries et al., 2006; Lin, 2007b; van den Hooff et al., 2004). Perceptions and interpretation of others' knowledge sharing intentions might influence their knowledge sharing behaviours (Wang & Noe, 2010). There are two types of knowledge sharing behaviours: Knowledge donating and collecting (de Vries et al., 2006; van den Hooff & Ridder, 2004). Knowledge donating in this context is referred to as communicating one's knowledge to others, whereas knowledge collecting describes the process of asking others to share their knowledge (de Vries et al., 2006).

Adhering to the concept of knowledge sharing behaviours by de Vries et al. (2006), this study maintains the distinction between knowledge sharing behaviours, specifically knowledge donating and knowledge collecting. This helps to better understand the relationship between knowledge sharing and team effectiveness in HATs by analysing these distinct behaviours.

Knowledge sharing is linked to numerous positive outcomes for teams and broader organisational effectiveness. Studies consistently show that when team members exchange information, organisations benefit from enhanced trust and collaboration, particularly in virtual and geographically dispersed teams (Alsharo et al., 2017). For example, knowledge sharing fosters a collaborative climate, leading to reduced production costs and faster project completion times. It also promotes innovation and contributes directly to an overall firm performance, including revenue growth and the successful development of new services and products (e.g., Arthur & Huntley, 2005; Collins & Smith, 2006; Cummings, 2004; Hansen, 2002; Lin, 2007b; Mesmer-Magnus & DeChurch, 2009). Furthermore, the process of sharing knowledge between team members has been shown to improve team collaboration and problem-solving (Cummings, 2004), as well as to accelerate task completion and increase efficiency (Hansen, 2002), while it is linked to improve team performance in dynamic settings (Choi et al., 2010). Besides positively influencing team performance, knowledge sharing is considered a vital performance behaviour that contributes to the achievement, continuity, and enhancement of team effectiveness in unpredictable and challenging environments (Edmondson et al., 2007; Mesmer-Magnus & DeChurch, 2009; Yoo et al., 2022).

Research also emphasises the value of knowledge sharing as a mechanism for enhancing team effectiveness by creating learning opportunities and nurturing member satisfaction. As a result, it is recognised as an essential link between team emergent states and outcomes related to team effectiveness (Wang & Noe, 2010; Zhang et al., 2021). For this reason, organisations often implement knowledge sharing systems to boost their knowledge-driven resources and capabilities. By promoting various forms of interaction, for example socialisation, these systems facilitate the creation of new knowledge, which in turn leads to improved employee performance (Argote et al., 2003; Von Krogh et al., 2001).

In virtual teams, knowledge sharing is crucial due to the lack of face-to-face interaction, which can limit trust and collaboration (Alsharo et al., 2017; Kauppila et al., 2011). These positive effects are reinforced by findings from Wang and Wang (2012) who observed that knowledge sharing supports team performance by improving collaboration, reducing redundancies, and creating alignment on task goals. In addition, virtual teams often rely on digital communication tools, making it essential for team members to share knowledge effectively to overcome the barriers of time zones and cultural differences (Killingsworth et al., 2016). Further studies have shown that trust, motivation, and positive attitudes toward knowledge sharing are essential for fostering collaboration in virtual teams (Chiu et al., 2006).

Applying these insights to HATs is particularly compelling. In HATs, where human members collaborate with AI agents, knowledge sharing bridges the gap between human cognition and AI interpretability. AI systems rely heavily on structured and explicit data. Thus, sharing relevant contextual information helps AI align with human objectives and act as an effective, collaborative team member (Schneider et al., 2021). This structured sharing supports agents in understanding and responding to team needs, contributing to improved team performance. Nevertheless, there is evidence that HATs not only enhance team effectiveness but also introduce unique challenges in communication and coordination that can impact overall performance. Demir et al. (2017), investigating UAS operations tasks, emphasised the critical role of "pushing information", which refers to proactively sharing knowledge, versus "pulling information", which refers to actively seeking knowledge. Their research revealed that HATs demonstrate reduced effectiveness in both behaviours, which contributed to their lower performance relative to human-only teams. These findings highlight a recurring issue where the integration of an AI team member can hinder essential team processes like communication and coordination, ultimately diminishing the team's ability to communicate effectively (Demir et al., 2017; Schmutz et al., 2024), which will be discussed in the next chapter.

However, there is a lack of knowledge sharing research in HAT. Given the fact that knowledge sharing among individuals is essential in traditional and virtual human-only teams, the present work assumes that it is also important in HATs. In conclusion, the proven benefits of knowledge sharing in human teams suggest that similar positive impacts can be expected in HATs. By facilitating a cohesive environment where both human and AI members share relevant information, knowledge sharing can impact team effectiveness. This leads to the hypothesis:

Hypothesis 1: Knowledge sharing between human and AI team members is positively related to team effectiveness.

Hypothesis 1a: Knowledge donating between human and AI team members is positively related to team effectiveness.

Hypothesis 1b: Knowledge collecting between human and AI team members is positively related to team effectiveness.

2.4 Team Coordination in Human-Agent Teams

In team-based work environments, coordination is a fundamental process that allows teams to effectively synchronise their actions and achieve complex, interdependent goals (Salas et al., 2008). Coordination is especially important in settings where team tasks involve high interdependence and uncertainty, as it enables the team to respond collectively to changing requirements (Bergström et al., 2010; Rico et al., 2019). High-performing teams require coordination strategies that support seamless interaction between team members. These mechanisms facilitate not only task alignment but also a shared understanding of team roles and objectives, ensuring that team members work cohesively towards a common goal. This ability of coordinating individual adaptations towards a shared goal is however often absent in multi-agent systems and emerges as a critical characteristic of members in high-performing teams (Schneider et al., 2021).

In defining team coordination, researchers have emphasised the processes by which team members manage interdependencies in tasks, actions, and roles (Espinosa et al., 2004). Team coordination is classified as implicit or explicit (Marques-Quinteiro et al., 2013; Rico et al., 2008). Explicit coordination is characterised by direct communication and structured interaction, including pre-defined schedules, task assignments, and explicit verbal exchanges (Espinosa et al., 2004). This form of coordination is essential in teams where roles and task requirements are well-defined, as it allows team members to actively plan and align their actions to meet specific objectives. In HATs, explicit coordination may involve giving specific instructions to an AI or human team member to ensure synchronised actions, for example directing a sensor operator to adjust settings based on real-time needs (Schneider et al., 2021). Although agent transparency and integrated user interfaces enhance the operator's awareness of agents, thus leading to improved coordination (Stowers et al., 2016), agents often lack an understanding of the operator's perception of the task and situation. Consequently, current AAs depend on explicit communication for coordination with human teammates (Klein et al., 2004; Schneider et al., 2021)

In contrast, implicit coordination relies on unspoken, anticipatory actions based on shared mental models and team cognition, where team members anticipate and adapt to each other's actions without overt communication (Espinosa et al., 2004; Marques-Quinteiro et al., 2013; Rico et al., 2019). Implicit coordination are mechanisms that are derived from shared cognition, which allows team members to predict each other's needs based on their mutual understanding of the task and team dynamics, supporting fluid responses to changing task demands (Espinosa et al., 2004). It relies on the development of a TMS and shared cognition that are developed through team reflection. This allows team members to align their behaviour with the needs of others (Rico et al., 2008). In contrast, teams lacking shared cognition and TMS must rely on explicit coordination, requiring continuous communication of their actions. Evidence from a field study of medical teams demonstrated that improvements in collective memory and shared cognition were associated with reduced reliance on explicit coordination and a corresponding increase in implicit coordination (Riethmüller et al., 2012). Implicit coordination is particularly valuable in high-stakes environments where verbal communication may be limited or infeasible, for instance in emergency response teams or military operations (Marques-Quinteiro et al., 2013; Rico et al., 2019). It enables teams to perform adaptively by encouraging anticipatory actions under high-stress conditions (Marques-Quinteiro et al., 2013; Rico et al., 2008).

While explicit coordination is characterised by structured communication for the purpose of aligning actions (Rico et al., 2019; Schneider et al., 2021), implicit coordination involves multi-functional communication or non-verbal cues that team members interpret within their shared context (Rico et al., 2008). In high-performing teams, both types of coordination are used flexibly depending on situational demands. For example, during routine phases, implicit coordination prevails, while explicit coordination is often reserved for transitions or unexpected events that require more direct intervention (Rico et al., 2019; Schneider et al., 2021).

The importance of team coordination lies in its direct impact on team effectiveness, as it strengthens the team's ability to navigate changing environments and respond to unexpected challenges (Bergström et al., 2010; Rico et al., 2019). Effective coordination promotes shared situational awareness, allowing team members to make real-time adjustments without the need for constant verbal communication, which is crucial in fast-paced scenarios (Demir et al., 2019). In HAT settings, coordination gains importance as AI agents require specific design features to interpret and respond to human intentions in a way that complements human actions. This process helps fostering a feeling of trust and cohesion within the team (Schneider et al., 2021; Talamadupula et al., 2014). The significance of coordination in HATs is not only to improve performance but also to ensure that AI agents function as cooperative team members rather than mere tools, thus enhancing overall team functioning (Demir et al., 2019).

In traditional human-only teams, tasks of significant complexity or criticality necessitate collaboration because they require a diverse range of skills, knowledge, and abilities that exceed the capacity of any single operator. In order to allow them to manage complex tasks, human teams are intentionally composed of members with varied expertise. This helps to enhance cognitive and physical capacity (Cooke et al., 2013; Salas et al., 1992). The dynamics in teams are shaped by interpersonal skills, including social sensitivity and emotional engagement, alongside intensive role-specific training that promotes interdependent work patterns (Delise et al., 2010). Effective coordination in those teams often involves both explicit communication through direct verbal instructions and implicit coordination, where team members anticipate each other's needs based on shared mental models and task familiarity. As teams grow familiar with tasks and each other, coordination typically shifts from explicit to implicit over time, enhancing efficiency and reducing cognitive load during critical task phases (Espinosa et al., 2004; Strack et al., 2011).

Conversely, HATs introduce AAs that, while capable of performing specialised tasks, face limitations in adapting flexibly to team coordination demands. Unlike human teammates, agents lack natural social awareness and intuitive understanding of implicit cues. Therefore, they necessitate structured and explicit communication from human members to synchronise tasks effectively. Current AAs require precise commands, as they are unable to adapt their responses based on subtle contextual cues (Klein et al., 2004). This reliance on explicit communication during time-sensitive phases can increase the cognitive and operational load on human team members, as it shifts coordination costs to critical action phases rather than allowing for implicit adjustments common in human teams (Schneider et al., 2021). As Schneider et al. (2021) noted, for AAs to integrate into high-performing teams, they must evolve to support implicit coordination structures and intent inference capabilities, which could eventually reduce the explicit communication burden within HATs.

The benefits of effective coordination extend beyond task performance, as it also fosters adaptability, shared mental models, and situational awareness. Coordinated teams have been shown to excel in high-pressure contexts due to their ability to manage task dependencies and rapidly adjust their strategies in response to new information (Rico et al., 2019). In HATs, coordination facilitates the integration of AI agents into the team's cognitive processes which promotes trust among human teammates. This, in turn, leads to improved task efficiency and reduced error rates, as human operators are less burdened with the need to constantly monitor and guide AI actions (Schneider et al., 2021).

Team coordination's impact on effectiveness is well-documented, especially in settings that require rapid response to environmental changes. For instance, Bergström et al. (2010) demonstrated that well-coordinated teams in escalating scenarios exhibit superior capacity to regulate task progression and mitigate cognitive overload, which is essential for sustaining performance under pressure. Furthermore, the coordination of actions both within and across component teams has been identified as a crucial factor influencing the performance of multiteam systems (Rico et al., 2018). In HATs, studies indicated that coordination is essential for team effectiveness and resilience, as it supports the adaptability of AI agents to adjust to human collaborators' strategies and objectives as needed. This adaptability is key to enhancing team cohesion and reducing the risks associated with AI misinterpretation of human intentions, which could otherwise hinder team performance (Demir et al., 2019). Dell'Acqua et al. (2023) observed that replacing a human team member with an AI agent in a video game context resulted in heightened coordination failures and diminished performance, particularly among low- and medium-skilled teams, due to decreased effort from human members. Similarly, Johnson et al. (2023) identified communication challenges in HATs under degraded conditions, emphasising that coordination training significantly improved performance, especially in underperforming HATs. Furthermore, Demir et al. (2017) found that HATs demonstrated poorer coordination and performance compared to both novice and expert human-only teams. These studies collectively indicate that coordination within HATs significantly influences team effectiveness. Challenges including failure in coordination, communication breakdowns, and reduced effort among human members underscore the pressing need for effective coordination strategies to enhance effectiveness in HATs.

Given the growing reliance on AI in collaborative work environments, studying coordination in HATs is crucial to understand its role on the relationship of knowledge sharing and team effectiveness, particularly how interaction patterns between human and AI agents influence team outcomes. Recognising that coordination significantly affects team performance, this section explores how implicit and explicit coordination might moderate the relationship between knowledge sharing and team effectiveness in HATs. Two hypotheses are presented, supported by theoretical reasoning and empirical evidence, to illustrate how coordination mechanisms can increase the positive effects of knowledge sharing on team effectiveness. This study claims that both implicit and explicit coordination strengthen the relationship between knowledge sharing and team effectiveness in HATs. Implicit coordination is especially important in environments with temporal or technical interdependencies, enabling team members to adapt swiftly without excessive communication (Espinosa et al., 2007). This coordination style boosts knowledge sharing by allowing information to flow smoothly without the need for constant verbal communication, thus freeing up cognitive resources and facilitating rapid responses to changes in the environment (Demir et al., 2017; Demir et al., 2019; Schneider et al., 2021). In highly interdependent tasks, implicit coordination fosters a proactive approach, wherein team members anticipate each other's needs and intentions. This promotes quicker adaptation and cohesive action (Rico et al., 2019). While explicit coordination requires time and cognitive resources, implicit coordination operates without verbal communication, which helps teams conserve resources for immediate tasks and decisions, thus fostering greater efficiency in team performance (Marques-Quinteiro et al., 2013).

Empirical research supports the idea that implicit coordination reinforces team effectiveness, especially in high-stakes or complex environments where explicit communication can slow down operations. Marques-Quinteiro et al. (2013) found that police tactical teams performing in high-stress, nonroutine environments benefit significantly from implicit coordination, as it allows team members to anticipate one another's actions without verbal cues. Lowry et al. (2013) demonstrated that teams utilising shared cognition and implicit coordination perform better than those relying on explicit coordination alone. Consequently, implicit coordination is associated with improved team effectiveness, as it allows teams to allocate more time and cognitive resources to task-related activities. Similarly, in HATs, implicit coordination structures are crucial for AI agents to interpret human behaviours and adjust accordingly. Studies by Demir et al. (2017) and Demir et al. (2019) presented that teams with a high degree of implicit coordination achieved better performance due to their ability to maintain stable and adaptable communication patterns in high demand tasks. This approach reduced cognitive demands on human operators, allowing them to focus on higher-order decision-making while AI systems flexibly adapted to changes in the task environment. However, Demir et al. (2019) revealed in their study that synthetic teams exhibited rigid team coordination dynamics due to their inability to anticipate their team members' needs. Therefore, they struggled to adjust to environmental changes. This inability and the inflexible team processes appeared to be related to low performance in this context. For this reason, if AI agents are to function effectively in teams, they must be able to interact adaptively, anticipate team members' needs, and communicate constructively (Demir et al., 2019). Additionally, Espinosa et al. (2007) indicated that implicit coordination enhances team performance in geographically distributed software development team, where frequent explicit communication is impractical, and task awareness is paramount for effective coordination. These findings suggest that implicit coordination will strengthen the positive impact of knowledge sharing on effectiveness in HATs by designing AI agents that are not only proficient in task execution, but also overcome their lack of cognition and awareness, and therefore to leverage implicit coordination. This ability is the foundation for improving their effectiveness as collaborative teammates with humans and allowing HATs to become high-performing teams, especially in time-critical execution periods (Burke, 2004; Marlow et al., 2018; Schneider et al., 2021; Stout et al., 1999). Therefore, this study hypothesises the following:

Hypothesis 2: Implicit coordination strengthens the positive relationship between knowledge sharing and team effectiveness in HATs.

Hypothesis 2a: Implicit coordination strengthens the positive relationship between knowledge donating and team effectiveness in HATs.

Hypothesis 2b: Implicit coordination strengthens the positive relationship between knowledge collecting and team effectiveness in HATs.

Explicit coordination mechanisms, like schedules and task assignments, are crucial for managing complex tasks, as they ensure team members have clear, actionable information to coordinate complex tasks effectively (Espinosa et al., 2007). This systematic approach reinforces the alignment of knowledge sharing with team goals and clarifies task dependencies, leading to improved overall performance (Espinosa et al., 2004).

Studies demonstrated that explicit coordination is beneficial in settings where task complexity and team diversity demand high levels of organised communication (Rico et al., 2019). Espinosa et al. (2004) found that teams performing interdependent tasks achieved better outcomes when explicit coordination structures, such as schedules and formal planning sessions, were used to organise task dependencies and communication flows. Furthermore, Espinosa et al. (2007) revealed that in geographically dispersed teams, explicit coordination is crucial for maintaining awareness and managing interdependent tasks effectively. This coordinated approach was shown to improve team performance by providing a reliable communication framework, reducing ambiguity, and ensuring alignment on task responsibilities. While explicit communication is beneficial for team performance, as confirmed by a meta-analysis of 150 studies conducted by Marlow et al. (2018), it can become a challenge in time-sensitive environments where high-speed execution constrains the ability to communicate coordinating information (Entin & Serfaty, 1999). To support this, Konradt et al. (2021) argued that continued reliance on explicit coordination may hinder improvements in team performance, as it demands greater time and cognitive resources for managing interactions. Compared to implicit coordination, this approach reduces the time available for core task activities such as problem-solving, diminishing team efficiency and effectiveness. Additionally, explicit coordination without any implicit coordination mechanism is highly uncommon in human-to-human communication (Schneider et al., 2021).

In the context of HAT, nevertheless, explicit coordination is crucial for integrating AI agents into human-led teams, because structured communication protocols improve the AI's ability to operate in sync with human teammates and reduced the cognitive load on human operators (Espinosa et al., 2004; Strack et al., 2011). Furthermore, research by Talamadupula et al. (2014) indicated that explicit coordination strategies in human-robot teams help clarify task expectations. This allows AI agents to perform effectively within defined roles while humans are enabled to focus on strategic aspects of the task. Consequently, explicit coordination is expected to enhance the effect of knowledge sharing on team effectiveness due to the positive effects in human-only teams as well as the AI agents' current lack of anticipating other's needs (Demir et al., 2019). Therefore, the following hypothesis is suggested:

Hypothesis 3: Explicit coordination strengthens the positive relationship between knowledge sharing and team effectiveness in HATs.

Hypothesis 3a: Explicit coordination strengthens the positive relationship between knowledge donating and team effectiveness in HATs.

Hypothesis 3b: Explicit coordination strengthens the positive relationship between knowledge collecting and team effectiveness in HATs.

These hypotheses propose that both implicit and explicit coordination serve as moderators in the relationship between knowledge sharing and team effectiveness in HATs. Coordination is recognised as a key process essential for team effectiveness and is fundamental to realising the goal of teams composed of both humans and AI (Schneider et al., 2021). Explicit coordination has a dual effect on team performance. While essential for effective task processing and achieving performance goals, it can be costly in terms of time and resources, potentially limiting performance improvement over time (Konradt et al., 2021; Marques-Quinteiro et al., 2013). In line with previous research, high-performing teams are expected to gradually rely less on explicit coordination, favouring implicit coordination as they develop, which can enhance efficiency in the long run (Riethmüller et al., 2012). Together, these hypotheses aim to provide a comprehensive understanding if coordination mechanisms can strengthen the effect of knowledge sharing on team effectiveness in HATs.

2.5 Conceptual Model

To advance existing literature on HAT, this study is aimed to examine the relationship between knowledge sharing behaviours and team effectiveness in HATs, and the potential moderating effect of implicit and explicit coordination. This study hypothesises that knowledge donating (*H*1a) and knowledge collecting (*H*1b) between human and AI team members is positively associated with team effectiveness in HATs. Additionally, implicit coordination and explicit coordination are expected to strengthen these positive relationships as moderating variables (*H*2, *H*3). By investigating these hypotheses, this study contributes to the understanding of the relationship between knowledge sharing processes, team coordination, and team effectiveness in HATs. The research model guiding this investigation is illustrated in Figure 2.1.

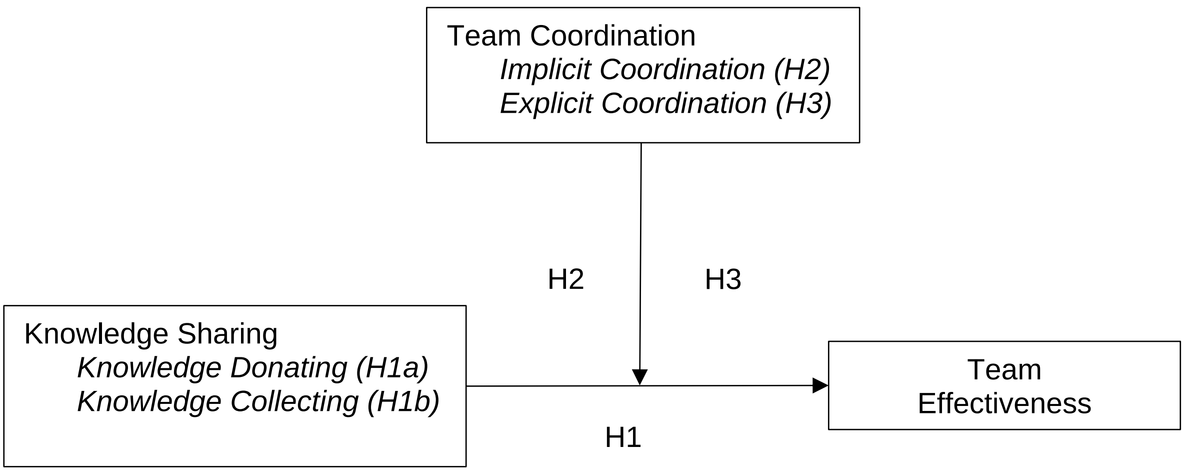

Figure 2.1: *Research Model*

3. Methodology

3.1 Sample and Procedure

This correlational study employs a quantitative research design using an online survey to examine human team members' and leaders' perceptions of dynamics within HATs on a team level. This approach can be justified due to limited access to existing HATs. Many organisations have not yet fully integrated AI agents as active team members but rather as supporting tools (e.g., Schmutz et al., 2024) which makes it difficult to study HATs in real-world settings.

Perceptual evaluations allow the researchers to investigate attitudes and expectations in teams where HATs are not yet operational. By asking participants to imagine working with an AI agent, this study can simulate how teams might function when an AI agent is introduced. For instance, participants consider how they would share knowledge, coordinate tasks, and evaluate team effectiveness in a hypothetical HAT.

The survey was designed on Qualtrics and offered in three languages: English, Portuguese, and German. Participants were asked to imagine working with an AI agent integrated into their team and provide responses based on this scenario. To ensure they clearly understand the research purpose and context, a detailed introduction was provided (see Annex A and B). The survey was part of a broader research project conducted by several researchers from the ISCTE Business School which explains why it included additional questions than those analysed in the present study.

The sampling approach used was non-probabilistic and convenience-based, targeting teams known to the researchers and easily accessible. Participant recruitment targeted companies in knowledge-based industries, operating in IT or consulting, which are likely to engage with HATs in the future. The sample included teams with at least two members and one designated team leader, selected for their involvement in collaborative projects to ensure robust team functioning. To capture a holistic team-level perspective, distinct versions of the questionnaire were distributed to team members and leaders. This approach reduces common methods variance by collecting data from diverse sources, respectively team members and team leaders (Fuller et al., 2016; Podsakoff et al., 2003). Team members provided information on knowledge sharing behaviours and team coordination, while team leaders evaluated team effectiveness both in traditional human-only contexts and HATs. By sourcing predictor and outcome variable from different respondents, the study minimises the risk of inflated relationships due to common method bias (Fuller et al., 2016; Podsakoff et al., 2003). As Podsakoff et al. (2003) emphasised, separating measurement sources is a key procedural remedy for reducing common method variance, and as Fuller et al. (2016) highlighted, these design choices can significantly reduce potential biases in business research settings. Finally, the data were aggregated at the team level to ensure theoretical alignment between the level of measurement and the level of analysis (Costa et al., 2013, 2015). This approach strengthens the validity of the results and provides a more robust basis for team-level analyses.

Each team received a unique questionnaire link, enabling responses to be accurately grouped and analysed at the team level. Confidentiality was ensured during the data collection process, with all responses anonymised during data analysis. This helped fostering openness and reducing social desirability bias. Additionally, participants completed their questionnaires independently, mitigating the risk of response bias caused by influence from other team members.

A total of 31 teams took part in the survey. However, two of the teams were excluded from the sample because they consisted of only one team member each. Therefore, the final sample comprised 29 teams, consisting of 115 team members and 29 leaders. The team size reached from 2 to 8 members with an average team size of 3.97 individuals per team. The sample consisted of 53.0% female and 45.2% male, with 1.7% not having inserted any value. The mean age of team members was 33.18 years (*SD* = 8.68 years). The most significant nationalities in the sample were German (35.7%) and Portuguese (31.3%), together making up 67.0% of the respondents. Additionally, the Dutch (13.9%) represented a notable portion, while other nationalities each account for less than 3% of the total sample. The majority of employees have been with the company for 1 to 3 years (39.1%), followed by those with less than 1 year (21.7%). Together, these groups make up 60.8% of the workforce. 14.8% of employees have been with the company for more than 5 years. On average, the company affiliation was approximately 3 years (*M* = 2.54, *SD* = 1.33). In addition, 91.3% of participants reported that they do not have any AI agent in their team, although the answers differed within the teams.

Among the leaders, 55.2% were female and 44.8% male. The most represented age groups were 34 and 41 years, each comprising 13.8% of the sample, with an average age of 40.5 years (*SD* = 8.5 years). Most leaders were German (27.6%) and Portuguese (27.6%), making up more than half of the sample. Other notable nationalities include Dutch (17.2%) and British (10.3%), while the remaining leaders represented diverse backgrounds, each accounting for 3.4% of the total. Nearly half of the leaders (48.3%) have been with the organisation for more than 7 years, followed by 24.1% with 5 to 7 years and 20.7% with 1 to 3 years, while none have a tenure of less than 1 year. On average, leaders have been with the company for 6 years (*M* = 4.00, *SD* = 1.20).

3.2 Measures

All variables were measured using 7-point Likert-type scales (1 = *strongly disagree* to 7 = *strongly agree*) to allow for finer discrimination in responses. The independent variables defined in this work included knowledge sharing and team coordination. The dependent variable was team effectiveness. Additionally, a reliability analysis was conducted to determine the consistency of the scales.

Knowledge Sharing

Knowledge sharing was assessed from the team members' perspective using two behaviour scales of knowledge sharing, knowledge collecting and knowledge donating. The scales were adapted from van den Hooff and Hendrix (2004) (see also de Vries et al., 2006; van den Hooff & Ridder, 2004). This set of question was introduced by a scenario where this team would be collaborating with not only their human colleagues but also an AI agent as part of their team. They were asked to reflect on how working in a team with human and non-human team members might impact their behaviour.

Knowledge collecting, which captures behaviours focused on seeking information from others, was measured with the following items: “When I need certain knowledge, I would ask my colleagues about it”; “I would like to be informed of what my colleagues know”; “I would ask my colleagues about their abilities when I need to learn something”; “When a colleague is good at something, I would ask them to teach me how to do it”.

Knowledge donating, which reflects behaviours where individuals actively share their own expertise, was measured with these items: “When I’ve learned something new, I would tell my colleagues about it”; “I would share information I have with my colleagues”; “I think it is important that my colleagues know what I am doing”; “I would regularly tell my colleagues what I am doing”.

In this study, the Cronbach’s alpha for knowledge collecting was .88, while for knowledge donating it was .84.

Team Coordination

The moderating variable of team coordination was assessed using a shortened version of the explicit and implicit coordination scales. The set of questions on team coordination was answered by the team members.

Explicit coordination, which evaluates structured communication and planning efforts within teams, was measured using a five-items scale developed by Lewis (2004) (see also Konradt et al., 2021; Rico et al., 2019): “Our team works in a well-coordinated manner”; “Our team has very few misunderstandings about what to do”; “Our team often needs to go back and start over (R)”; “We perform tasks smoothly and efficiently”; “There is a lot of confusion about how to perform tasks (R)”.

Implicit coordination, capturing the unspoken alignment of actions and anticipation of team members' needs, was measured using the following three items adapted by Rico et al. (2008) (see also Marques-Quinteiro et al., 2013): “We anticipate what each team member does / needs at a given moment”; “We adjust our behaviour to anticipate the actions of other members”; “We synchronise our work with minimal necessary communication”. Those items reflect on the two components of implicit coordination, namely anticipatory behaviour and dynamic adjustment behaviours as suggested by Rico et al. (2008). As the questionnaire comprised questions from various researchers, the original 17-item scale for implicit coordination was shortened to reduce the time required for participants to complete it.

In this study, the explicit coordination scale had a Cronbach’s alpha of .69, while the implicit coordination scale had a Cronbach’s alpha of .79.

Team Effectiveness

The dependent variable team effectiveness was measured twice. First, the general team effectiveness scale was evaluated, consisting of five items developed by Costa et al. (2015) and González-Romá et al. (2009). Secondly, the team effectiveness scale within HAT was measured using an eight-item scale developed based on the team effectiveness concept by Mathieu and Gilson (2012) and adapted from Costa et al. (2015) and González-Romá et al. (2009). These sets of questions were evaluated exclusively by team leaders. This approach has been employed in previous research to obtain an objective and comprehensive evaluation (e.g., Marques-Quinteiro et al., 2013). The team effectiveness measure in HAT was introduced by a scenario where the leader would be leading a team consisting of not only their human team members but also an AI agent as part of their team. They were asked to reflect on how leading this team with human and non-human team members might impact their behaviour and the team effectiveness.

The team effectiveness variable in HATs was measured using the following items: "When an AI agent is integrated into the team, the quality of the work will increase"; "When an AI agent is integrated into this team, the quantity of the work will increase"; "When an AI agent is integrated into this team, the general effectiveness will increase"; "When an AI agent is integrated into this team, it will be more productive"; "When an AI agent is integrated into this team, it will be more efficient"; "When an AI agent is integrated into this team, team members could work well on future projects"; "When an AI agent is integrated into this team, team members will be satisfied working together"; "When an AI agent is integrated into this team, the team members would be willing to continue working in this team". This scale captures performance-related outcomes, team satisfaction, and viability. In this study, the Cronbach's alpha was .92.

The general team effectiveness scale consisted of the following items: "This team has a good performance"; "Members are satisfied in working in this team"; "This team is effective"; "I would not hesitate to ask this team to work on other projects"; "This team could work well on future projects". The Cronbach's alpha for this variable was .80.

For the data analysis in this study only team performance as one measure of team effectiveness was analysed. Team performance is related to the tangible outputs of a team (Cohen & Bailey, 1997; Yoo et al., 2022) and determines how the team works. This approach was chosen due to difficulties in finding significant results for team effectiveness. Team performance, therefore, was assessed in both human-only teams and hypothetical HAT scenarios.

For the traditional team performance measure which refers to the leaders' current team performance assessment of the human-only team (status quo), the following items were used, developed by González-Romá et al. (2009): "This team has a good performance"; "This team is effective". The intercorrelation was .40 (p = .025).

Additionally, the more modern approach for team performance in HATs was measured, using the five performance-related items adapted from Mathieu and Gilson (2012): “When an AI agent is integrated into the team, the quality of the work will increase”; “When an AI agent is integrated into this team, the quantity of the work will increase”; “When an AI agent is integrated into this team, the general effectiveness will increase”; “When an AI agent is integrated into this team, it will be more productive”; “When an AI agent is integrated into this team, it will be more efficient”. For this variable, the Cronbach’s alpha was 0.88.

Control Variables

In addition to the primary variables under investigation, one control variable was incorporated into the analysis to account for potential confounding factors that may influence the relationship between knowledge sharing, team coordination, and team performance. Specifically, the presence of an AI agent within the team was assessed to determine whether the respective teams could be classified as HATs.

4. Results

4.1 Aggregation

Given the team-focus of the study, collected individual responses were aggregated at the team level (Costa et al., 2013). To assess the appropriateness of this aggregation process, the within-group agreement index, rwg(j), was computed. A commonly used threshold for adequate agreement is a mean rwg(j) of .70 or higher (James et al., 1993), though this benchmark has been criticised as arbitrary. Biemann et al. (2012) highlighted a key limitation of rwg(j), namely the uncertainty surrounding the choice of a null distribution for comparison. They defined finer gradations for the within-group agreement. Values between .00 and .30 show a lack of agreement. Values ranging from .00 to .30 indicate a lack of agreement; values between .31 and .50 reflect weak agreement; values from .51 to .70 represent moderate agreement; values between .71 and .90 indicate strong agreement; and values from .91 to 1.00 demonstrate very strong agreement. In the present study, these categorical assessments of agreement strength from Biemann et al. (2012) are adopted.

The mean rwg(j) values were calculated for four key constructs: Explicit coordination, implicit coordination, knowledge donating, and knowledge collecting. For all variables, a sample of 29 teams was included in the analysis. The mean rwg(j) for explicit coordination was .82, with scores ranging from −.12 to 1.00. Approximately 79.3% of teams had values ≥ .70, indicating strong levels of agreements across most teams. 6.9% reported weak agreement of which one team scored below zero which suggests a lack of agreement. Implicit coordination had a slightly higher average agreement (rwg(j) = .85), with values between .11 and 1.00. The distribution revealed that 86.2% of teams had rwg(j) scores above .70, supporting strong team-level convergence. Again, 6.9% of the values indicate weak to no agreement. Regarding knowledge donation, the mean rwg(j) was .82, ranging from .22 to 1.00. Although the lower end suggests some teams lacked consensus with 3.4% and showed weak agreement with 6.9%, the vast majority of teams demonstrated moderate to strong agreement, with 89.7% of values of 0.62 or higher. For knowledge collection, the average rwg(j) was .83, with scores ranging from .05 to 1.00. Like the other constructs, a large proportion of teams displayed moderate (6.9%) and strong agreement levels (86.2%), while a few outliers suggested weak within-group agreement (3.4%) or even lack of agreement (3.4%).

Overall, these results support the aggregation of individual scores to the team level for these constructs. As the number of cases with weak or no agreement is limited, it was decided to include these teams on the assumption that their inclusion would not significantly affect the overall results.

4.2 Hypotheses Testing

Table 4.1 displays the correlations, means, and standard deviations for the study variables. Due to the lack of AI agents within the teams, it can be concluded that there is no variability within the teams at the moment. Therefore, the control variable *Presence of AI agents within the team* is not shown in Table 4.1. Significant positive correlations were found between the knowledge sharing behaviours and coordination variables. Specifically, knowledge donating was positively correlated with knowledge collecting (r = .554, p = .002), explicit coordination (r = .549, p = .002), and implicit coordination (r = .403, p = .028). Similarly, knowledge collecting was strongly associated with explicit coordination (r = .624, p < .001) and implicit coordination (r = .484, p = .008). Notably, explicit coordination and implicit coordination also showed a strong, positive correlation (r = .795, p < .001). In contrast, neither team performance in human-only teams nor team performance in HATs showed significant correlations with the knowledge sharing or coordination variables. Traditional and HAT performance ratings marginally correlated (r = −.403, p = .030).

Table 4.1

Correlations and Descriptive Statistics

	M	*SD*	1	2	3	4	5	6
1. Knowledge donating	5.48	0.45	1					
2. Knowledge collecting	5.72	0.47	.55**	1				
3. Explicit coordination	5.04	0.67	.55**	.62***	1			
4. Implicit coordination	4.55	0.65	.40*	.48**	.80***	1		
5. Team performance	5.62	0.64	.18	.22	.26	.20	1	
6. HAT performance	4.81	1.11	−.02	−.01	.15	.13	.40*	1

Note. n = 29 teams.

***p < 0.001; **p < 0.01; *p < 0.05.

Table 4.1 additionally provides information on a direct relationship between knowledge sharing (*H*1), which is operationalised via knowledge donating (*H*1a) and collecting (*H*1b), and team performance. Contrary to expectations, the results do not provide support for Hypothesis 1a, which predicted a positive relationship between knowledge donating and team performance. Knowledge donating showed a weak and nonsignificant correlation with both team performance in human-only teams (r = .183, p = .342) and in HATs (r = −.023, p = .904). Similarly, Hypothesis 1b, which focused on knowledge collecting, was not supported. The correlations between knowledge collecting and both team performance in human-only teams (r = .216, p = .261) and in HATs (r = −.007, p = .970) were close to zero and statistically nonsignificant. These findings suggest that while knowledge donating and collecting are conceptually and empirically linked to each other and to coordination processes, their direct association with team performance, whether in traditional teams or HATs, may be limited or potentially influenced by additional moderating or mediating factors.

To test Hypothesis 2 and 3 and therefore potential moderation effects of explicit and implicit coordination on the relationship between knowledge donating and team performance, as well as between knowledge collecting and team performance, PROCESS, a computational tool designed for the analysis of conditional process models (Hayes, 2022), was used. PROCESS applies ordinary least squares (OLS) regression to estimate model coefficients and supports the use of bootstrapping techniques. Bootstrapping is a resampling technique that repeatedly draws samples from the data to estimate the sampling distribution of a statistic to provide stronger inference, particularly with small sample sizes (Marques-Quinteiro et al., 2013). According to Hayes (2012), the use of PROCESS offers several advantages over traditional regression methods. PROCESS can test moderation and mediation effects simultaneously, does not require the assumption of normally distributed sampling distributions, can reduce the number of statistical tests and thus the risk of Type I errors, and has greater statistical power than traditional methods such as the Sobel test, especially in smaller samples. Due to the smaller sample size in the present study, this approach was considered appropriate to test Hypothesis 2 and 3 and examine whether the effects of knowledge donating and collecting on team performance were moderated by the levels of explicit or implicit coordination. All the models were tested with a sample size of 29 teams (n = 29).

First, Hypothesis 2a was tested which proposed that implicit coordination strengthens the positive relationship of knowledge donating on team performance. To assess this potential interaction effect, knowledge donating was entered as the independent variable (X), traditional team performance as the dependent variable (Y), and implicit coordination as the moderator (W). The overall model was not statistically significant, $F(3, 25) = 1.59$, $p = .217$, explaining 16.0% of the variance in team performance ($R^2 = .160$). The interaction term between knowledge donating and implicit coordination was also not statistically significant (b = 0.79, SE = 0.44, t = 1.78, p = .088, 95% *CI* [−0.12, 1.70]), although it approached significance. The simple slope analysis further revealed that the conditional effect of knowledge donating on team performance varied across levels of implicit coordination but did not reach statistical significance at any level. At low levels of implicit coordination, the relationship was negative and nonsignificant (-1 *SD:* b = −0.21, p = .567, 95% *CI* [−0.94, 0.53]). At the mean level of implicit coordination, the relationship was positive but nonsignificant (*M:* b = 0.30, p = .312, 95% *CI* [−0.30, 0.91]). At high levels of implicit coordination, the relationship was stronger and marginally significant (+1 *SD:* b = 0.81, p = .089, 95% *CI* [−0.13, 1.76]). This indicates a potential positive effect of knowledge donating on performance when implicit coordination is high. The coefficients for the main effects were likewise nonsignificant. Knowledge donating showed no significant association with team performance (b = −3.28, p = .107), nor did implicit coordination (b = −4.31, p = .099). Taken together, these results suggest that implicit coordination does not significantly moderate the relationship between knowledge donating and traditional team performance in this sample. Therefore, Hypothesis 2a is not supported. Although the interaction between knowledge donating and implicit coordination did not reach statistical significance, the marginal p-value of .088, and the direction of the conditional effects suggest a potential positive moderation trend. Specifically, knowledge donating tended to strengthen team performance when implicit coordination was high, whereas this relationship was negligible or even negative when implicit coordination was low.

When considering team performance in HATs, the findings were similar, though even less supportive. The overall model was not statistically significant, $F(3, 25) = 0.40$, $p = .753$, $R^2 = .046$. The interaction effect between knowledge donating and implicit coordination was again nonsignificant (b = −0.61, SE = 0.81, t = −0.75, p = .460, 95% *CI* [−2.28, 1.06]). This indicates that there is no statistical evidence of a moderating effect. Furthermore, neither the main effect of knowledge donating (b = 2.45, p = .503) nor implicit coordination (b = 3.74, p = .426) significantly predicted team performance in HATs. These results suggest that, like traditional teams, implicit coordination does not significantly moderate the effect of knowledge donating on team performance in HATs.

Hypothesis 2b suggested that implicit coordination strengthens the positive relationship of knowledge collecting on team performance. In this model, knowledge collecting was specified as the independent variable (X), traditional team performance as the dependent variable (Y), and implicit coordination as the moderator (W). The overall model was not statistically significant, $F(3, 25) = 0.61$, $p = .617$, and accounted for 6.8% of the variance in traditional team performance ($R^2 = .068$). The interaction between knowledge collecting and implicit coordination was nonsignificant ($b = -0.20$, $SE = 0.43$, $t = -0.47$, $p = .642$, 95% CI [−1.08, 0.68]), indicating that implicit coordination does not significantly moderate the relationship between knowledge collecting and team performance. Neither the main effect of knowledge collecting ($b = 1.16$, $p = .576$) nor that of implicit coordination ($b = 1.27$, $p = .607$) reached statistical relevance.

A similar pattern of results emerged for team performance in HATs. The overall model was again not statistically significant, $F(3, 25) = 0.60$, $p = .619$, $R^2 = .068$. The interaction effect between knowledge collecting and implicit coordination was nonsignificant ($b = -0.79$, $SE = 0.74$, $t = -1.08$, $p = .291$, 95% CI [−2.31, 0.72]). Likewise, the main effects of knowledge collecting ($b = 3.53$, $p = .325$) and implicit coordination ($b = 4.83$, $p = .263$) did not reach statistical importance. Thus, the findings from both traditional teams and HATs consistently suggest that implicit coordination does not significantly moderate the relationship between knowledge collecting and team performance. Hypothesis 2b is not supported in either context.

Hypothesis 3a posited that explicit coordination strengthens the relationship between knowledge donating and team performance. Knowledge donating was entered as the independent variable (X), team performance as the dependent variable (Y), and explicit coordination as the moderator (W). The overall model was marginally significant, $F(3, 25) = 2.77$, $p = .063$. It accounted for approximately 24.95% of the variance in traditional team performance ($R^2 = .250$). The interaction term between knowledge donating and explicit coordination was significant ($b = 1.19$, $SE = 0.48$, $t = 2.45$, $p = .022$, 95% CI [0.19, 2.18], see also Table 4.2), indicating a moderation effect. The simple slope analysis showed that the relationship between knowledge donating, and team performance varied depending on the level of explicit coordination. At low levels of explicit coordination, the relationship was negative and nonsignificant (-1 SD: $b = -0.65$, $p = .136$, 95% CI [–1.51, 0.22]). This indicates that when explicit coordination was low, increased knowledge donating was not associated with higher team performance and may even have had a detrimental effect. At the mean level of explicit coordination, the relationship was positive but not statistically significant (M: $b = 0.14$, $p = .629$, 95% CI [–0.47, 0.76]). This suggests no significant association between knowledge donating and performance under average coordination conditions. However, at high levels of explicit coordination, the relationship between knowledge donating and team performance was positive and statistically significant (+1 *SD*: *b* = 0.94, *p* = .051, 95% *CI* [–0.01, 1.88]). This implies that knowledge donating tended to strengthen traditional team performance when teams engaged more strongly in explicit coordination (see Table 4.2 and Figure 4.1). These results provide support for Hypothesis 3a.

Table 4.2

Results of Moderation Analysis (Hypothesis 3a)

Predictor variable	*b*	*SE*	*t*	*p*
DV: Team performance; R^2 = .250; *p* = .063				
Constant	35.66	12.98	2.75	.011
Knowledge donating	−5.82	2.43	−2.30	.024
Explicit coordination	−6.16	2.61	−2.36	.027
Knowledge donating * Explicit coordination	1.19	0.48	2.45	.022
Explicit coordination conditional indirect effect at Knowledge donating = *M* ± 1 *SD*	Unstandardised boot indirect effects	Boot *SE*	Boot LLCI	Boot ULCI
-1 *SD*	0.65	0.42	−1.51	0.22
M 0.00	0.14	0.30	−0.47	0.76
+1 *SD*	0.94	0.46	−0.01	1.88

Note. Listwise *n* = 29. DV = Dependent variable; LL = lower limit; CI = Confidence interval; UL = upper limit. Bootstrap sample size = 5,000. All predictor variables were mean-centred.

When examining team performance in HATs, the results did not support a moderating effect of explicit coordination. The overall model was not statistically significant, *F*(3, 24) = 0.30, *p* = .822, R^2 = .037. The interaction between knowledge donating and explicit coordination was also nonsignificant (*b* = 0.03, *SE* = 0.98, *t* = 0.03, *p* = .976, 95% *CI* [−1.88, 2.01]). Furthermore, neither knowledge donating (*b* = −0.50, *p* = .919) nor explicit coordination (*b* = 0.22, *p* = .968) were relevant predictors of team performance in HATs. These findings suggest that, unlike in traditional teams, explicit coordination does not significantly influence the effect of knowledge donating on performance in the context of human-AI collaboration. Unlike implicit coordination, which showed no significant interaction in the prior analysis, explicit coordination does appear to significantly strengthen the effect of knowledge donating on team performance in traditional teams. Therefore, Hypothesis 3a is supported in the context of traditional team performance, but not for HATs.

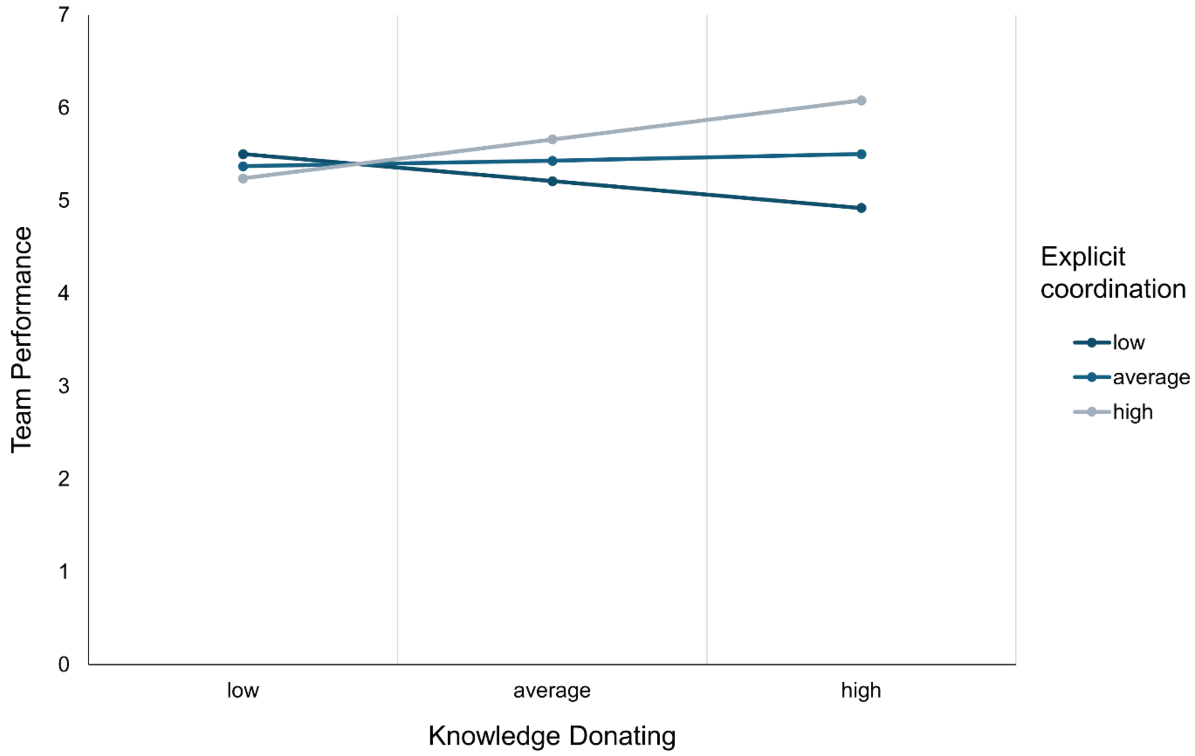

Figure 4.1: *Graph for the two-way interaction (Hypothesis 3a)*

Hypothesis 3b proposed that explicit coordination strengthens the positive effect of knowledge collecting on team performance. In this model, knowledge collecting served as the independent variable (X), team performance as the dependent variable (Y), and explicit coordination as the moderator (W). The overall model did not reach statistical significance, $F(3, 25) = 0.66$, $p = .585$, $R^2 = .073$. The interaction effect between knowledge collecting and explicit coordination was also not significant ($b = -0.07$, $SE = 0.43$, $t = -0.17$, $p = .870$, 95% CI [−0.95, 0.81), suggesting that explicit coordination does not significantly alter the impact of knowledge collecting on team performance. Additionally, the direct effects of both knowledge collecting ($b = 0.49$, $p = .831$) and explicit coordination ($b = 0.59$, $p = .808$) show no statistical significance, indicating no meaningful predictive value on their own within this model.

When analysing team performance in HATs, the pattern of results was similar. The model was not statistically significant, $F(3, 25) = 0.35$, $p = .789$, $R^2 = .040$. The interaction between knowledge collecting and explicit coordination was again nonsignificant ($b = -0.01$, $SE = 0.75$, $t = -0.02$, $p = .986$, 95% CI [−1.55, 1.53]), and neither the main effect of knowledge collecting ($b = -0.32$, $p = .937$) nor explicit coordination ($b = 0.50$, $p = .907$) showed a statistically significant relationship with performance in HATs.

Overall, the results indicate that explicit coordination does not moderate the relationship between knowledge collecting and team performance whether in traditional team contexts or in HATs in this study. In contrast to the previously observed significant interaction between knowledge donating and explicit coordination, the present analysis revealed that the effect of knowledge collecting on traditional team performance was not moderated by explicit coordination, as evidenced by a nonsignificant interaction term. Hypothesis 3b therefore is not supported.

Finally, no statistically significant interactions were found between knowledge sharing behaviours and coordination in predicting HAT-specific team performance. This further underscores the complexity of knowledge processes and team dynamics in HATs and highlights the potential need for further investigations in the future.

5. Discussion

This study aimed to investigate if knowledge sharing between human and AI team members is positively related to team effectiveness in HATs, and whether this relationship is moderated by coordination mechanisms. Specifically, the distinct knowledge sharing behaviours of donating and collecting, as conceptualised by de Vries et al. (2006) and van den Hooff and Ridder (2004), were analysed in relation to team effectiveness outcomes. As significant results for overall team effectiveness were difficult to obtain, the focus was narrowed to team performance, measured both in human-only teams and in hypothetical HAT settings rated by team leaders. Importantly, none of the participating teams currently included AI agents, highlighting the hypothetical nature of HAT assessments. In the following sections, the results related to the direct effects of knowledge donation and collecting on team performance (*H*1, *H*1a, *H*1b) is discussed first. Then, the moderating role of implicit (*H*2, *H*2a, *H*3b) and explicit coordination (*H*3, *H*3a, *H*3b) on this relationship is elaborated.

Direct Effects of Knowledge Donating and Collecting on Team Performance

Hypotheses 1, 1a, and 1b proposed that knowledge donating and collecting would have a direct positive effect on team performance. Contrary to expectations and prior empirical findings, stating that knowledge sharing directly contributes to team performance (Choi et al., 2010; Mesmer-Magnus & DeChurch, 2009), the results showed no significant direct effects of knowledge sharing behaviours on team performance rated by team leaders. Previous insights suggests that knowledge sharing enhances not just team performance but also broader organisational outcomes by improving collaboration, minimising redundancies, and aligning on task objectives (Wang & Wang, 2012).

The results imply that the effects of knowledge sharing on performance may be complex and dependent on contextual or moderating variables. As highlighted by Mesmer-Magnus and DeChurch (2009), while information sharing predicts team performance, the strength of this relationship depends on the team task type, discussion structure, and the uniqueness of the shared information. This underscores that not merely sharing knowledge, but also how and in what context knowledge is exchanged, critically determines its effect on team outcomes.

Furthermore, it is possible that in early-stage or short-lived team settings and interactions, knowledge sharing does not have enough time to translate into tangible performance outcomes and determine how the team works. This assumption is based on team development theories which suggest that emergent states like trust, shared mental models, and cohesion are necessary for knowledge sharing to manifest its full benefits over time (Marks et al., 2001; Mathieu et al., 2008). The present study's setting may not have allowed these processes to develop fully, particularly given the absence of real-time interaction with AI agent, limiting the impact of knowledge sharing behaviours on performance. Therefore, it would be interesting to assess the length of HAT affiliation, and on which projects the teams collaborate in future studies.

Moreover, Lin (2007a) proposed that knowledge sharing is a pro-social behaviour, "voluntary in nature, and cannot be directly or explicitly rewarded, because of its intangibility" (p. 458). People choose voluntarily to share what they know. Whether or not they decide to do so, depends heavily on the social environment and the organisational culture around them, which makes knowledge sharing difficult to assess. In HATs, the inclusion of AI agents can disrupt traditional patterns of team interaction. Schmutz et al. (2024) stressed that "adding an AI teammate often reduces coordination, communication, and trust" (p. 1), all of which are crucial for team performance (Marks et al., 2001). If these elements weaken, team performance may suffer. Because knowledge sharing thrives in positive, trust-based environments, disruptions caused by the presence of AI could make team members less willing or less able to share knowledge effectively. This contextual issue could explain the lack of a direct relationship between knowledge sharing and team performance rated by the leaders in the present study.

Additionally, in literature there exists a distinction between the intention to share knowledge and the knowledge sharing behaviours. The current investigation captured the two knowledge sharing behaviours which are considered active processes (de Vries et al., 2006), however, did not assess participants' underlying intentions to share knowledge which may influence the behaviour types in HATs (van den Hooff et al., 2004; van den Hooff & Hendrix, 2004). Research by van den Hooff and Ridder (2004) differentiated between knowledge donating and collecting not just behaviourally but in terms of agency and engagement. Donating is proactive and autonomous, whereas collecting depends on a recipient's ability to respond and reciprocate. In HATs, where AI agents may not have the same ability to interpret and respond reasonably to knowledge requests as humans do (Schmutz et al., 2024) and therefore might struggle with the knowledge collecting part, the effectiveness of this exchange may be diminished. Even if humans want to share, the interaction might break down because the AI cannot properly engage in the process. The lack of this ability needs to be investigated further and considered in future AI design.

Finally, these findings could also reflect a measurement issue. The effectiveness of knowledge sharing may not be adequately captured through traditional performance metrics alone. As Wang and Noe (2010) argued, knowledge sharing impacts a broader spectrum of outcomes, including innovation, adaptability, and learning which are dimensions that may not have been fully captured in the current performance-focused outcome variables. Future studies could benefit from including multidimensional indicators to better assess the value of knowledge sharing in HAT contexts.

Moreover, because the participating teams did not include AI agents, leaders' assessments of HAT performance were based on hypothetical judgment regarding how team processes and outcomes might differ if an AI agent were present, and not on direct observation or experience. This scenario-based evaluation introduces potential validity limitations, as leaders may lack the necessary experience to accurately assess how performance will be in HATs. Assessing the current performance of human-only teams is a task for which most leaders are well-equipped and experienced. However, evaluating hypothetical HATs requires an understanding of how coordination, responsiveness, and contribution manifest in a system where at least one member does not communicate, adapt, or collaborate in human-like ways. Given the absence of embodied experience in HATs, leaders may rely on assumptions, stereotypes, or technical expectations rather than observable team interaction, which could lead to biased or inconsistent ratings. This discrepancy underscores a key challenge in HAT research which entails evaluating team performance in the absence of actual human-agent interaction. It also highlights the need for future research to develop empirically validated performance assessment tools specifically tailored to the unique characteristics of HATs. These tools would allow for more accurate and grounded evaluations, particularly as AI systems are integrated into real-world team settings.

In sum, the absence of a direct relationship between knowledge sharing behaviours and team performance likely reflects a combination of context sensitivity, developmental timing, disrupted team dynamics due to AI inclusion, differences in knowledge sharing agency, and measurement challenges. Future research should adopt longitudinal designs, include real human-AI interaction data, and employ multidimensional performance indicators to develop a deeper understanding of knowledge sharing mechanisms in HAT settings.

Moderation Effect of Implicit Coordination

Hypothesis 2 proposed that implicit coordination would strengthen the positive relationship between knowledge donating and team performance (*H*2a), as well as knowledge collecting and team performance (*H*2b). However, contrary to expectations and prior empirical findings, neither interaction effect, for both traditional and HAT performance assessed by team leaders, reached statistical significance.

This finding is noteworthy given the extensive evidence supporting the role of implicit coordination in enhancing team performance, especially in high-pressure or highly interdependent settings (Espinosa et al., 2004; Marques-Quinteiro et al., 2013; Rico et al., 2008, 2018, 2019). Moreover, shared mental models and TMS are key antecedents of implicit coordination (Mohammed et al., 2010; Rico et al., 2008) and the quality of team coordination (Ellwart et al., 2014; Moreland & Myaskovsky, 2000; Wiedow et al., 2013), all of which have all been linked to improved team performance (Konradt et al., 2021; Lowry et al., 2013; Marques-Quinteiro et al., 2013). In human teams, implicit coordination has been shown to be particularly effective in facilitating quick adaptation and efficient use of cognitive resources (e.g., Rico et al., 2008). For instance, Marques-Quinteiro et al. (2013) demonstrated that tactical police teams using implicit coordination and having a developed TMS performed more adaptively under pressure. Similarly, Espinosa et al. (2007) found that distributed software teams which rely on implicit coordination achieved higher performance despite communication constraints. According to Marks et al. (2001), implicit coordination becomes increasingly important as teams gain experience. It helps convert shared knowledge into synchronised action without the need for constant verbal cues, which conserves cognitive resources and improves performance.

Although the interaction between knowledge donating and implicit coordination was not statistically significant in the leader-rated data (p = .088), the marginal trend and conditional effects indicated that knowledge donating was positively associated with team performance only when implicit coordination was high. This pattern aligns with theoretical assumptions that team performance benefits from higher levels of implicit coordination (e.g., Marques-Quinteiro et al., 2013; Rico et al., 2008). When implicit coordination is present, teams may better transform donated knowledge into practice with minimal verbal communication. Conversely, in low implicit coordination conditions, donated knowledge may remain unused or unrecognised, and limiting its potential benefit. While these trends did not reach significance in this study, they suggest a potential moderating role that warrants further exploration in larger and more experienced samples.

Several factors likely contributed to the absence of a significant moderation effect. This study relied on a relatively small sample (n = 29 teams), which reduces statistical power and the ability to detect subtle interaction effects. Additionally, knowledge sharing behaviours were assessed based on a hypothetical HAT scenario rather than through observation of real-time interactions. Furthermore, the absence of significant moderating effects in the current study may reflect a disconnect between the prerequisites for implicit coordination and the current capabilities of AI agents in HATs.

Cognitive misalignments may be central to this issue. Shared mental models, trust, and team cognition, which are critical for effective implicit coordination, are often underdeveloped in HATs (Andrews et al., 2023). As Schelble et al. (2022) also found, "human-agent teams trusted agent teammates less when working with only agents and no other humans, perceived less team cognition with agent teammates than human ones, and had significantly inconsistent levels of team mental model similarity when compared to human-only teams" (p. 1). Without aligned cognitive frameworks, high levels of knowledge donating or collecting are unlikely to translate into coordinated action, particularly when communication must occur implicitly.

Moreover, technological constraints exacerbate these issues. Schneider et al. (2021) and Klein et al. (2004) emphasised that current AAs rely on explicit forms of communication to achieve coordination with human team members and often lack situational awareness or context sensitivity. This constraint reduces their ability to engage in anticipatory behaviours, which are central to implicit coordination, and may significantly limit the viability of implicit processes in HATs, thereby undermining the moderating effect on the knowledge sharing-performance relationship. Demir et al. (2019) observed that synthetic teams composed of agents often exhibited rigid team coordination dynamics due to their inability to anticipate their team members' needs, ultimately leading to performance deficits. Similarly, Demir et al. (2017) reported that HATs demonstrated reduced effectiveness in both pushing knowledge and pulling knowledge, in part due to poor coordination quality.

This limitation becomes especially problematic in the context of knowledge collecting, where benefits depend not only on the seeker's behaviour but also on the responsiveness and contextual appropriateness of the teammate's reply (de Vries et al., 2006). When AI agents cannot autonomously recognise when to share relevant information or respond adaptively, the advantages of implicit coordination diminish, regardless of how well human team members coordinate among themselves.

In addition, no team in the present study has actual experience with working with AI agents as teammates, meaning that opportunities for developing implicit coordination mechanisms were absent (Marks et al., 2001; Rico et al., 2008). Short-term, synthetic, or newly formed HATs often lack the trust, shared situational awareness, and interactive history that naturally evolve in human-only teams (Endsley, 2023; Georganta & Ulfert, 2024; Ulfert & Georganta, 2020). The current findings therefore align with the view that implicit coordination structures are not yet reliably replicable or supportable by AAs. Unlike in human-only teams, where coordination can evolve organically through shared experience and trust (Marks et al., 2001; Rico et al., 2008), HATs often lack the interactional depth or adaptability needed for implicit mechanisms to emerge (Andrews et al., 2023; Schelble et al., 2022). Although implicit coordination may become more viable as teams gain experience and human-AI alignment improves, the current technological landscape suggests it is not yet a suitable moderator for enhancing the effects of knowledge sharing.

Importantly, the study by Espinosa et al. (2007) provides a key contrast. In geographically distributed human teams, where frequent explicit communication is impractical, implicit coordination improved performance significantly. These results highlight what could potentially be achievable in HATs if AI systems were equipped with greater context awareness and adaptive coordination capabilities. Marginal trends observed in this study suggest that supporting implicit processes should remain a design goal. Embedding mechanisms that simulate shared mental models, enhance context sensitivity, and foster anticipatory interactions could substantially improve coordination quality.

In sum, although implicit coordination is widely recognised as a crucial amplifier of team effectiveness and knowledge sharing in human teams (Lowry et al., 2013), its benefits may not yet fully translate into HATs. The present study underscores the critical need for the development of intelligent systems capable of human-like, adaptive coordination behaviours to truly leverage the potential of implicit processes in future human-agent collaborations. Future design of AI teammates could benefit from embedding mechanisms that simulate shared mental models and promote anticipatory interactions to promote implicit coordination.

Moderation Effect of Explicit Coordination

Hypothesis 3 posited that the relationship between knowledge donating (*H*3a), collecting (*H*3b) and team performance would be moderated by explicit coordination. While Hypothesis 3b was not supported, Hypothesis 3a emerged as a key finding. Explicit coordination significantly strengthened the positive effect of knowledge donating on traditional team performance evaluated by team leaders in human-only teams, particularly when explicit coordination was high.

This result resonates with existing literature emphasising the critical role of coordination and communication for team performance (Demir et al., 2016; McNeese et al., 2021a). In human teams, organised communication practices, including formal schedules, clear task delegation, and feedback loops, help maintain alignment, particularly in distributed or technologically mediated contexts (Espinosa et al., 2004, 2007). Explicit coordination provides scaffolding that enables donated knowledge to be directed appropriately and integrated into team activities, increasing its likelihood of improving team performance. In environments where knowledge must be shared proactively, for example in complex task settings, structured coordination ensures that vital information reaches the right team members at the right time (de Vries et al., 2006).

From a theoretical perspective, this finding highlights that donating is a proactive knowledge sharing behaviour. Its effectiveness depends on the organisational structures and coordination practices that allow for efficient reception and use of the shared knowledge.

Explicit coordination serves as a catalyst, ensuring that proactive knowledge contributions are effectively absorbed and translated into team action, thereby enhancing performance. Importantly, in human-only teams, participants may naturally engage in and benefit from structured exchanges, further supporting the observed significant moderation effect. However, it must be acknowledged that the success of explicit coordination for knowledge donating may, at least partly, reflect the familiarity and experienced participants have with human team settings rather than mixed human-AI environments. Future research should examine whether the same pattern holds in teams with direct, ongoing HAT experience.

In contrast, the relationship between knowledge collecting and team performance was not significantly moderated by explicit coordination, and Hypothesis 3b was not supported. Several factors may explain this finding. Prior research suggests that teams collaborating with AI agents tend to exhibit reduced information exchange, less nonverbal coordination, and lower levels of task planning compared to human teams (Demir et al., 2018; Demir et al., 2017; Musick et al., 2021). Even when explicit communication protocols are followed, AI systems often fail to engage proactively or respond adaptively to human teammates (Zhang et al., 2021). Therefore, HATs demonstrate lower levels of communication, coordination, and task engagement compared to all-human teams (Zercher & Jussupow, 2023), which can critically limit the effectiveness of knowledge collecting, a behaviour that depends on timely and context-sensitive responses from team members.

Furthermore, the lack of real HAT experience in the sample at hand may have limited participants' ability to simulate effective human-AI collaboration dynamics in the hypothetical scenario, thus influencing the findings regarding knowledge collecting.

Beyond immediate team behaviours, explicit coordination in HATs is influenced by other factors such as prior collaboration experience, individual attitudes toward AI (Zhang et al., 2021), the technological capabilities of the AI system, and the duration of the collaboration (Zercher & Jussupow, 2023). For instance, McNeese et al. (2021b) found that, unlike human-only teams whose coordination stagnate, teams working with AI showed continuous improvement in coordination over time. These improvements might involve both explicit and emerging implicit coordination structures. However, without direct, longitudinal engagement with AI systems, the development of coordination structures remains speculative in the present study.

Finally, it is important to recognise that over-reliance on explicit coordination may have drawbacks. While explicit coordination is vital for organising team activities, an exclusive focus on formal processes may detract from task-focused activities like problem-solving and adaptive behaviour (Konradt et al., 2021). Over time, human teams typically evolve toward a blend of explicit and implicit coordination (Marks et al., 2001; Schneider et al., 2021). Therefore, while explicit coordination is critical, especially in early HAT development phases, fostering conditions for the emergence of implicit coordination will be crucial for sustainable, high-performing human-agent collaboration.

In sum, the present study highlights the vital role of explicit coordination in strengthening the link between knowledge donating and team performance in human-only teams. It also points to important challenges in replicating similar effects for knowledge collecting, particularly in the context of HATs. Future research should explore how explicit and implicit coordination mechanisms evolve over time in both newly established and experiences HATs, considering both human and AI learning trajectories.

5.1 Implications

Theoretical Implications

This study offers important contributions to the growing body of research on HATs, knowledge sharing, and team coordination.

First, it addresses a critical gap in the HAT literature by empirically examining knowledge sharing behaviours, specifically knowledge donating and collecting, in a hypothetical HAT context. While previous research has extensively explored knowledge sharing in human-only teams (e.g., de Vries et al., 2006; Mesmer-Magnus & DeChurch, 2009), little was known about how these cognitive processes might differ when AI teammates are introduced. By disentangling the effects of donating and collecting, following the distinction made by de Vries et al. (2006) and van den Hooff and Ridder (2004), the study demonstrates that human-to-AI knowledge transfer is not a straightforward extension of human-to-human dynamics. This insight extends prior theories by highlighting that established models of team cognition and performance must be adapted to account for relational and technological asymmetries in HATs.

Second, the study contributes to the team cognition literature by challenging assumptions around the universality of implicit coordination. In human-only teams, implicit coordination, supported by shared mental models and TMS (Mohammed et al., 2010; Rico et al., 2008), is a known driver of performance. However, the findings reveal that in HATs, sharing goals explicitly and communicating action-related better supports the development of team cognition (Schelble et al., 2022). This differentiation offers important theoretical insights by demonstrating that cognitive alignment processes must be reevaluated when AI agents are involved.

Third, the study opens a new avenue for investigation cognitive and affective states in HATs. While the current research focused on knowledge donating and collecting, the findings suggest that psychological mechanisms including trust, psychological safety, and team cohesion are likely to play a crucial role in HAT performance. Integrating affective, emotional, and motivational constructs into future models could provide a holistic understanding of collaboration in modern team contexts.

Fourth the methodological approach advances the field by gathering data from actual organisational teams and sourcing evaluations from both leaders and team members, thereby enhancing external validity. Although based on hypothetical scenarios, the multi-source design strengthens the reliability of findings and highlights the need for longitudinal, real-world HAT research to capture the evolution of team functioning over time.

Finally, the study underscores the necessity of refining classical models of team effectiveness (e.g., Hackman & Morris, 1975; McGarth, 1964; Salas et al., 2005; Shiflett, 1979) to incorporate HAT-specific dimensions, including technological capabilities of agents, human-agent trust asymmetries, and the balance between explicit and implicit coordination. The different findings regarding knowledge donating versus collecting suggest that these processes should be treated as distinct phenomena in future HAT theories.

Practical Implications

Beyond theoretical contributions, the study provides actionable insights for organisations, team leaders, and technology developers seeking to optimise human-AI collaboration.

First, the results highlight that explicit coordination mechanisms are critical for ensuring effective knowledge sharing in HATs. Teams working with AI agents must establish structured communication systems, namely clear role allocations, explicit task goals, feedback routines, and standardised handover points, to bridge the cognitive and behavioural gaps between human and non-human teammates. Given AI agents' current limitations in inferring context or anticipate team needs, structured and overt communication ensures that knowledge donating behaviours lead to performance gains. Shared digital dashboards where tasks, responsibilities, and deadlines are continuously updated can serve as vital communication hub, assuring that AI agents have the necessary data to function effectively.

Second, organisations must invest in specialised training programs for leaders and members to foster effective knowledge sharing in HATs. Traditional leadership skills may not be sufficient. Leaders will need to be trained to actively manage and facilitate structured knowledge exchange processes, recognise potential misunderstandings between human and AI teammates, and warrant that communication tools, for example status boards or real-time project tracking systems, are consistently applied. Effective training should also focus on enhancing leaders' ability to create psychological safety when working with AI by openly discussing the AI's role, strengths, and limitations, and normalising initial uncertainty or mistakes when interacting with AI teammates. For instance, scenario-based training simulations where leaders practice resolving breakdowns in human-AI communication can facilitate these objectives. Additionally, team members require training on how to work and interact with AI agents on a daily basis to normalise this collaboration.

Third, regarding the type of knowledge sharing required, the study indicates that high levels of explicit knowledge sharing when it comes to knowledge donating (humans transfer knowledge to AI team member) is likely to boost effectiveness in HATs, at least under current technological capabilities. This has practical consequences for team design and task structuring. Tasks should be broken down into clear units with well-defined information to support explicit communication flows. In addition, teams should focus on making their communications clear, detailed, and verifiable. For example, instead of using vague statements, clear prompts should specify the requirements. Tasks should be decomposed into modular, well-specified elements to reduce ambiguity. Using checklist-based workflows or task management systems could further support explicit knowledge flows.

Fourth, AI system designers should prioritise the development of adaptive AI agents that can move toward interpreting tacit signals and participating in implicit coordination processes. Fostering AI team cognition could involve training AI models to detect contextual signals (e.g., task switching cues, emotional tone from text inputs), embedding machine learning models that adjust agent behaviours based on team dynamics over time, and developing AI interfaces that visualise their understanding of shared goals and task status to enhance mutual awareness. For instance, implementing AI teammates that proactively ask clarifying questions when faced with ambiguity could gradually reduce reliance on fully explicit inputs. Until that point, however, human team members must compensate for this limitation by ensuring that critical information is not assumed but explicitly shared at all stages of teamwork.

Fifth, organisations should introduce trust-building interventions, for instance, "getting to know the AI" workshops, where team members interact with AI in low-risk settings to build comfort and familiarity. Furthermore, transparent performance feedback systems that allow humans to see and understand how and why the AI made decisions could help build trust among the team. Regular team debriefings focusing on human-AI interaction and including AI agents in planning or retrospective sessions can further strengthen team cohesion.

Finally, the findings emphasise the need for new performance evaluation tools specifically tailored to HATs. Traditional human team assessment frameworks may overlook critical aspects of coordination or responsiveness when AI agents are involved. Creating metrics that can capture both cognitive (knowledge sharing effectiveness) and affective (trust development, perceived cohesion) outcomes will be critical for managing HAT performance over time. Moreover, longitudinal research and practice should explore how knowledge sharing behaviours evolve as teams gain experience with AI agents and how the balance between explicit and implicit sharing shifts as trust and familiarity develops.

5.2 Limitations and Future Research

While this study offers important contributions by advancing the understanding of knowledge sharing and coordination mechanisms within HATs, and by investigating these dynamics in a field setting with multiple levels of performance assessment, several limitations remain. Recognising these limitations not only provides important contexts for interpreting the findings but also offer valuable future research directions to further refine and extend these insights.

First, the sample consisted exclusively of human-only teams evaluating hypothetical scenarios of HATs. Although scenario-based designs are a recognised method to investigate emergent fields where real-world data is limited (e.g., Schelble et al., 2022), it restricts the validity of the results. Evaluations of knowledge sharing and team performance may differ significantly in actual HATs, where interaction with AI agents introduces challenges and opportunities. Future research should therefore prioritise empirical studies in real-world HAT settings, for instance in the hospitality, healthcare, or logistics sectors, where AI teammates are deployed more frequently. Therefore, in the future, the results from human-only teams should be compared to them from HATs to derive insights on how teamwork in HATs differs from traditional team settings.

Second, the relatively small sample size (n = 29 teams) may have reduced the statistical power needed to detect subtle interaction effects, particularly for moderation analyses. Scholars like Aguinis and Stone-Romero (1997) emphasised that small samples can inflate Type II errors, potentially obscuring true effects. Statistical power could be increased by conducting experiments or simulations in which extraneous variables are controlled (Aguinis et al., 2017). Additionally, teams varied in size, and the inclusion of very small teams (fewer than three members) raises conceptual concerns about whether these groups functioned as true "teams" in the theoretical sense. Future research should use larger samples (Aguinis et al., 2017), and consider minimum team size thresholds to ensure robust testing of team-level phenomena. Moreover, exploring divergent individual perceptions within teams, particularly differences in views on knowledge sharing or coordination, may offer valuable insights into internal team functioning and the emergence of shared cognitive and relational structures.

Third, the absence of direct measurements of antecedent cognitive constructs, including shared mental models and TMS, represents an important conceptual limitation. Prior work (Mohammed et al., 2010; Rico et al., 2008, 2019) highlighted that these constructs are critical for explaining the emergence and effectiveness of coordination mechanisms. Without directly modelling these antecedents, conclusions about the factors driving implicit or explicit coordination remain inferential. Future studies should incorporate mediators like TMS, team trust, or team psychological safety to clarify the pathways through which knowledge sharing behaviours impact team outcomes.

Furthermore, the study did not model knowledge sharing intentions, communication styles, or individual predispositions toward working with non-human teammates. As de Vries et al. (2006) emphasised, knowledge collecting and donating are distinct active processes that are differentially influenced by various psychological factors. Without accounting for antecedents like willingness to share knowledge or attitudes toward AI agents (e.g., van den Hooff & Hendrix, 2004), the interpretation of the knowledge sharing–performance relationship remains incomplete. Future studies should incorporate individual and organisational factors like exchange ideology (Lin, 2007a), knowledge self-efficacy, the enjoyment of helping others, and top management support (Lin, 2007b) to enrich explanatory models of knowledge sharing in HATs.

Beyond these primary limitations, other considerations warrant attention. Data were collected cross-sectionally, providing only a snapshot of team dynamics. As Marks et al. (2001) demonstrated in their temporally based framework of team processes, coordination behaviours and knowledge sharing practices unfold over time and across task cycles. Future longitudinal research should examine how coordination and knowledge sharing evolve, particularly as HATs gain experience and familiarity.

Moreover, the lack of team tenure measurement may be a confounding factor. Teams newly formed are less likely to exhibit mature implicit coordination strategies (Marks et al., 2001; Mathieu et al., 2008), potentially explaining the nonsignificant moderating effect observed. Capturing variables like team tenure, history of collaboration, and prior experience with AI teammates could provide important explanatory power. In addition to that, coordination mechanisms and team performance in newly formed as well as established human teams and HATs should be investigated and the results compared to better understand the differences in teamwork in both team settings and to derive further strategies for effective human-AI collaboration.

Additionally, future research should examine leadership functions in HATs and their role in developing team processes. Leadership is conceptualised as a flexible set of behaviours supporting critical team needs such as trust, shared cognition, and coordination (Morgeson et al., 2010). As Larson and DeChurch (2020) highlighted, leaders in technology-enabled teams must adapt to manage both human and AI collaboration by fostering trust and ensuring cognitive alignment. Future studies could investigate the role of leadership behaviours (e.g., empowering, or participative leadership) on the relationship of knowledge sharing and team effectiveness, with special attention to support both explicit and implicit forms of coordination.

Finally, while this study focused on cognitive knowledge sharing behaviours (donating and collecting), affective and emotional processes were not addressed. As highlighted by research on team affect (e.g., Barsade & Knight, 2015), emotional states, including trust, cohesion, and psychological safety, play a critical role in supporting knowledge sharing and coordination.

Future studies should examine whether similar cognitive-affective mechanisms emerge in HATs and how emotional intelligence – both human and artificial – can support effective teamwork.

Taken together, these limitations underscore several promising directions for future research, including the extension to real-world applications, the adoption of longitudinal study designs, the modelling of cognitive antecedents and mediating processes, and the examination of how cognitive and emotional factors interact in the context of human–agent collaboration.

6. Conclusion

This research aimed to deepen the understanding of whether knowledge sharing processes between human and AI team members affect team effectiveness in both current team settings and HATs, with particular focus on the moderating role of implicit and explicit coordination strategies. Building on established theories from knowledge management, team cognition, and coordination, this study bridges important gaps by examining these concepts within the emerging domain of HATs. Using a quantitative approach, and analysing team-level perspectives, the study investigated the effects of knowledge donating and collecting behaviours on team performance, and how coordination strategies interact with these knowledge processes.

The findings reveal that knowledge donating and collecting, while widely recognised as pivotal team behaviours, did not significantly relate to team performance in either traditional or hypothetical HAT settings. This implies that knowledge sharing does not straightforwardly translate into improved team performance. Although previous research consistently highlighted the benefits of knowledge sharing for organisational outcomes (e.g., Mesmer-Magnus & DeChurch, 2009; Wang & Wang, 2012), the present results indicate that additional contextual and cognitive factors, including the maturity of coordination mechanisms, are crucial for realising these benefits in HATs. This study contributes to the literature by showing that knowledge sharing alone, especially in newly formed or hypothetical teams, may not suffice to boost performance without appropriate coordination structures and relational trust.

Moreover, by distinguishing between implicit and explicit coordination, this research provides a differentiated understanding of how different coordination types affect human-AI interaction. A core finding of this research suggested that explicit coordination significantly strengthened the positive effects of knowledge donating on current, human-only team performance. This empirical evidence offers support for theoretical perspectives (e.g., Schneider et al., 2021), emphasising the importance of explicit communication structures in HAT environments. By contrast, implicit coordination did not significantly moderate the relationship between knowledge sharing and performance, highlighting the current limitations of relying on non-verbal or anticipatory coordination processes in human-AI settings.

Another important contribution of this study lies in examining how human team members imagine working with AI teammates in a structured scenario, despite the lack of actual HAT experience. This approach, though limited by its hypothetical nature, provides early-stage insights into how cognitive processes like knowledge sharing might evolve in future HATs. Furthermore, by highlighting the potential relevance of affective states (e.g., trust and shared understanding) for knowledge sharing effectiveness, this study lays the groundwork for future research to integrate both cognitive and emotional aspects of team functioning.

On the practical side, this research suggests that organisations preparing to implement AI teammates should not merely focus on technological capabilities but should also proactively promote systematic coordination practices. Leaders should be trained to encourage effective explicit knowledge sharing strategies and support environments that facilitate gradual development of implicit coordination over time. Particularly, training programs for leaders in HATs should emphasise clarity, structured task communication, and scenario-based simulations to bridge cognitive gaps between human and AI team members.

Finally, although this study brings valuable insights, several limitations must be acknowledged. The sample was small (*n* = 29 teams), which may have reduced statistical power and the ability to detect finer interaction effects (Aguinis et al., 2017). Moreover, the hypothetical nature of the HAT scenario, absence of real human-agent collaborations, potential biases between leader and member perceptions, and lack of measurement for predictors of knowledge sharing behaviour (e.g., intention to share knowledge with AI teammates; see de Vries et al., 2006) are critical factors that future research should address.

Future research should additionally focus on investigating HAT dynamics in real-world settings, particularly in service industries, where human-agent collaboration is gaining prominence. Studies could explore mediation effects (e.g., TMS mediating the knowledge sharing–performance relationship) and the influence of leadership behaviours (e.g., empowering, or participative leadership) on fostering effective knowledge sharing in HATs (Morgeson et al., 2010). Additionally, personal factors like enjoyment in helping others or exchange ideology, and organisational factors such as top management support (Lin, 2007b; Lin, 2007a) could serve as critical determinants for improved knowledge sharing with AI teammates.

In sum, this study underscores that while knowledge sharing remains foundational for team success, its impact within HATs hinges on the right blend of structured coordination, especially explicit coordination mechanisms. As organisations continue to integrate AI into team settings, a deeper understanding and proactive development of coordination and knowledge sharing processes will be essential to fully realise the potential of HATs in the future.

Bibliographical references

Aguinis, H., Edwards, J. R., & Bradley, K. J. (2017). Improving Our Understanding of Moderation and Mediation in Strategic Management Research. *Organizational Research Methods, 20*(4), 665–685. https://doi.org/10.1177/1094428115627498

Aguinis, H., & Stone-Romero, E. F. (1997). Methodological artifacts in moderated multiple regression and their effects on statistical power. *Journal of Applied Psychology, 82*(1), 192–206. https://doi.org/10.1037/0021-9010.82.1.192

Ajoudani, A., Zanchettin, A. M., Ivaldi, S., Albu-Schäffer, A., Kosuge, K., & Khatib, O. (2018). Progress and prospects of the human–robot collaboration. *Autonomous Robots, 42*(5), 957–975. https://doi.org/10.1007/S10514-017-9677-2/FIGURES/2

Alavi, M., & Leidner, D. E. (2001). Review: Knowledge management and knowledge management systems. *MIS Quarterly, 25*(1), 107–136. https://doi.org/10.2307/3250961

Alsharo, M., Gregg, D., & Ramirez, R. (2017). Virtual team effectiveness: The role of knowledge sharing and trust. *Information & Management, 54*(4), 479–490. https://doi.org/10.1016/J.IM.2016.10.005

Andrews, R. W., Lilly, J. M., Srivastava, D., & Feigh, K. M. (2023). The role of shared mental models in human-AI teams: a theoretical review. *Theoretical Issues in Ergonomics Science, 24*(2), 129–175. https://doi.org/10.1080/1463922X.2022.2061080

Arakpogun, E. O., Elsahn, Z., Olan, F., & Elsahn, F. (2021). Artificial Intelligence in Africa: Challenges and Opportunities. In A. Hamdan, A. E. Hassanien, A. Razzaque, & B. Alareeni (Eds.), *The Fourth Industrial Revolution: Implementation of Artificial Intelligence for Growing Business Success* (Vol. 935, pp. 375–388). Springer. https://doi.org/10.1007/978-3-030-62796-6_22

Argote, L., McEvily, B., & Reagans, R. (2003). Managing knowledge in organizations: An integrative framework and review of emerging themes. *Management Science, 49*(4), 571–582. https://doi.org/10.1287/MNSC.49.4.571.14424

Arthur, J. B., & Huntley, C. L. (2005). Ramping up the Organizational Learning Curve: Assessing the Impact of Deliberate Learning on Organizational Performance Under Gainsharing. *Academy of Management Journal, 48(*6), 1159–1170. https://doi.org/10.5465/AMJ.2005.19573115

Barsade, S. G., & Knight, A. P. (2015). Group Affect. *Annual Review of Organizational Psychology and Organizational Behavior, 2*(1), 21–46. https://doi.org/10.1146/annurev-orgpsych-032414-111316

Bartol, K. M., & Srivastava, A. (2002). Encouraging Knowledge Sharing: The Role of Organizational Reward Systems. *Journal of Leadership & Organizational Studies, 9*(1), 64–76. https://doi.org/10.1177/107179190200900110

Bergström, J., Dahlström, N., Henriqson, E., & Dekker, S. (2010). Team Coordination in Escalating Situations: An Empirical Study Using Mid-Fidelity Simulation. *Journal of Contingencies and Crisis Management, 18*(4), 220–230. https://doi.org/10.1111/j.1468-5973.2010.00618.x

Biemann, T., Cole, M. S., & Voelpel, S. (2012). Within-group agreement: On the use (and misuse) of rWG and rWG(J) in leadership research and some best practice guidelines. *The Leadership Quarterly, 23*(1), 66–80. https://doi.org/10.1016/j.leaqua.2011.11.006

Breazeal, C., Kidd, C. D., Thomaz, A. L., Hoffman, G., & Berlin, M. (2005). Effects of nonverbal communication on efficiency and robustness in human-robot teamwork. *2005 IEEE/RSJ International Conference on Intelligent Robots and Systems,* 708–713. https://doi.org/10.1109/IROS.2005.1545011

Burke, C. S. (2004). How to turn a team of experts into an expert medical team: guidance from the aviation and military communities. *BMJ Quality & Safety 2004, 13*(1), i96–i104. https://doi.org/10.1136/qshc.2004.009829

Cabrera, E. F., & Cabrera, A. (2005). Fostering knowledge sharing through people management practices. *International Journal of Human Resource Management, 16*(5), 720–735. https://doi.org/10.1080/09585190500083020

Calantone, R. J., Cavusgil, S. T., & Zhao, Y. (2002). Learning orientation, firm innovation capability, and firm performance. *Industrial Marketing Management, 31*(6), 515–524. https://doi.org/10.1016/S0019-8501(01)00203-6
Chakraborti, T., Kambhampati, S., Scheutz, M., & Zhang, Y. (2017). AI Challenges in Human-Robot Cognitive Teaming. https://doi.org/10.48550/arXiv.1707.04775
Chiu, C. M., Hsu, M. H., & Wang, E. T. G. (2006). Understanding knowledge sharing in virtual communities: An integration of social capital and social cognitive theories. *Decision Support Systems, 42*(3), 1872–1888. https://doi.org/10.1016/j.dss.2006.04.001
Choi, S., Lee, H., & Yoo, Y. (2010). The Impact of Information Technology and Transactive Memory Systems on Knowledge Sharing, Application, and Team Performance: A Field Study. *MIS Quarterly, 34*(4), 855–870. https://doi.org/10.2307/25750708
Cohen, S. G., & Bailey, D. E. (1997). What makes teams work: Group effectiveness research from the shop floor to the executive suite. *Journal of Management, 23*(3), 239–290. https://doi.org/10.1177/014920639702300303
Collins, C. J., & Smith, K. G. (2006). Knowledge exchange and combination: The role of human resource practices in the performance of high-technology firms. *Academy of Management Journal, 49*(3), 544–560. https://doi.org/10.5465/AMJ.2006.21794671
Cooke, N. J., Gorman, J. C., Myers, C. W., & Duran, J. L. (2013). Interactive team cognition. *Cognitive Science, 37*(2), 255–285. https://doi.org/10.1111/cogs.12009
Costa, P. L., Graça, A. M., Marques-Quinteiro, P., Santos, C. M., Caetano, A., & Passos, A. M. (2013). Multilevel research in the field of organizational behavior: An empirical look at 10 years of theory and research. *SAGE Open, 3*(3), 1–17. https://doi.org/10.1177/2158244013498244
Costa, P. L., Passos, A. M., & Barata, M. C. (2015). Multilevel influences of team viability perceptions. *Team Performance Management, 21*(1/2), 19–36. https://doi.org/10.1108/TPM-03-2014-0020
Cuevas, H. M., Fiore, S. M., Caldwell, B. S., & Strater, L. (2007). Augmenting team cognition in human-automation teams performing in complex operational environments. *Aviat Space Environ Med, 78*(5 II), B63–B70.
Cummings, J. N. (2004). Work Groups, Structural Diversity, and Knowledge Sharing in a Global Organization. *Management Science, 50*(3), 352–364. https://doi.org/10.1287/MNSC.1030.0134
Damodaran, L., & Olphert, W. (2000). Barriers and facilitators to the use of knowledge management systems. *Behaviour and Information Technology, 19*(6), 405–413. https://doi.org/10.1080/014492900750052660
Davenport, T. H., & Prusak, L. (1998). Working Knowledge: How Organizations Manage What They Know. *Harvard Business School Press.* https://doi.org/10.1145/348772.348775
de Vries, R. E., van Den Hooff, B., & de Ridder, J. A. (2006). Explaining knowledge sharing: The role of team communication styles, job satisfaction, and performance beliefs. *Communication Research, 33*(2), 115–135. https://doi.org/10.1177/0093650205285366
DeCostanza, A. H., Marathe, A. R., Bohannon, A., Evans, A. W., Palazzolo, E. T., Metcalfe, J. S., & McDowell, K. (2018). Enhancing Human-Agent Teaming with Individualized, Adaptive Technologies: A Discussion of Critical Scientific Questions. https://doi.org/10.13140/RG.2.2.12666.39364
Delise, L. A., Gorman, C. A., Brooks, A. M., Rentsch, J. R., & Steele-Johnson, D. (2010). The effects of team training on team outcomes: A meta-analysis. *Performance Improvement Quarterly, 22*(4), 53–80. https://doi.org/10.1002/PIQ.20068
Dell'Acqua, F., Kogut, B., & Perkowski, P. (2023). Super Mario Meets AI: Experimental Effects of Automation and Skills on Team Performance and Coordination. *Review of Economics and Statistics 2023,* 1–47. https://doi.org/10.1162/rest_a_01328
Demir, M., Amazeen, P. G., McNeese, N. J., Likens, A., & Cooke, N. J. (2017). Team coordination dynamics in human-autonomy teaming. *Proceedings of the Human Factors and Ergonomics Society, 61*(1), 236. https://doi.org/10.1177/1541931213601542

Demir, M., & Cooke, N. J. (2014). Human Teaming Changes Driven by Expectations of a Synthetic Teammate. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting, 58*(1), 16–20. https://doi.org/10.1177/1541931214581004
Demir, M., Likens, A. D., Cooke, N. J., Amazeen, P. G., & McNeese, N. J. (2019). Team coordination and effectiveness in human-autonomy teaming. *IEEE Transactions on Human-Machine Systems, 49*(2), 150–159. https://doi.org/10.1109/THMS.2018.2877482
Demir, M., McNeese, N. J., & Cooke, N. J. (2016). Team communication behaviors of the human-automation teaming. *2016 IEEE International Multi-Disciplinary Conference on Cognitive Methods in Situation Awareness and Decision Support,* 28–34. https://doi.org/10.1109/COGSIMA.2016.7497782
Demir, M., McNeese, N. J., & Cooke, N. J. (2017). Team situation awareness within the context of human-autonomy teaming. *Cognitive Systems Research, 46*, 3–12. https://doi.org/10.1016/j.cogsys.2016.11.003
Demir, M., McNeese, N. J., & Cooke, N. J. (2018). The Impact of Perceived Autonomous Agents on Dynamic Team Behaviors. *IEEE Transactions on Emerging Topics in Computational Intelligence, 2*(4), 258–267. https://doi.org/10.1109/TETCI.2018.2829985
Demir, M., McNeese, N. J., & Cooke, N. J. (2020). Understanding human-robot teams in light of all-human teams: Aspects of team interaction and shared cognition. *International Journal of Human Computer Studies, 140.* https://doi.org/10.1016/j.ijhcs.2020.102436
Edmondson, A. C., Dillon, J. R., & Roloff, K. S. (2007). Three Perspectives on Team Learning. *Academy of Management Annals, 1*(1), 269–314. https://doi.org/10.5465/078559811
Ellwart, T., Konradt, U., & Rack, O. (2014). Team Mental Models of Expertise Location. *Small Group Research, 45*(2), 119–153. https://doi.org/10.1177/1046496414521303
Endsley, M. R. (2023). Supporting Human-AI Teams: Transparency, explainability, and situation awareness. *Computers in Human Behavior, 140*. https://doi.org/10.1016/j.chb.2022.107574
Entin, E. E., & Serfaty, D. (1999). Adaptive Team Coordination. *Human Factors: The Journal of the Human Factors and Ergonomics Society, 41*(2), 312–325. https://doi.org/10.1518/001872099779591196
Espinosa, J. A., Lerch, F. J., & Kraut, R. E. (2004). Explicit versus implicit coordination mechanisms and task dependencies: One size does not fit all. In E. Salas & S. M. Fiore (Eds.), *Team cognition: Understanding the factors that drive process and performance* (pp. 107–129). American Psychological Association. https://doi.org/10.1037/10690-006
Espinosa, J. A., Slaughter, S. A., Kraut, R. E., & Herbsleb, J. D. (2007). Team knowledge and coordination in geographically distributed software development. *Journal of Management Information Systems, 24*(1), 135–169. https://doi.org/10.2753/MIS0742-1222240104
Fan, X., McNeese, M., & Yen, J. (2010). NDM-Based Cognitive Agents for Supporting Decision-Making Teams. *Human-Computer Interaction, 25*(3), 195–234. https://doi.org/10.1080/07370020903586720
Fan, X., & Yen, J. (2011). Modeling Cognitive Loads for Evolving Shared Mental Models in Human–Agent Collaboration. *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics), 41*(2), 354–367. https://doi.org/10.1109/TSMCB.2010.2053705
Flathmann, C., Schelble, B. G., Zhang, R., & McNeese, N. J. (2021). Modeling and Guiding the Creation of Ethical Human-AI Teams. *AIES 2021 - Proceedings of the 2021 AAAI/ACM Conference on AI, Ethics, and Society,* 469–479. https://doi.org/10.1145/3461702.3462573
Fuller, C. M., Simmering, M. J., Atinc, G., Atinc, Y., & Babin, B. J. (2016). Common methods variance detection in business research. *Journal of Business Research, 69*(8), 3192–3198. https://doi.org/10.1016/j.jbusres.2015.12.008
Georganta, E., Peus, C., & Niess, J. (2024). Interactive technologies through the lens of team effectiveness: an interdisciplinary systematic literature review. *European Journal of Work and Organizational Psychology, 33*(2), 172–187. https://doi.org/10.1080/1359432X.2023.2178904

Georganta, E., & Ulfert, A. S. (2024). Would you trust an AI team member? Team trust in human–AI teams. *Journal of Occupational and Organizational Psychology, 97*(3), 1212–1241. https://doi.org/10.1111/joop.12504

Göksel, A., & Aydintan, B. (2017). How can tacit knowledge be shared more in organizations? A multidimensional approach to the role of social capital and locus of control. *Knowledge Management Research & Practice, 15*(1), 34–44. https://doi.org/10.1057/KMRP.2015.22

González‐Romá, V., Fortes‐Ferreira, L., & Peiró, J. M. (2009). Team climate, climate strength and team performance. A longitudinal study. *Journal of Occupational and Organizational Psychology, 82*(3), 511–536. https://doi.org/10.1348/096317908X370025

Grimm, D. A., Demir, M., Gorman, J. C., & Cooke, N. J. (2018). Team Situation Awareness in Human-Autonomy Teaming: A Systems Level Approach. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting, 62*(1), 149. https://doi.org/10.1177/1541931218621034

Groom, V., & Nass, C. (2007). Can robots be teammates?: Benchmarks in human–robot teams. *Interaction Studies, 8*(3), 483–500. https://doi.org/10.1075/IS.8.3.10GRO

Hackman, J. R. (1983). Normative Model of Work Team Effectiveness.

Hackman, J. R. (1987). The design of work teams. In J. Lorsch (Ed.), *Handbook of organizational behavior.* Prentice-Hall.

Hackman, J. R., & Morris, C. G. (1975). Group Tasks, Group Interaction Process, and Group Performance Effectiveness: A Review and Proposed Integration. *Advances in Experimental Social Psychology, 8*, 45–99. https://doi.org/10.1016/S0065-2601(08)60248-8

Hagemann, V., & Kluge, A. (2017). Complex problem solving in teams: The impact of collective orientation on team process demands. *Frontiers in Psychology, 8*, Article 1730. https://doi.org/10.3389/fpsyg.2017.01730

Hansen, M. T. (2002). Knowledge networks: Explaining effective knowledge sharing in multiunit companies. *Organization Science, 13*(3), 232–248. https://doi.org/10.1287/ORSC.13.3.232.2771

Hayes, A. F. (2012). PROCESS: *A versatile computational tool for observed variable mediation, moderation, and conditional process modeling* [White paper]. http://www.afhayes.com/public/process2012.pdf

Hayes, A. F. (2022). *Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-Based Approach* (3rd ed.). Guilford publications.

Hinds, P. J., Patterson, M., & Pfeffer, J. (2001). Bothered by abstraction: the effect of expertise on knowledge transfer and subsequent novice performance. *The Journal of Applied Psychology, 86*(6), 1232–1243. https://doi.org/10.1037/0021-9010.86.6.1232

Huber, G. P. (1991). Organizational Learning: The Contributing Processes and the Literatures. *Organization Science, 2*(1), 88–115. https://doi.org/10.1287/ORSC.2.1.88

Iftikhar, R., Chiu, Y. Te, Khan, M. S., & Caudwell, C. (2024). Human-Agent Team Dynamics: A Review and Future Research Opportunities. *IEEE Transactions on Engineering Management, 71*, 10139–10154. https://doi.org/10.1109/TEM.2023.3331369

Ilgen, D. R., Hollenbeck, J. R., Johnson, M., & Jundt, D. (2005). Teams in Organizations: From Input-Process-Output Models to IMOI Models. *Annual Review of Psychology, 56*(1), 517–543. https://doi.org/10.1146/annurev.psych.56.091103.070250

James, L. R., Demaree, R. G., & Wolf, G. (1993). rwg: An assessment of within-group interrater agreement. *Journal of Applied Psychology, 78*(2), 306–309. https://doi.org/10.1037/0021-9010.78.2.306

Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. *Business Horizons, 61*(4), 577–586. https://doi.org/10.1016/J.BUSHOR.2018.03.007

Johnson, C. J., Demir, M., McNeese, N. J., Gorman, J. C., Wolff, A. T., & Cooke, N. J. (2023). The Impact of Training on Human–Autonomy Team Communications and Trust Calibration. *Human Factors: The Journal of the Human Factors and Ergonomics Society, 65*(7), 1554–1570. https://doi.org/10.1177/00187208211047323

Johnson, M., Bradshaw, J. M., Feltovich, P. J., Jonker, C., van Riemsdijk, B., & Sierhuis, M. (2012). Autonomy and interdependence in human-agent-robot teams. *IEEE Intelligent Systems, 27*(2), 43–51. https://doi.org/10.1109/MIS.2012.1

Katz-Navon, T., Unger-Aviram, E., & Block, C. (2016). Examining the Cross-Level Influence of Dispositional and Team Goal Orientations on Employee Self-Regulation and Performance in a Complex Task Environment. *The Journal of Applied Behavioral Science, 52*(4), 396–421. https://doi.org/10.1177/0021886316665460

Kauppila, O. P., Rajala, R., & Jyrämä, A. (2011). Knowledge sharing through virtual teams across borders and boundaries. *Management Learning, 42*(4), 395–418. https://doi.org/10.1177/1350507610389685

Kerstholt, J., Barnhoorn, J., Hueting, T., & Schuilenborg, L. (2018). *Automation as an Intelligent Teammate: Social Psychological Implications.*

Killingsworth, B., Xue, Y., & Liu, Y. (2016). Factors influencing knowledge sharing among global virtual teams. *Team Performance Management, 22*(5–6), 284–300. https://doi.org/10.1108/TPM-10-2015-0042

Klein, G., Woods, D. D., Bradshaw, J. M., Hoffman, R. R., & Feltovich, P. J. (2004). Ten challenges for making automation a 'team player' in joint human-agent activity. *IEEE Intelligent Systems, 19*(6), 91–95. https://doi.org/10.1109/MIS.2004.74

Kogut, B., & Zander, U. (1992). Knowledge of the firm, combinative capabilities, and the replication of technology. *Organization Science, 3*(3), 383–397. https://doi.org/10.1287/ORSC.3.3.383

Konradt, U., Schippers, M. C., Krys, S., & Fulmer, A. (2021). Teams in Transition: A Three-Wave Longitudinal Study of Reflection, Implicit and Explicit Coordination and Performance Improvements. *Frontiers in Psychology, 12,* Article 677896. https://doi.org/10.3389/fpsyg.2021.677896

Kozlowski, S. W. J., & Ilgen, D. R. (2006). Enhancing the Effectiveness of Work Groups and Teams. *Psychological Science in the Public Interest, 7*(3), 77–124. https://doi.org/10.1111/j.1529-1006.2006.00030.x

Larson, L., & DeChurch, L. A. (2020). Leading teams in the digital age: Four perspectives on technology and what they mean for leading teams. *Leadership Quarterly, 31*(1). https://doi.org/10.1016/j.leaqua.2019.101377

Lewis, K. (2004). Knowledge and performance in knowledge-worker teams: A longitudinal study of transactive memory systems. *Management Science, 50*(11), 1519–1533. https://doi.org/10.1287/MNSC.1040.0257

Lewis, K., Lange, D., & Gillis, L. (2005). Transactive memory systems, learning, and learning transfer. *Organization Science, 16*(6), 581–598. https://doi.org/10.1287/ORSC.1050.0143

Lin, C. P. (2007a). To share or not to share: Modeling knowledge sharing using exchange ideology as a moderator. *Personnel Review, 36*(3), 457–475. https://doi.org/10.1108/00483480710731374

Lin, H. F. (2007b). Knowledge sharing and firm innovation capability: An empirical study. International *Journal of Manpower, 28*(3–4), 315–332. https://doi.org/10.1108/01437720710755272/FULL/PDF

Lowry, P. B., Roberts, T. L., & Romano, N. C. (2013). What signal is your inspection team sending to each other? Using a shared collaborative interface to improve shared cognition and implicit coordination in error-detection teams. *International Journal of Human-Computer Studies, 71*(4), 455–474. https://doi.org/10.1016/J.IJHCS.2012.11.004

Mahaini, I. M., Li, S., & Sağlam, R. B. (2019). *Building Taxonomies based on Human-Machine Teaming: Cyber Security as an Example.* https://doi.org/10.1145/3339252.3339282

Marks, M. A., Mathieu, J. E., & Zaccaro, S. J. (2001). A Temporally Based Framework and Taxonomy of Team Processes. *Academy of Management Review, 26*(3), 356–376. https://doi.org/10.5465/amr.2001.4845785

Marlow, S. L., Lacerenza, C. N., Paoletti, J., Burke, C. S., & Salas, E. (2018). Does team communication represent a one-size-fits-all approach?: A meta-analysis of team communication and performance. *Organizational Behavior and Human Decision Processes, 144*, 145–170. https://doi.org/10.1016/j.obhdp.2017.08.001

Marques-Quinteiro, P., Curral, L., Passos, A. M., & Lewis, K. (2013). And now what do we do? The role of transactive memory systems and task coordination in action teams. *Group Dynamics, 17*(3), 194–206. https://doi.org/10.1037/a0033304

Mathieu, J. E., Gallagher, P. T., Domingo, M. A., & Klock, E. A. (2019). Embracing Complexity: Reviewing the Past Decade of Team Effectiveness Research. *Annual Review of Organizational Psychology and Organizational Behavior, 6(*1), 17–46. https://doi.org/10.1146/annurev-orgpsych-012218-015106

Mathieu, J. E., & Gilson, L. L. (2012). Criteria Issues and Team Effectiveness. In S. W. J. Kozlowski (Ed.), *The Oxford handbook of organizational psychology* (Vol. 2, pp. 910–930). Oxford University Press. https://doi.org/10.1093/OXFORDHB/9780199928286.013.0027

Mathieu, J. E., Goodwin, G. F., Heffner, T. S., Salas, E., & Cannon-Bowers, J. A. (2000). The influence of shared mental models on team process and performance. *The Journal of Applied Psychology, 85*(2), 273–283. https://doi.org/10.1037/0021-9010.85.2.273

Mathieu, J. E., Maynard, T. M., Rapp, T., & Gilson, L. (2008). Team effectiveness 1997-2007: A review of recent advancements and a glimpse into the future. *Journal of Management, 34*(3), 410–476. https://doi.org/10.1177/0149206308316061

Maynard, M. T., Mathieu, J. E., Rapp, T. L., & Gilson, L. L. (2012). Something(s) old and something(s) new: Modeling drivers of global virtual team effectiveness. *Journal of Organizational Behavior, 33*(3), 342–365. https://doi.org/10.1002/job.1772

McGarth, J. E. (1964). *Social psychology: A brief introduction*. Holt.

McNeese, N. J., Demir, M., Chiou, E. K., & Cooke, N. J. (2021a). Trust and Team Performance in Human–Autonomy Teaming. *International Journal of Electronic Commerce, 25*(1), 51–72. https://doi.org/10.1080/10864415.2021.1846854

McNeese, N. J., Demir, M., Cooke, N. J., & Myers, C. (2018). Teaming With a Synthetic Teammate: Insights into Human-Autonomy Teaming. *Human Factors, 60*(2), 262–273. https://doi.org/10.1177/0018720817743223

McNeese, N. J., Demir, M., Cooke, N. J., & She, M. (2021b). Team Situation Awareness and Conflict: A Study of Human–Machine Teaming. *Journal of Cognitive Engineering and Decision Making, 15*(2–3), 83–96. https://doi.org/10.1177/15553434211017354

Mesmer-Magnus, J. R., & DeChurch, L. A. (2009). Information Sharing and Team Performance: A Meta-Analysis. *Journal of Applied Psychology, 94*(2), 535–546. https://doi.org/10.1037/a0013773

Mohammed, S., Ferzandi, L., & Hamilton, K. (2010). Metaphor No More: A 15-Year Review of the Team Mental Model Construct. *Journal of Management, 36*(4), 876–910. https://doi.org/10.1177/0149206309356804

Moreland, R. L., & Myaskovsky, L. (2000). Exploring the Performance Benefits of Group Training: Transactive Memory or Improved Communication? *Organizational Behavior and Human Decision Processes, 82(*1), 117–133. https://doi.org/10.1006/obhd.2000.2891

Morgeson, F. P., DeRue, D. S., & Karam, E. P. (2010). Leadership in Teams: A Functional Approach to Understanding Leadership Structures and Processes. *Journal of Management, 36*(1), 5–39. https://doi.org/10.1177/0149206309347376

Musick, G., O'Neill, T. A., Schelble, B. G., McNeese, N. J., & Henke, J. B. (2021). What Happens When Humans Believe Their Teammate is an AI? An Investigation into Humans Teaming with Autonomy. *Computers in Human Behavior, 122*, Article 106852. https://doi.org/10.1016/j.chb.2021.106852

Nonaka, I. (1994). A dynamic theory of organizational knowledge creation. *Organization Science, 5*(1), 14–37. https://doi.org/10.1287/ORSC.5.1.14

Nonaka, I. (2009). A dynamic theory of organizational knowledge creation*. Organization Science, 5*(1), 14–37. https://doi.org/10.1287/ORSC.5.1.14

Nonaka, I., & von Krogh, G. (2009). Tacit knowledge and knowledge conversion: Controversy and advancement in organizational knowledge creation theory. *Organization Science, 20*(3), 635–652. https://doi.org/10.1287/ORSC.1080.0412

Oh, C., Song, J., Choi, J., Kim, S., Lee, S., & Suh, B. (2018). I lead, you help but only with enough details: Understanding the user experience of co-creation with artificial intelligence. *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems (CHI '18),* 1-13. https://doi.org/10.1145/3173574.3174223

Olan, F., Ogiemwonyi Arakpogun, E., Suklan, J., Nakpodia, F., Damij, N., & Jayawickrama, U. (2022). Artificial intelligence and knowledge sharing: Contributing factors to organizational performance. *Journal of Business Research, 145*, 605–615. https://doi.org/10.1016/j.jbusres.2022.03.008

O'Neill, T. A., McNeese, N. J., Barron, A., & Schelble, B. (2022). Human-Autonomy Teaming: A Review and Analysis of the Empirical Literature. *Human Factors, 64*(5), 904–938. https://doi.org/10.1177/0018720820960865

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology, 88*(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879

Pulakos, E. D., Dorsey, D. W., & Borman, W. C. (2003). Hiring for Knowledge-Based Competition. in S. E. Jackson, A. DeNisi & M. A. Hitt (Eds.), *Managing Knowledge for Sustained Competitive Advantage: Designing Strategies for Effective Human Resource Management* (pp. 155-177), Pfeiffer.

Rico, R., Gibson, C. B., Sánchez-Manzanares, M., & Clark, M. A. (2019). Building team effectiveness through adaptation: Team knowledge and implicit and explicit coordination. *Organizational Psychology Review, 9*(2–3), 71–98. https://doi.org/10.1177/2041386619869972

Rico, R., Hinsz, V. B., Davison, R. B., & Salas, E. (2018). Structural influences upon coordination and performance in multiteam systems. *Human Resource Management Review, 28*(4), 332–346. https://doi.org/10.1016/j.hrmr.2017.02.001

Rico, R., Sánchez-Manzanares, M., Gil, F., & Gibson, C. (2008). Team implicit coordination processes: A team knowledge-based approach. *Academy of Management Review, 33*(1), 163–184. https://doi.org/10.5465/AMR.2008.27751276

Riethmüller, M., Fernandez Castelao, E., Eberhardt, I., Timmermann, A., & Boos, M. (2012). Adaptive coordination development in student anaesthesia teams: a longitudinal study. *Ergonomics, 55*(1), 55–68. https://doi.org/10.1080/00140139.2011.636455

Salas, E., Cooke, N. J., & Rosen, M. A. (2008). On teams, teamwork, and team performance: Discoveries and developments. *Human Factors*, *50*(3), 540-547. https://doi.org/10.1518/001872008X288457

Salas, E., Dickinson, T. L., Converse, S. A., & Tannenbaum, S. I. (1992). Toward an understanding of team performance and training. In R. W. Swezey & E. Salas (Eds.), *Teams: Their training and performance* (pp. 3–29). Ablex Publishing.

Salas, E., Shuffler, M. L., Thayer, A. L., Bedwell, W. L., & Lazzara, E. H. (2015). Understanding and Improving Teamwork in Organizations: A Scientifically Based Practical Guide. *Human Resource Management, 54*(4), 599–622. https://doi.org/10.1002/hrm.21628

Salas, E., Sims, D. E., & Shawn Burke, C. (2005). Is there A 'big five' in teamwork? *Small Group Research*, *36*(5), 555-599. https://doi.org/10.1177/1046496405277134

Santos, C. M., Passos, A. M., Uitdewilligen, S., & Nübold, A. (2016). Shared temporal cognitions as substitute for temporal leadership: An analysis of their effects on temporal conflict and team performance. *The Leadership Quarterly, 27*(4), 574–587. https://doi.org/10.1016/j.leaqua.2015.12.002

Schelble, B. G., Flathmann, C., McNeese, N. J., Freeman, G., & Mallick, R. (2022). Let's Think Together! Assessing Shared Mental Models, Performance, and Trust in Human-Agent Teams. *Proceedings of the ACM on Human-Computer Interaction, 6*(GROUP), Article 13. https://doi.org/10.1145/3492832

Schmutz, J. B., Outland, N., Kerstan, S., Georganta, E., & Ulfert, A. S. (2024). AI-teaming: Redefining collaboration in the digital era. *Current Opinion in Psychology, 58*, Article 101837. https://doi.org/10.1016/j.copsyc.2024.101837

Schneider, M., Miller, M., Jacques, D., & Peterson, G. (2021). Exploring the Impact of Coordination in Human-Agent Teams. *Journal of Cognitive Engineering and Decision Making, 15*(2-3), 97-115. https://doi.org/10.1177/15553434211010573

Seeber, I., Bittner, E., Briggs, R. O., de Vreede, T., de Vreede, G. J., Elkins, A., Maier, R., Merz, A. B., Oeste-Reiß, S., Randrup, N., Schwabe, G., & Söllner, M. (2020). Machines as teammates: A research agenda on AI in team collaboration. *Information and Management, 57*(2). https://doi.org/10.1016/j.im.2019.103174

Shiflett, S. (1979). Toward a General Model of Small Group Productivity. *Psychological Bulletin, 86*(1), 67–79. https://doi.org/10.1037/0033-2909.86.1.67

Stout, R. J., Cannon-Bowers, J. A., Salas, E., & Milanovich, D. M. (1999). Planning, Shared Mental Models, and Coordinated Performance: An Empirical Link Is Established. *Human Factors, 41*(1), 61–71. https://doi.org/10.1518/001872099779577273

Stowers, K., Kasdaglis, N., Newton, O., Lakhmani, S., Wohleber, R., & Chen, J. (2016). Intelligent Agent Transparency. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting, 60*(1), 1706–1710. https://doi.org/10.1177/1541931213601392

Strack, M., Kolbe, M., & Boos, M. (2011). Dimensions of group coordination: Applicability test of the coordination mechanism circumplex model. In M. Boss, M. Kolbe, P. M. Kappeler, & T. Ellwart (Eds.), *Coordination in Human and Primate Groups* (pp. 57–73). Springer. https://doi.org/10.1007/978-3-642-15355-6_4

Talamadupula, K., Briggs, G., Chakraborti, T., Scheutz, M., & Kambhampati, S. (2014). Coordination in human-robot teams using mental modeling and plan recognition. *IEEE International Conference on Intelligent Robots and Systems,* 2957–2962. https://doi.org/10.1109/IROS.2014.6942970

Turner, J., Baker, R., Ali, Z., & Thurlow, N. (2020). A new multiteam system (MTS) effectiveness model. *Systems, 8*(2), 1–19. https://doi.org/10.3390/SYSTEMS8020012

Ulfert, A. S., & Georganta, E. (2020). A model of team trust in human-agent teams. *Companion Publication of the 2020 International Conference on Multimodal Interaction (ICMI '20 Companion),* 171–176. https://doi.org/10.1145/3395035.3425959

van den Hooff, B., de Ridder, J., & Aukema, E. (2004). Exploring the Eagerness to Share Knowledge: The Role of Social Capital and ICT in Knowledge Sharing. In M. Huysman & V. Wulf (Eds.), *Social Capital and Information Technology*. The MIT Press. https://doi.org/10.7551/mitpress/6289.003.0010

van den Hooff, B., & Hendrix, L. (2004). EAGERNESS AND WILLINGNESS TO SHARE : THE RELEVANCE OF DIFFERENT ATTITUDES TOWARDS KNOWLEDGE SHARING.

van den Hooff, B., & Ridder, J. A. (2004). Knowledge sharing in context: The influence of organizational commitment, communication climate and CMC use on knowledge sharing. *Journal of Knowledge Management, 8*(6), 117–130. https://doi.org/10.1108/13673270410567675/FULL/XML

Von Krogh, G., Nonaka, I., & Aben, M. (2001). Making the Most of Your Company's Knowledge: A Strategic Framework. *Long Range Planning, 34*(4), 421–439. https://doi.org/10.1016/S0024-6301(01)00059-0

Wang, D., Weisz, J. D., Muller, M., Ram, P., Geyer, W., Dugan, C., Tausczik, Y., Samulowitz, H., & Gray, A. (2019). Human-AI Collaboration in Data Science: Exploring Data Scientists' Perceptions of Automated AI. *Proceedings of the ACM on Human-Computer Interaction, 3(CSCW),* Article 211. https://doi.org/10.1145/3359313

Wang, S., & Noe, R. A. (2010). Knowledge sharing: A review and directions for future research. *Human Resource Management Review, 20*(2), 115–131. https://doi.org/10.1016/j.hrmr.2009.10.001

Wang, Z., & Wang, N. (2012). Knowledge sharing, innovation and firm performance. *Expert Systems with Applications, 39*(10), 8899–8908. https://doi.org/10.1016/j.eswa.2012.02.017

Whiting, K. (2024, January 23). *From Sam Altman to António Guterres: Here's what 10 leaders said about AI at Davos 2024*. World Economic Forum. https://www.weforum.org/stories/2024/01/what-leaders-said-about-ai-at-davos-2024/

Wiedow, A., Konradt, U., Ellwart, T., & Steenfatt, C. (2013). Direct and indirect effects of team learning on team outcomes: A multiple mediator analysis. *Group Dynamics: Theory, Research, and Practice, 17*(4), 232–251. https://doi.org/10.1037/a0034149
Wildman, J. L., Nguyen, D., Thayer, A. L., Robbins-Roth, V. T., Carroll, M., Carmody, K., Ficke, C., Akib, M., & Addis, A. (2024). Trust in Human-Agent Teams: A Multilevel Perspective and Future Research Agenda. *Organizational Psychology Review, 14*(3), 373–402. https://doi.org/10.1177/20413866241253278
Wright, M. C., & Kaber, D. B. (2005). Effects of Automation of Information-Processing Functions on Teamwork. *Human Factors, 47*(1), 50–66. https://doi.org/10.1518/0018720053653776
Yoo, S., Joo, B. K., & Noh, J. H. (2022). Team emergent states and team effectiveness: the roles of inclusive leadership and knowledge sharing. *Journal of Organizational Effectiveness, 9*(3), 353–371. https://doi.org/10.1108/JOEPP-05-2021-0120
Zercher, D., & Jussupow, E. (2023). When AI joins the Team: A Literature Review on Intragroup Processes and their Effect on Team Performance in Team-AI Collaboration. *ECIS 2023 Research Papers, 307.* https://aisel.aisnet.org/ecis2023_rp/307
Zhang, R., McNeese, N. J., Freeman, G., & Musick, G. (2021). 'An Ideal Human': Expectations of AI Teammates in Human-AI Teaming. *Proceedings of the ACM on Human-Computer Interaction, 4*(CSCW3). https://doi.org/10.1145/3432945

Annexes

Annex A: Questionnaire Team Members

SURVEY

1. This questionnaire is part of a research project conducted by a team of researchers from ISCTE – University Institute of Lisbon, focusing on team effectiveness in a business context. The main objective of this project is to identify the factors related to teamwork that contribute to the success of projects and the satisfaction of both clients and consultants.
2. The data collected will be analyzed exclusively by the research team, and anonymity is guaranteed.
3. The questions are designed so that you only need to select the answer you find most suitable. Try to respond without spending too much time on each question.
4. There are no right or wrong answers. What matters to us is solely your personal opinion.
5. For each question, there is a scale. You can use any point on the scale as you see fit.
6. Please complete the entire questionnaire in one session without interruptions.

For any clarification or additional information about the study, please contact: Prof. Ana Margarida Passos (ana.passos@iscte-iul.pt).

Thank you for your collaboration!

Please answer this questionnaire by reflecting on the project you are currently involved in and the team you are working with.

1. The following questions aim to describe team behaviors. Indicate to what extent you agree with each statement using the response scale below.

Totally disagree	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree	Totally agree
1	2	3	4	5	6	7

My team is effective in…

1.	Taking creative actions to solve problems that lack straightforward answers.	1	2	3	4	5	6	7
2.	Finding innovative ways to handle unexpected situations.	1	2	3	4	5	6	7
3.	Adapting and managing unforeseen events by quickly refocusing and taking appropriate actions.	1	2	3	4	5	6	7
4.	Developing alternative action plans in a short time to address contingencies.	1	2	3	4	5	6	7
5.	Seeking and developing new skills to respond to situations/problems.	1	2	3	4	5	6	7
6.	Adjusting each member's personal style to the team's collective approach.	1	2	3	4	5	6	7
7.	Improving interpersonal relationships while considering the needs and aspirations of each member.	1	2	3	4	5	6	7
8.	Maintaining focus even when handling multiple situations and responsibilities.	1	2	3	4	5	6	7

2. The following statements refer to feelings some teams experience about their work. Use the same response scale as before.

1.	At our work, we feel bursting with energy.	1	2	3	4	5	6	7
2.	At our job, we feel strong and vigorous.	1	2	3	4	5	6	7
3.	We are enthusiastic about our job.	1	2	3	4	5	6	7
4.	Our job inspires us.	1	2	3	4	5	6	7
5.	When we arrive at work, we feel like starting to work.	1	2	3	4	5	6	7
6.	We feel happy when we are working intensely.	1	2	3	4	5	6	7
7.	We are proud of the work that we do in the organization.	1	2	3	4	5	6	7
8.	We are immersed in our work.	1	2	3	4	5	6	7
9.	We get carried away when we are working.	1	2	3	4	5	6	7

3. The following questions relate to how your team works.

1.	Our team works in a well-coorinated manner.	1	2	3	4	5	6	7
2.	Our team has very few misunderstandings about what to do.	1	2	3	4	5	6	7
3.	Our team often has to go back and start over.	1	2	3	4	5	6	7
4.	We perform tasks smoothly and efficiently.	1	2	3	4	5	6	7
5.	There is a lot of confusion about how to perform tasks.	1	2	3	4	5	6	7
6.	We anticipate what each team member does / needs at a given moment.	1	2	3	4	5	6	7
7.	We adjust our behavior to anticipate the actions of other members.	1	2	3	4	5	6	7
8.	We synchronize our work with the minimal necessary communication.	1	2	3	4	5	6	7

4. The following questions concern the leader's behavior. Indicate to what extent you agree with each of the following statements.

Totally disagree	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree	Totally agree
1	2	3	4	5	6	7

The leader of my team…

1.	Changes the way the team interprets events of situations the team is faced with.	1	2	3	4	5	6	7
2.	Alters the way the team thinks about events or situations the team is faced with.	1	2	3	4	5	6	7
3.	Modifies how the team thinks about events or situations the team is faced with.	1	2	3	4	5	6	7
4.	Encourages the team to collectively interpret things that happen to the team.	1	2	3	4	5	6	7
5.	Promotes team discussions about different perspectives of events or situations.	1	2	3	4	5	6	7
6.	Encourages team members to provide their unique viewpoint on events or situations.	1	2	3	4	5	6	7
7.	Promotes the development of a shared understanding of events or situations among the team members.	1	2	3	4	5	6	7

5. Regarding the leader's behavior, please indicate to what extent you agree or disagree with each of the following statements.

The leader of my team...

1.	Encourages all of us to voice our opinions.	1	2	3	4	5	6	7
2.	Ensures that all members are valued for their contributions.	1	2	3	4	5	6	7
3.	Makes sure that everyone's unique strengths are leveraged.	1	2	3	4	5	6	7
4.	Creates an environment in which we can be ourselves.	1	2	3	4	5	6	7
5.	Encourages everyone to be unique.	1	2	3	4	5	6	7
6.	Enables us to see differences as an advantage rather than as a disadvantage.	1	2	3	4	5	6	7
7.	Helps us to see how differences among us can be an added value for our team.	1	2	3	4	5	6	7
8.	Helps us to solve disagreements to make better decisions for the team.	1	2	3	4	5	6	7
9.	Encourages us to listen to perspectives that are different from our own.	1	2	3	4	5	6	7
10.	Helps us to understand that different views are needed to understand the bigger picture.	1	2	3	4	5	6	7

6. Now think about how your team works. Please indicate to what extent you agree or disagree with each of the following statements.

1.	In my team, we actively attack problems.	1	2	3	4	5	6	7
2.	In my team, we quickly use opportunities to attain goals.	1	2	3	4	5	6	7
3.	In my team, we usually do more than we are asked to do.	1	2	3	4	5	6	7
4.	In my team, we are particularly good at realizing ideas.	1	2	3	4	5	6	7

7. Please continue thinking of your team as a whole. Indicate to what extent you agree or disagree with each of the following statements:

1.	If we find ourselves in a jam, we can think of many ways to get out of it.	1	2	3	4	5	6	7
2.	Right now, we see ourselves as being pretty successful as a team.	1	2	3	4	5	6	7
3.	We can think of many ways to reach our current goals.	1	2	3	4	5	6	7
4.	We are looking forward to the life ahead of us.	1	2	3	4	5	6	7
5.	The future holds a lot of good in store for us.	1	2	3	4	5	6	7
6.	Overall, we expect more good things to happen to us than bad.	1	2	3	4	5	6	7
7.	Sometimes, we make ourselves do things whether we want to or not.	1	2	3	4	5	6	7
8.	When we're in a difficult situation, we can usually find our way out of it.	1	2	3	4	5	6	7
9.	It's okay if there are people who don't like us.	1	2	3	4	5	6	7
10.	We are confident that we could deal efficiently with unexpected events.	1	2	3	4	5	6	7
11.	We can solve most problems if we invest the necessary effort.	1	2	3	4	5	6	7
12.	We can remain calm when facing difficulties because we can rely on our coping abilities.	1	2	3	4	5	6	7

8. Please now think about the results of your team's work and indicate to what extent you agree or disagree with each of the following statements:

Totally disagree	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree	Totally agree
1	2	3	4	5	6	7

1.	My team has a good performance.	1	2	3	4	5	6	7
2.	We are satisfied to be working in this team.	1	2	3	4	5	6	7
3.	My team is effective.	1	2	3	4	5	6	7
4.	I would not hesitate to work with this team on other projects.	1	2	3	4	5	6	7
5.	This team could work well on future projects.	1	2	3	4	5	6	7

9. Think now about how your team members relate to each other.

1.	I am able to count on my team members for help if I have difficulties with my job.	1	2	3	4	5	6	7
2.	I am confident that my team members will take my interests into account when making work-related decisions.	1	2	3	4	5	6	7
3.	I am confident that that my team members will keep me informed about issues that concern my work.	1	2	3	4	5	6	7
4.	I can rely on my team members to keep their word.	1	2	3	4	5	6	7
5.	I trust my team members.	1	2	3	4	5	6	7
6.	It is safe for me to make suggestions.	1	2	3	4	5	6	7
7.	It is safe to give my opinions.	1	2	3	4	5	6	7
8.	It is safe for me to speak up around here.	1	2	3	4	5	6	7

10. Think now about the project your team is involved in.

Totally disagree	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree	Totally agree
1	2	3	4	5	6	7

1.	We are well aware of the environment in which the project is being developed.	1	2	3	4	5	6	7
2.	We clearly understand the variables that influence the success of the project.	1	2	3	4	5	6	7
3.	We quickly identify changes that may influence our work.	1	2	3	4	5	6	7
4.	We have clear information about the tasks/project we are developing.	1	2	3	4	5	6	7

11. Think now about the organization you work for and respond to the following questions. Indicate to what extent you agree with each of the following statements:

1.	In my organization, there are opportunities for career progression.	1	2	3	4	5	6	7
2.	It is possible to communicate openly and directly about career aspirations.	1	2	3	4	5	6	7
3.	The organization helps me identify other positions within the organization that match my interests.	1	2	3	4	5	6	7
4.	This organization is a springboard for future employment opportunities.	1	2	3	4	5	6	7
5.	In my organization, salaries are adequate.	1	2	3	4	5	6	7
6.	There are rewards for additional work.	1	2	3	4	5	6	7
7.	HR practices are designed to meet personal needs.	1	2	3	4	5	6	7
8.	The organization recognizes exceptional work.	1	2	3	4	5	6	7
9.	The organization has a good reputation and is perceived as socially responsible.	1	2	3	4	5	6	7
10.	I feel good about working for this organization.	1	2	3	4	5	6	7
11.	My organization's HR practices are guided by ethical principles.	1	2	3	4	5	6	7
12.	My organization contributes significantly to society through solidarity actions.	1	2	3	4	5	6	7

12. Think about your team as a whole and indicate to what extent you agree with each of the following statements:

Totally disagree	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree	Totally agree
1	2	3	4	5	6	7

1.	My team is globally very diverse.	1	2	3	4	5	6	7
2.	My team is very diverse in terms of ethnic composition.	1	2	3	4	5	6	7
3.	My team is very diverse in terms of gender.	1	2	3	4	5	6	7
4.	My team is very diverse in terms of academic background.	1	2	3	4	5	6	7
5.	My team is very diverse in terms of age.	1	2	3	4	5	6	7
6.	I am very aware of the differences among my colleagues.	1	2	3	4	5	6	7

13. Now focus on yourself and indicate how much you agree with each of the following statements:

Totally disagree	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree	Totally agree
1	2	3	4	5	6	7

1.	In this team, I can be my unique self.	1	2	3	4	5	6	7
2.	In this team, I can use my unique skills and abilities.	1	2	3	4	5	6	7
3.	In this team, I feel that I belong.	1	2	3	4	5	6	7
4.	In this team I feel connected with other team members.	1	2	3	4	5	6	7
5.	In this team, I feel like an outsider.	1	2	3	4	5	6	7

13. In the next set of questions, we ask you to imagine a scenario where you would be collaborating with not only your human colleagues but also an AI agent as part of your team. An AI agent, in this context, is an autonomous system that acts as a team member with a clear, distinct role and collaborates interdependently with the team. Please reflect on how working in a team with human and non-human team members might impact your behaviour.
Your insights will help us understand the potential benefits, challenges, and dynamics of collaboration between humans and AI agents.

Totally disagree	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree	Totally agree
1	2	3	4	5	6	7

1.	When I've learned something new, I would tell my colleagues about it.	1	2	3	4	5	6	7
2.	I would share information I have with my colleagues.	1	2	3	4	5	6	7
3.	I think it is important that my colleagues know what I am doing.	1	2	3	4	5	6	7
4.	I would regularly tell my colleagues what I am doing.	1	2	3	4	5	6	7
5.	When I need certain knowledge, I would ask my colleagues about it.	1	2	3	4	5	6	7
6.	I would like to be informed of what my colleagues know.	1	2	3	4	5	6	7
7.	I would ask my colleagues about their abilities when I need to learn something.	1	2	3	4	5	6	7
8.	When my colleague is good at something, I would ask them to teach me how to do it.	1	2	3	4	5	6	7

Finally, we would like to ask some socio-demographic data, essential to data analysis:

1.Gender: ☐ Female ☐ Male ☐ Non-binary ☐ Other **2. Age:** ______________ years

3. Which nationality do you identify with most?: ____

4. Job function in the organization: ____

5. How long have you been working in this organization?
☐ Less than 1 year ☐ 1 to 3 years ☐ 3 to 5 years ☐ 5 to 7 years ☐ More than 7 years

6.Team Size (excluding the leader): _________________

7. **Do you have a hybrid working model?** (In this context, hybrid includes all working models that do not require a full-time, on-site presence and have implications for an inclusive workplace with less or no face-to-face interaction.)
☐ Yes ☐ No

8. **Do you have any agent /AI member) in your team?**
☐ Yes ☐ No

THANK YOU VERY MUCH FOR YOUR PARTICIPATION!

Annex B: Questionnaire Team Leaders

SURVEY

1. This questionnaire is part of a research project conducted by a team of researchers from ISCTE – University Institute of Lisbon, focusing on team effectiveness in a business context. The main objective of this project is to identify the factors related to teamwork that contribute to the success of projects and the satisfaction of both clients and consultants.
2. The data collected will be analyzed exclusively by the research team, and anonymity is guaranteed.
3. The questions are designed so that you only need to select the answer you find most suitable. Try to respond without spending too much time on each question.
4. There are no right or wrong answers. What matters to us is solely your personal opinion.
5. For each question, there is a scale. You can use any point on the scale as you see fit.
6. Please complete the entire questionnaire in one session without interruptions.

For any clarification or additional information about the study, please contact: Prof. Ana Margarida Passos (ana.passos@iscte-iul.pt).

Thank you for your collaboration!

To answer this questionnaire, think about the TEAM and the specific project you are leading.

1. The following questions aim to describe your team's behaviors. Please indicate to what extent you agree with each of them using the response scale below:

Totally disagree	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree	Totally agree
1	2	3	4	5	6	7

1.	This team has a good performance.	1	2	3	4	5	6	7
2.	Members are satisfied working in this team.	1	2	3	4	5	6	7
3.	This team is effective.	1	2	3	4	5	6	7
4.	I would not hesitate to ask this team to work on other projects.	1	2	3	4	5	6	7
5.	This team could work well on future projects.	1	2	3	4	5	6	7
6.	This team actively attacks problems.	1	2	3	4	5	6	7
7.	This team quickly uses opportunities to attain goals.	1	2	3	4	5	6	7
8.	This team usually does more than they are asked to do.	1	2	3	4	5	6	7
9.	This team is particularly good at realizing ideas.	1	2	3	4	5	6	7

2. Now think about your behavior as a leader. Indicate to what extent you agree with each of the following statements:

1.	I encourage all team members to voice their opinions.	1	2	3	4	5	6	7
2.	I ensure that all team members are valued for their contributions.	1	2	3	4	5	6	7
3.	I make sure that everyone's unique strengths are leveraged.	1	2	3	4	5	6	7
4.	I create an environment in which team members can be themselves.	1	2	3	4	5	6	7
5.	I encourage everyone to be unique.	1	2	3	4	5	6	7
6.	I enable the team to see differences as an advantage rather than as a disadvantage.	1	2	3	4	5	6	7
7.	I help the team to see how differences among them can be an added value for our team.	1	2	3	4	5	6	7
8.	I help team members to solve disagreements to make better decisions for the team.	1	2	3	4	5	6	7
9.	I encourage team members to listen to perspectives that are different than their own.	1	2	3	4	5	6	7
10.	I help team members to understand that different views are needed to understand the bigger picture.	1	2	3	4	5	6	7

3. Now think about yourself in relation to the team. Indicate the extent to which you agree with each of the following statements:

1.	In this team, I can be my unique self.	1	2	3	4	5	6	7
2.	In this team, I can use my unique skills and abilities.	1	2	3	4	5	6	7
3.	In this team, I feel that I belong.	1	2	3	4	5	6	7
4.	In this team, I feel connected with the other members.	1	2	3	4	5	6	7
5.	In this team, I feel like an outsider.	1	2	3	4	5	6	7

4. The following questions aim to describe team behaviors. Please indicate to what extent you agree with each of the following statements:

Totally disagree	**Strongly disagree**	**Disagree**	**Neither agree nor disagree**	**Agree**	**Strongly agree**	**Totally agree**
1	2	3	4	5	6	7

This team is...

1.	Taking creative actions to solve problems that lack straightforward answers.	1	2	3	4	5	6	7
2.	Finding innovative ways to handle unexpected situations.	1	2	3	4	5	6	7
3.	Adapting and managing unforeseen events by quickly refocusing and taking appropriate actions.	1	2	3	4	5	6	7
4.	Developing alternative action plans in a short time to adress contingencies.	1	2	3	4	5	6	7
5.	Seeking and developing new skills to respond to situations/problems.	1	2	3	4	5	6	7
6.	Adjusting each member's personal style to the team's collective approach.	1	2	3	4	5	6	7
7.	Improving interpersonal relationships while considering the needs and aspirations of each member.	1	2	3	4	5	6	7
8.	Maintaining focus even when handling multiple situations and responsibilities.	1	2	3	4	5	6	7

5. In the next set of questions, we ask you to imagine a scenario where you would be leading a team not only with your human colleagues but also an AI agent as part of the team. An AI agent, in this context, is an autonomous system that acts as a team member with a clear, distinct role and collaborates independently with the team.

Please reflect on how leading a team with human and non-human team members might impact your behavior and the team's effectiveness. Your insights will help us understand the potential benefits, challenges, and dynamics of collaboration between humans and AI agents.

1.	I would encourage the team to collectively interpret things that happen to the team.	1	2	3	4	5	6	7
2.	I would promote team discussions about different perspectives of events or situations.	1	2	3	4	5	6	7
3.	I would encourage team members to provide their individual viewpoint on events or situations.	1	2	3	4	5	6	7
4.	I would promote the development of a shared understanding of events or situations among the team members.	1	2	3	4	5	6	7
5.	When an AI agent is integrated into the team, the quality of the work will increase.	1	2	3	4	5	6	7
6.	When an AI agent is integrated into this team, the quantity of the work will increase.	1	2	3	4	5	6	7
7.	When an AI agent is integrated into this team, the general effectiveness will increase.	1	2	3	4	5	6	7
8.	When an AI agent is integrated into this team, it will be more productive	1	2	3	4	5	6	7
9.	When an AI agent is integrated into this team, it will be more efficient.	1	2	3	4	5	6	7
10.	When an AI agent is integrated into this team, team members could work well on future projects.	1	2	3	4	5	6	7
11.	When an AI agent is integrated into this team, team members will be satisfied working together.	1	2	3	4	5	6	7
12.	When an AI agent is integrated into this team, the team members would be willing to continue working in this team.	1	2	3	4	5	6	7

Finally, we would like to ask some socio-demographic data, essential to data analysis:

1.Gender: ☐ Female ☐ Male ☐ Non-binary ☐ Other **2. Age:** ______________ years

3. Which nationality do you identify with most?: ____

4. Job function in the organization: ____

5. How long have you been working in this organization?
☐ Less than 1 year ☐ 1 to 3 years ☐ 3 to 5 years ☐ 5 to 7 years ☐ More than 7 years

THANK YOU VERY MUCH FOR YOUR PARTICIPATION!