LUND UNIVERSITY

SCHOOL OF ECONOMICS AND MANAGEMENT

Team Learning in AI-Integrated Work Processes

A Qualitative Study of AI use and its implications for Team Learning Behaviors within Professional Service Firms

by

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June 2026

Master's Programme in Management

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Abstract

Artificial intelligence (AI) is increasingly integrated into knowledge-intensive work, shaping how employees seek information, develop knowledge, and collaborate. While existing research has primarily focused on human-AI collaboration, technological capabilities, and performance outcomes, less attention has been paid to how AI becomes embedded in the interpersonal learning processes through which teams learn in everyday work. This study examines how and why the use of AI in work processes shapes team learning behaviors within Professional Service Firms (PSFs). Drawing on a qualitative multiple-case study of two Swedish PSFs operating within audit and accounting, the empirical material consists of twelve semi-structured interviews. Adopting an abductive approach, the study combines a sociotechnical systems perspective with the concept of team learning behaviors to explore how AI becomes integrated into team learning processes. The findings show that employees frequently use AI when encountering uncertainty, allowing them to gain orientation, clarify questions, and develop preliminary understanding before involving colleagues. Rather than replacing collaboration, AI becomes embedded in existing work practices as an additional layer between individual uncertainty and interpersonal interaction. This reshapes how team members share knowledge, co-construct understanding, engage across boundaries, and participate in learning-related activities. At the same time, learning processes that occur through individual human-AI interactions may become less visible to the wider team. The study further shows that AI-mediated team learning is shaped by organisational and situational conditions, including time and efficiency pressure, accessibility of support and perceived interpersonal risk-taking. It concludes that AI becomes embedded in sociotechnical work systems and reconfigures how team learning behaviors are enacted, distributed, and made visible within teams.

Keywords: Team Learning Behaviors, Sociotechnical systems, Artificial Intelligence, Interpersonal risk-taking, Professional Service Firms

Acknowledgements

We would like to extend our heartfelt thanks to all fourteen participants in this study. Your insights and reflections provided valuable perspectives that made this research both possible and engaging to conduct. We are also very grateful to our supervisor, Martin Blom, for his continuous guidance and constructive support throughout the process. Finally, we would like to thank our fellow students for their helpful feedback and contributions during the development of this work.

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1. Introduction

1.1 Background and Problem Statement

Over the past decades, technological development has transformed how organisations structure work, coordinate activities, and collaborate in everyday work processes (Brynjolfsson & McAfee, 2014). These developments highlight the interdependence between social and technical systems, a relationship long emphasized within sociotechnical systems (STS) theory, which argues that organisational outcomes emerge through the interaction between social structures and technologies rather than from either system in isolation (Trist & Bamforth, 1951). Similarly, research within human-computer interaction (HCI) emphasizes that technologies not only support task execution, but also shape communication patterns, collaboration, and how individuals engage in work practices (Wu & Guo, 2025). Together, these perspectives suggest that technological change cannot be understood independently from the social and interactional contexts in which technologies become embedded.

Currently, organisations across industries are undergoing rapid transformation as artificial intelligence (AI) becomes increasingly integrated into everyday work practices (OECD, 2026; Pendell, 2025). In this study, AI is defined in accordance with Jetha et al. (2025) stating that "AI is an umbrella term broadly referring to the use of computing machines to solve problems traditionally requiring human intelligence, including detecting patterns, making predictions and decisions, or optimizing processes" (p.2). Unlike earlier computational systems primarily designed for structured and rule-based tasks, contemporary AI systems increasingly support cognitive and knowledge-intensive activities such as information retrieval, analysis, writing, idea generation, and decision support (Stark & Vanden Broeck, 2024; Tang et al., 2023). As a result, AI is both transforming how work tasks are performed, but also how employees seek information, solve problems and engage in collaborative work processes.

Professional service firms (PSFs) constitute a particularly relevant context for examining such developments. PSFs are knowledge-intensive organisations whose work relies heavily on employees' expertise, professional judgement, and the application of specialized knowledge to client-specific problems (von Nordenflycht, 2010). These organisations rely on employees’ expertise, collaboration, and continuous learning in order to create value for clients. Work processes are often characterized by high levels of interdependence, ongoing coordination, and extensive knowledge sharing between colleagues. At the same time, PSFs are shaped by strong efficiency pressures, high workloads, and increasing expectations to leverage technologies in order to streamline work processes and deliver services effectively (KPMG, 2025). As AI becomes increasingly integrated into these environments, questions emerge regarding how such technologies shape the interpersonal and learning-related processes through which work is coordinated and knowledge is developed within teams.

Research on teamwork and learning has long emphasized that learning in teams is inherently social and interactional. Learning behaviors such as asking questions, seeking feedback, sharing knowledge, discussing mistakes, and reflecting on work processes are considered central mechanisms through which teams develop collective understanding and adapt to changing conditions (Edmondson, 1999; Wiese et al., 2021). This study uses the term team learning behaviors (TLBs), referring to seven interrelated behaviors: knowledge sharing, co-construction, constructive conflict, boundary crossing, team activity, team reflexivity and storage and retrieval (Widmann & Mulder, 2025). However, engaging in such behaviors often involves interpersonal risk, as individuals may fear appearing uninformed, incompetent, or disruptive when exposing uncertainty or asking for help (Edmondson, 2003). Psychological safety, conceptualised in this study as perceived interpersonal risk-taking, has therefore been identified as an important condition enabling individuals to engage in learning-related interaction within teams (Edmondson, 1999; 2003).

At the same time, AI-integrated work processes may reshape the conditions under which TLBs unfold. As employees increasingly gain access to AI systems capable of answering questions, generating explanations, summarizing information, and supporting problem-solving, learning-related interactions may no longer occur exclusively between colleagues. Instead, AI may become integrated into the social processes through which team learning behaviors unfold. Initial research on teaming in the context of AI has suggested that AI influences communication patterns, information sharing, and collaboration within teams (Demir et al., 2017a; Johnson et al., 2021; Schmutz., 2024). Emerging studies have also begun to conceptualize interaction with AI as a form of learning process, where individuals develop knowledge and capabilities through repeated engagement with AI systems (Lu et al., 2025).

However, despite growing research on human-AI teaming and collaboration, existing literature has primarily focused on performance outcomes, system effectiveness, trust, and dyadic human-AI interaction. Comparatively less attention has been paid to how AI becomes embedded in the interpersonal and collaborative processes through which teams learn in everyday work. In particular, limited research has examined how AI shapes specific team learning behaviors (Widmann & Mulder, 2025) within knowledge-intensive teams. Consequently, it remains unclear how AI may reshape, substitute and complement such behaviors unfolding within teams.

Addressing these developments, the present study adopts a socio-technical and team learning behavior-centered perspective to examine how AI becomes integrated into interpersonal learning processes within Professional Service Firms.

1.2 Research Purpose and Research Questions

The aim of this study is to explore how employees within Professional Service Firms (PSFs) perceive the use of AI in work processes, and how AI becomes integrated into team learning and interpersonal interaction. More specifically, the study examines how AI shapes team learning behaviors, drawing on seven interrelated behaviors, and how these are perceived and enacted in AI-integrated work contexts. The study also considers how interpersonal conditions, particularly perceived interpersonal risk-taking, may influence employees' engagement in such behaviors. Rather than examining AI as an isolated technological system, the study approaches AI as embedded within sociotechnical work practices, where human interaction and AI-supported activities become intertwined in everyday work. To address this aim, the study is guided by the following research question:

Research Question:
How and why does the use of AI in work processes shape team learning behaviors within Professional Service Firms?

1.3 Delimitations

This study focuses on AI-integrated work processes within Professional Service Firms (PSFs) in Sweden. PSFs were chosen as a relevant empirical context because they represent knowledge-intensive work settings where collaboration, professional judgement, support-seeking, and continuous learning are central to everyday work. The firms are used as empirical contexts for exploring how AI use is experienced in relation to team learning and interpersonal interaction in knowledge-intensive work. Furthermore, as the study focuses on how AI-integrated work processes are experienced in relation to team learning behaviors, it does not examine the design of AI systems or assess organisational performance outcomes related to AI implementation.

In addition, the study does not measure team-level constructs in an aggregated sense. The empirical material and analysis focuses on individual perceptions of team learning behaviors and interpersonal risk-taking within their respective work contexts. Therefore, psychological safety, a facilitator of TLBs, is not examined as a direct team-level construct, but as part of the broader theoretical framing for understanding how interpersonal risk may shape learning-related interaction.

Given the qualitative and context-dependent design of the study, the findings are not intended for statistical generalisation. Instead, the study aims to provide an in-depth understanding of how AI may shape team learning behaviors within knowledge-intensive work settings. The findings should therefore be interpreted in relation to the specific contexts in which participants operate, while offering analytical insights that may be relevant for similar organisational environments.

1.4 Outline of the Thesis

This thesis is structured into five main chapters. Following the introduction, Chapter 2 presents the theoretical foundation of the study by reviewing existing literature on AI in knowledge-intensive work, sociotechnical systems, team learning behaviors, psychological safety, and AI-integrated learning processes. Together, these perspectives provide the conceptual framework used to examine how AI becomes embedded in workplace learning and collaboration.

Chapter 3 outlines the methodological approach of the study. It describes the qualitative and abductive research design, the multiple-case study approach, the sampling strategy, data collection through semi-structured interviews, and the thematic analysis process. The chapter also discusses considerations related to trustworthiness, limitations, use of AI and research ethics.

Chapter 4 presents the empirical material. First, the participating organisations and their use of AI are introduced to provide contextual understanding. Thereafter, the empirical findings are presented through the identified themes.

Chapter 5 discusses the findings in relation to the theoretical framework and existing literature. It analyses how AI shapes team learning behaviours, as well as the conditions that may influence why AI affects team learning behaviours in these particular ways. The thesis concludes by summarising the main findings and contributions of the study, followed by a discussion of its limitations and suggestions for future research.

2. Teaming in the context of AI

This chapter presents the theoretical foundation of the study by reviewing existing research on AI in organisational work contexts and introducing the key theoretical concepts used to analyse the empirical material. First, the chapter outlines how AI has become integrated into knowledge-intensive work and how prior research has conceptualized the relationship between humans and AI in organisational settings. Second, the chapter introduces team learning behaviors and psychological safety as central concepts for understanding how learning unfolds through interpersonal interaction within teams. Finally, the chapter discusses how AI-integrated work processes may reshape learning-related interactions, support-seeking behaviors, and collaborative knowledge development in contemporary work environments. Together, these perspectives provide the theoretical foundation for examining how AI becomes embedded in interpersonal learning processes within Professional Service Firms (PSFs).

2.1 AI in knowledge-intensive work

Artificial intelligence (AI) generally refers to systems capable of performing tasks associated with human cognitive capabilities, such as information processing, pattern recognition, problem-solving, and decision support (Haenlein & Kaplan, 2019; Samoili et al., 2020). Although no single universally accepted definition exists, AI is commonly described as technologies that can process information, learn from data, generate inferences, and support or automate cognitive tasks previously dependent on human intelligence (Benbya et al., 2020; Enholm et al., 2022). Recent developments in generative AI and large language models (LLMs) have further expanded these capabilities by enabling conversational interaction, text generation, summarisation, interpretation, and analytical support within increasingly knowledge-intensive tasks (Tang et al., 2023).

The role of AI in organisations has evolved significantly over time. Early applications primarily focused on automating structured and repetitive tasks through rule-based systems (Ertel, 2011; McCarthy, 2007). In organisational settings, AI has increasingly moved beyond the automation of structured tasks toward supporting knowledge work and cognitive processes. Rather than only replacing human labour, AI is increasingly used to augment employees' capabilities by assisting with information retrieval, drafting, analysis, and problem-solving activities (Mikalef et al., 2022). In such configurations, AI systems may process large volumes of information and provide suggestions or preliminary outputs, while employees remain responsible for interpretation and contextual judgement. AI can therefore be understood not only as a technology for automation, but as a form of support that becomes integrated into everyday work practices and workflows (Deranty & Corbin, 2024).

These developments are particularly relevant within Professional Service Firms (PSFs). Employees in such organisations often work across multiple customers, projects, and team constellations simultaneously, while operating under strong efficiency pressures and high demands for responsiveness, accuracy, and professional judgement (von Nordenflycht, 2010). Learning and collaboration are therefore not separate from daily work, but central to how employees manage tasks, uncertainty, and develop knowledge over time. This makes it relevant to examine AI not only as an individual productivity tool, but as part of the broader work practices through which team learning behaviors are enacted, altered, or redistributed.

Building on Jetha et al.'s (2025, p.2) definition of AI as an umbrella term referring to the use of computing machines to solve problems traditionally associated with human intelligence, including pattern detection, prediction and decision-making, and process optimisation, this study adopts a broad understanding of AI in work processes in order to capture how employees themselves describe, interpret, and use AI technologies in everyday work. Rather than relying on a narrow or technically fixed definition, the study builds on prior research that understands AI as encompassing technologies that support cognitive and knowledge-intensive tasks to varying degrees (Haenlein & Kaplan, 2019; Samoili et al., 2020). This includes internally developed AI systems built on large language models, widely adopted tools such as Microsoft Copilot, and task-specific software applications that incorporate AI functionalities into existing work processes. AI in this study therefore includes both limited and more embedded forms of use, ranging from occasional task support to integration within core work practices. This broader understanding enables a more inclusive analysis of how AI is experienced and integrated into everyday work across similar organisational contexts.

2.2 A Socio-Technical perspective on AI-integrated work

To understand how AI shapes workplace learning and interaction within teams, this study adopts a sociotechnical systems (STS) perspective. STS theory is grounded in the idea that organisational outcomes emerge through the interaction between social and technical systems, which are interdependent and must be understood together rather than in isolation (Trist & Bamforth, 1951; Cherns, 1976). The technical system includes tools, technologies, infrastructures, and formal work processes, while the social system includes individuals, skills, communication patterns, relationships, norms, and collaborative practices (Appelbaum, 1997). From this perspective, technology is not viewed as a neutral tool that simply produces predefined effects. Rather, technologies shape, and are shaped by, the social practices through which they are used in everyday work (Sawyer & Jarrahi, 2014).

The relevance of STS theory becomes particularly clear in contexts where new technologies are introduced into already established work systems. Early STS research showed that technological change can disrupt social relations, work autonomy, and group cohesion when technical efficiency is prioritised without sufficient attention to the social organisation of work (Trist & Bamforth, 1951). This led to the principle of joint optimisation, which emphasizes that effective organisational functioning depends on aligning technical and social systems rather than optimising one at the expense of the other (Cherns, 1976). Applied to contemporary AI-integrated work, this suggests that the implications of AI should not only be understood in terms of productivity, automation, or task efficiency, but also in relation to how AI affects social practices, such as team learning behaviors.

This perspective is particularly relevant in relation to AI because AI systems increasingly support cognitive and knowledge-intensive activities. As such, AI may become involved in work processes that have traditionally relied on human judgement, expertise, and collaboration. This creates new forms of interdependence between employees, technologies, and organisational routines. From a sociotechnical perspective, the effects of AI therefore depend not only on what the technology can do, but also on how it is implemented, interpreted, adapted, and used within specific organisational contexts.

Recent extensions of STS theory in AI-enhanced work settings similarly emphasize that intelligent technologies create new forms of sociotechnical interdependence, where issues such as adaptation, transparency, trust, information flow, and collaborative sensemaking become central to effective human-technology collaboration (Ang et al., 2025). Furthermore similar technologies may have different implications depending on the work context, task structure, professional norms, and social conditions in which they are used (Sawyer &

Jarrahi, 2014). An STS perspective therefore enables analysis of AI as part of a broader work system, where technical capabilities and social arrangements mutually shape how work is performed and experienced.

2.3 Team Learning Behaviors

The concept of team learning has been conceptualized in diverse ways across the literature, especially in the growing body of research that emerged after Edmondson's (1999) seminal study on psychological safety and learning behavior, leading to conceptual ambiguity in the literature (Wiese & Burke, 2019). Following Edmondson's (1999) contribution, many studies conceptualised team learning primarily as a *behavioral process* in which team members engage in activities such as asking questions, seeking feedback, discussing errors, reflecting on outcomes, and experimenting. In this process-oriented view, team learning refers to the interpersonal behaviors through which teams examine experience, challenge assumptions, and adapt their understandings and actions (Wiese et al., 2021). Rather than occurring solely as an individual cognitive process, team learning unfolds through interpersonal activities (Edmondson, 1999; Decuyper et al., 2010).

Building on this perspective, Wiese and Burke (2019) and Wiese et al. (2021) conceptualize team learning behaviors as recurring interactional activities that enable teams to adapt, coordinate work, and develop collective knowledge over time. These activities enable team members to integrate expertise, clarify uncertainties, and develop shared understanding within complex and changing work environments. This becomes particularly important in contemporary work environments characterised by technological development, increasing complexity, and continuous change, such as Professional Service Firms. Widmann and Mulder (2025) argue that such conditions require organisations and teams to continuously adapt their work processes over time, making collective learning processes increasingly important in knowledge-intensive work.

Research further suggests that these processes contribute to important outcomes such as team effectiveness, innovativeness, and long-term adaptation (Widmann & Mulder, 2025). While learning behaviors in highly routine and standardised work environments can sometimes be perceived as inefficient, they become increasingly critical under conditions of change and uncertainty, where teams must continuously adapt, coordinate actions, and respond to evolving demands (Edmondson, 1999). This is particularly relevant in professional service firms (PSFs), where work is often structured around clear roles, procedures, and processes, yet is simultaneously shaped by changing conditions such as new laws, regulations, and the ongoing need to streamline operations to remain competitive (KPMG, 2025).

To better understand how learning unfolds within teams, it is necessary to distinguish between the specific behaviors through which collective learning occurs. Rather than treating team learning as a single process, Widmann and Mulder (2025), building on Decuyper et al. (2010), conceptualize team learning as a set of seven interrelated learning behaviors. These behaviors capture different forms of interaction through which team members exchange knowledge, develop shared understanding, seek information beyond the team, learn through collaborative work, reflect on their practices, and preserve knowledge for future use. While the seven behaviors represent distinct forms of team learning, prior research suggests that they often occur in combination and may vary in their frequency, duration, intensity, and quality over time (Widmann & Mulder, 2025). Together, the seven behaviors provide a comprehensive framework for examining how teams acquire, create, integrate, and retain knowledge in knowledge-intensive work environments. Given the study's interest in how AI shapes learning within teams, these seven behaviors serve as an analytical lens for understanding potential changes in team learning processes. The behaviors and their definitions are presented below.

Table 1. Team learning behaviors

Team learning behavior	**Description**
Knowledge sharing	The exchange of information, expertise, experiences, and ideas between team members.
Constructive conflict	Task-related discussions where differing perspectives, assumptions, and ideas are critically examined and challenged in a constructive manner.
Co-construction	Collaborative processes through which team members build, refine, and develop shared understanding, meaning, or solutions together.
Boundary crossing	The process of seeking, acquiring, and integrating knowledge, information, or expertise from individuals outside the immediate team context.

Team activity ("learning by doing")	Learning that occurs through collaborative task execution and shared work activities in everyday practice.
Team reflexivity	Collective reflection and evaluation of team goals, strategies, processes, and ways of working in order to improve future functioning.
Storage and retrieval	Processes through which teams document, preserve, access, and reuse knowledge and information over time.

Adapted from Widmann and Mulder (2025), building on Decuyper et al. (2010).

Within Professional Service Firms (PSFs), team learning behaviors become particularly important due to the knowledge-intensive and collaborative nature of the work. Employees frequently rely on colleagues for support, interpretation, feedback, and problem-solving while simultaneously working under conditions characterized by complexity, uncertainty, and continuous coordination across tasks and customer engagements. Consequently, workplace learning becomes closely connected to ongoing interaction within teams in everyday work practices. Importantly, however, engaging in team learning behaviors also involves interpersonal exposure, as individuals risk appearing inexperienced, uninformed, or incompetent in front of colleagues (Edmondson, 2003). Team learning behaviors therefore do not occur automatically, but are shaped by interpersonal and organisational conditions surrounding interaction within teams.

2.3.1 Psychological safety as a facilitator of team learning behaviors

Previous research has emphasised psychological safety as a key factor influencing whether team learning behaviors are enacted within teams (Newman et al., 2017). As mentioned, engaging in behaviors such as asking questions, seeking feedback, or admitting mistakes involves interpersonal risk, as these actions may expose uncertainty or lack of knowledge. Consequently, individuals may refrain from engaging in such behaviors if they fear negative evaluation or social consequences (Edmondson, 2003).

Edmondson (1999) defines psychological safety as a "shared belief held by members of a team that the team is safe for interpersonal risk taking" (p. 354). In psychologically safe environments, individuals feel confident that they will not be embarrassed, rejected, or punished for speaking up, which reduces the perceived risks associated with learning behaviors (Edmonson, 1999; 2003). Such dynamics become particularly relevant in knowledge-intensive environments where expertise, competence, and performance are highly valued, potentially leading employees to hesitate to engage in TLBs if they fear appearing incompetent or disruptive in front of colleagues.

As psychological safety has been shown as a crucial facilitator of team learning behavior, it is of high relevance to the study's research question. However, as psychological safety is a team construct (e.g *shared* belief), this study refers to participants' *perceived interpersonal risk-taking* when looking at this phenomena.

2.4 Team learning behavior in AI-integrated work processes

Although team learning behaviors and psychological safety, as well as their effects on aspects such as performance have been extensively studied in human teams, comparatively less research has examined how these processes unfold within teams in AI-integrated work environments. At the same time, as AI becomes increasingly embedded in everyday work processes, research has increasingly turned to understanding how humans and AI work together in practice. This phenomenon has been conceptualised in multiple ways across the literature, including human-AI interaction, human-AI collaboration and human-AI teaming (Berretta et al, 2023).

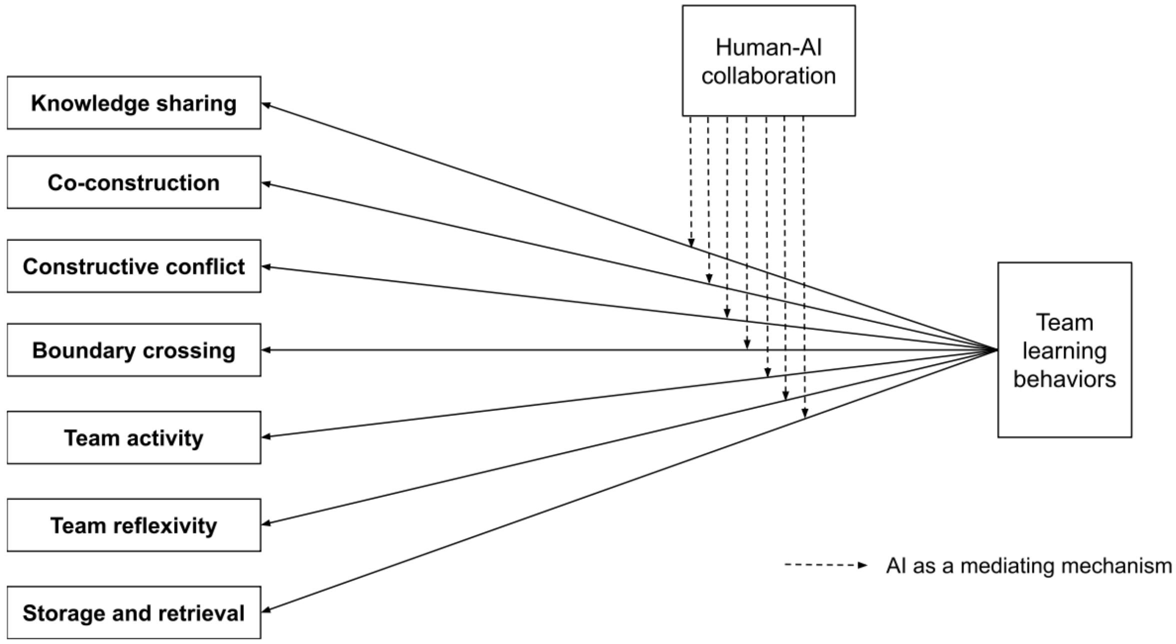
Within research on human-AI teaming, studies frequently adopt a technology-centred perspective, focusing on system capabilities, performance, and human responses to AI, rather than on how AI is embedded in everyday work practices and team processes (Berretta et al, 2023). This research has examined various team-level aspects, including team composition, processes, performance, trust, and shared cognition (Schmutz et al, 2024). Findings suggest that the inclusion of AI can complicate team functioning. For example, human-AI teams have been shown to exhibit lower levels of shared mental models, which are critical for effective collaboration (Mathieu et al., 2000), as well as reduced information sharing and seeking compared to human-only teams (Demir et al., 2017b). In other cases, the presence of an AI teammate has shown to impede performance and coordination (Dell'Acqua et al, 2023; Johnson et al., 2021; Demir et al., 2017a), and present challenges for communication (Johnson et al., 2021). Trust has also emerged as a central factor, with studies indicating that human-AI teams often experience lower levels of trust compared to human-only teams

(Glikson & Woolley, 2020; Georganta & Ulfert, 2024). Taken together, these findings suggest that while AI has the potential to support work processes, its integration into teams can introduce new challenges for coordination, communication, and collaboration.

As AI systems become increasingly integrated into knowledge-intensive work, the conditions under which team learning behaviors occur may change. Team learning can therefore not only be understood as a human-to-human process, but also as a process unfolding within sociotechnical work systems where human interaction and AI-supported activities coexist. These perspectives suggest that AI-integrated work processes are relevant to study not because AI is assumed to replace or improve team learning, but because AI becomes part of the sociotechnical setting in which learning behaviors are enacted. Existing research on human-AI collaboration and human-AI teaming has shown that AI can affect aspects of teamwork (Schmutz et al., 2024). However, less is known about how AI becomes embedded in the everyday learning-related interactions through which human teams seek support, exchange knowledge, and develop understanding in practice. Accordingly, this study brings together sociotechnical systems theory and team learning behaviors as complementary theoretical lenses to examine how learning-related behaviors are perceived and enacted when AI becomes part of the sociotechnical work environment

The conceptual framework developed for this study builds on Savelsbergh and van der Heijden's (2009) model of relationships between team learning behaviors and team performance, but adapts it to the purpose of the present study. Since the aim is not to examine team performance, this outcome dimension is removed. Instead, the model is refined through Widmann and Mulder's (2025) conceptualisation of team learning behaviors and extended by adding human-AI collaboration as a potential mediating mechanism within AI-integrated work processes. In this study, we use the term human-AI collaboration to refer to an individual interacting with AI in a work context. Although mediation is often associated with quantitative analysis and statistically tested indirect effects, qualitative research can also be used to identify and describe mediating mechanisms or intervening processes. Kim and MacKinnon (2025) argue that qualitative mediation analysis is particularly useful in exploratory studies, as interviews and other qualitative methods can generate insight into how and why certain processes unfold. In this study, the term mediating mechanism is therefore used in a qualitative and process-oriented sense. It does not refer to a statistically tested mediation effect, but to the possibility of examining how AI may become involved in the processes through which team learning behaviors are shaped in AI-integrated work contexts.

Figure 1. Conceptual framework of team learning behaviors in AI-integrated work contexts



3. Methodology

This chapter outlines the methodological approach of the study. First, the research philosophy and overall research design are presented. Thereafter, the chapter explains the study's theoretical positioning and analytical approach, followed by descriptions of sampling, data collection, interview procedures, and data analysis. Finally, methodological considerations concerning the study's trustworthiness, limitations, responsible use of AI and ethics are discussed.

3.1 Research Approach and Design

This study is grounded in a qualitative and interpretive research approach, where reality is understood as socially constructed through individuals' experiences, interactions, and interpretations of their work environments (Bryman & Bell, 2015; Cropley, 2023). From this perspective, the study does not aim to identify objective or universal truths regarding AI use in organisations, but rather to explore how employees within Professional Service Firms (PSFs) perceive and make sense of AI-integrated work processes in relation to collaboration and learning.

A qualitative approach was considered particularly suitable given the exploratory nature of the research questions. As AI becomes increasingly embedded in everyday work practices, limited research has examined how AI influences team learning behaviors within knowledge-intensive teams. Qualitative methods are particularly valuable when examining emerging or insufficiently understood phenomena, as they enable in-depth exploration of participants' experiences, interpretations, and social practices (Cropley, 2023).

Furthermore, the study adopts an abductive research approach, where empirical observations and theoretical understanding are developed iteratively through continuous movement between data and theory (Tavory & Timmermans, 2014). Existing research on team learning behaviors and psychological safety provides important theoretical foundations for understanding learning and interaction within teams. However, these theories have largely been developed in human-only contexts and may therefore not fully capture how learning processes unfold in AI-integrated work environments. Rather than treating theory as something to be strictly confirmed or rejected, the abductive approach enabled existing theoretical concepts to function as sensitizing concepts guiding interpretation throughout the study. Sociotechnical systems and team learning behaviors, including psychological safety, therefore informed the analytical focus while simultaneously remaining open to how these processes appeared to be reshaped in AI-integrated work contexts. The abductive approach enable theoretically informed interpretation while remaining attentive to unexpected and emergent patterns within the empirical material.

3.1.1 Multiple-Case study

This study adopts a qualitative case study design. A case study approach was considered appropriate because the study seeks to explore a contemporary phenomenon, the use of AI in team learning processes, within its real-life organisational context. Yin (2018) argues that case study research is suitable when the aim is to investigate a contemporary phenomenon in depth and in its real-world context, particularly when the researcher has little or no control over the events being studied. This was relevant for the present study, as AI use in work processes could not be meaningfully separated from the social and organisational context in which it occurred. Rather, AI use was embedded in everyday work practices, team structures, professional roles, and interaction patterns. A case study design therefore enabled the study to examine how AI shaped team learning behaviors as part of the broader sociotechnical work context.

Within this broader case study approach, a multiple-case design was chosen. The study focuses on two Professional Service Firms operating within accounting and auditing in Sweden. A multiple-case design was considered more suitable than a single-case design because the study aimed to explore how AI-integrated team learning processes appeared across more than one organisational setting. Including two cases made it possible to identify patterns that were present across both firms, while also capturing variation related to differences in work practices, team structures, and AI usage. In this sense, the cases were not treated as statistically representative, but as analytically relevant contexts for exploring the phenomenon.

The study is not designed as a comparative case study in the sense of evaluating one organization against the other. Instead, the two cases were used to support analytical variation and cross-case reflection. Following Yin’s (2018) logic of multiple-case study design, the purpose was to examine whether similar or contrasting patterns could be identified across cases. This allowed the researchers to develop a more nuanced understanding of how AI became integrated into team learning behaviors under different organisational and social conditions. The inclusion of more than one case therefore strengthened the analysis without making organisational comparison the primary aim of the study.

The cases were selected through theoretical rather than statistical sampling. Eisenhardt (1989) argues that case study research is useful for understanding the dynamics of a phenomenon within specific settings, and that cases should be selected for theoretical relevance rather than statistical representativeness. In this study, PSFs were considered particularly relevant empirical settings due to the knowledge-intensive, client-oriented, and collaborative nature of their work, where employees frequently engage in support-seeking, knowledge sharing, and continuous learning to perform complex tasks and deliver professional services. The inclusion of one accounting firm and one audit firm therefore provided variation within a shared broader context of professional service work, enabling the study to explore how AI use shaped team learning processes across related but distinct work settings.

3.2 Choice of Theory

The theoretical framework of this study is guided by the aim of understanding how AI becomes integrated into learning-related interaction processes within Professional Service Firms (PSFs). Rather than examining AI as an isolated technological system or primarily as an individual-level technology adoption phenomenon, the study focuses on how AI becomes embedded within everyday collaborative work practices, support-seeking activities, and workplace learning processes. To capture these dynamics, the study combines a socio-technical systems (STS) perspective with concepts of team learning behaviors.

The STS perspective functions as an overarching analytical lens for understanding how AI becomes integrated into organisational work systems and everyday work practices. STS theory conceptualizes organisational outcomes as emerging through the interaction between social and technical systems rather than from either dimension in isolation (Trist & Bamforth, 1951; Sawyer & Jarrahi, 2014). This perspective enables AI to be understood not merely as a tool supporting task execution, but as part of broader sociotechnical work processes that shape interaction, collaboration and learning within teams.

While STS provides the broader contextual framing, team learning behaviors constitute the primary analytical framework for examining workplace learning within teams. Research on team learning behaviors conceptualizes learning as enacted through observable interactional activities (Edmondson, 1999; Decuyper et al., 2010; Wiese et al., 2021). This perspective was selected because it enables examination of how learning unfolds through everyday interaction between team members rather than solely as an individual cognitive process. The framework is particularly relevant in relation to AI-integrated work environments where employees increasingly have access to AI tools that can support information retrieval, clarification, and problem-solving alongside interpersonal support structures. Consequently, learning-related activities that traditionally may have occurred directly between colleagues may increasingly involve AI.

Psychological safety is included as a complementary analytical concept for understanding the interpersonal conditions surrounding these learning behaviors. Rather than examining psychological safety as a measurable team-level construct, the concept is used to interpret how participants described interpersonal risks associated with questioning, uncertainty, support-seeking, and exposing limitations in knowledge (Edmondson, 1999; Edmondson, 2002). This is particularly relevant since PSFs are characterised by both highly routine, standardised structures alongside constant changes affecting work procedures, which means TLBs can be seen as both inefficient and fundamental in these organisations (Edmondson, 2002). Psychological safety remained part of the broader theoretical framing but was not treated as a central empirical construct due to its group-level nature and the lack of access to intact teams. Instead, the study refers to (perceived) interpersonal risk-taking when exploring participants' individual perceptions of psychological safety within their teams.

Importantly, the analytical framework was not applied through a strict pattern-matching logic where empirical observations were assessed as either confirming or contradicting existing theory. Instead, the theoretical concepts functioned as sensitizing concepts supporting interpretation of how AI-related learning processes unfolded in practice. The analysis therefore focused less on whether AI simply increased or decreased team learning behaviors, and more on how AI appeared to shape how such behaviors unfolded within teams.

3.3 Data collection

3.3.1 Sampling

The sampling strategy was guided by the study's aim to explore team learning behaviors in AI-integrated work processes within knowledge-intensive work environments. Professional Service Firms (PSFs), particularly accounting and audit firms, were selected because their work relies heavily on expertise, collaboration, communication, and continuous learning. In addition, PSFs are characterized by strong efficiency pressures and increasing expectations to leverage technology in order to streamline work processes and deliver services effectively (KPMG, 2025), making them particularly relevant contexts for examining AI integration in everyday work.

Organisations with more than 250 employees were specifically targeted, as larger organisations have been shown to adopt AI technologies to a greater extent than smaller firms (SCB, 2025). This increased the likelihood of identifying participants with practical experience of AI-supported work processes. Participants were primarily recruited through LinkedIn, supplemented by email contact and personal networks. The final sample consisted of 12 employees from two Professional Service Firms, one audit firm and one accounting firm. Participants were employed at different offices around Sweden and varied in seniority, team structures and extent of AI usage. The sample was not intended to be statistically representative. Rather, participants were strategically selected in order to capture diverse experiences of AI integration within knowledge-intensive work settings.

The primary inclusion criterion for participants was the use of AI in some form within their everyday work practices. This included both generative AI tools based on large language models (LLMs), such as ChatGPT, Microsoft Copilot, Claude, and Gemini, as well as internally developed AI-supported systems integrated into organisational workflows. During the sampling process, it became evident that participants differed substantially in both their extent of AI usage and in how they understood and defined AI in the workplace. Some participants initially stated that they did not use AI, but later recognized that they regularly interacted with AI-supported systems once concrete examples were discussed. This variation became analytically valuable, as it reflected how AI often becomes embedded in work processes without necessarily being consciously conceptualized as “AI” by employees themselves.

In addition to the 12 participants who formed the basis of the study’s empirical data, two pilot interviews were conducted. One participant worked at Company A, but in an advisory role, while the other worked in another Professional Service Firm within consultancy. The pilot interviews were conducted in line with the study’s abductive approach, as the researchers initially explored several related topics, including sociotechnical systems, AI, team learning behaviors, psychological safety, and other team-related phenomena.

The first pilot interview contributed to refining the scope of the study. It showed that the advisory role differed from the type of work context the study later aimed to examine. Advisory work was largely organised around project-based teams where members were assigned distinct areas of expertise and responsibility. While collaboration was clearly present, the work context made it more difficult to explore team learning behaviors in relation to recurring everyday support-seeking, questioning, and shared learning in comparable team settings. The interview also revealed methodological challenges related to studying psychological safety through individual interview accounts, which is further discussed in Section 3.3.2.

The second pilot interview provided richer empirical data and confirmed that the refined interview guide was better aligned with the study’s purpose than the initial version. The interview also indicated that audit work could provide a suitable empirical context for examining team learning behaviors. However, the participant worked in an Audit IT role, which differed from the type of audit work the study later aimed to examine. Although relevant insights were gained from the interview, the more specialized nature of Audit IT would have made it difficult to compare this role with the broader sample. The study therefore narrowed its focus toward employees working within more traditional audit roles, where everyday work processes and team-based learning practices were more comparable across participants.

These insights helped clarify both the empirical focus and the limitations of the study before the main interviews were conducted. The following table presents the final sample of the present study.

Table 2. Overview of participants

Participant	Company	Seniority	Duration of interview
Audit#1	Company A	2 years	1 hour and 11 minutes
Audit#2	Company A	8 months	54 minutes
Audit#3	Company A	5.5 years	53 minutes
Audit#4	Company A	1 year	1 hour and 2 minutes
Audit#5	Company A	4 years	1 hour and 7 minutes
Audit#6	Company A	2 years	1 hour and 12 minutes
Accounting#1	Company B	8 months	55 minutes
Accounting#2	Company B	9 months	1 hour and 3 minutes
Accounting#3	Company B	2.5 years	1 hour
Accounting#4	Company B	1.5 years	1 hour and 6 minutes
Accounting#5	Company B	1.5 years	1 hour and 11 minutes
Accounting#6	Company B	2 years	55 minutes

3.3.2 Semi-structured interviews

Data was collected through semi-structured interviews. This method was considered suitable for the exploratory nature of the study, as interviews allow researchers to examine what is happening within a particular research area and develop a deeper understanding of its context (Saunders et al., 2023). Semi-structured interviews are particularly useful when the purpose is to explore participants' experiences and perspectives in depth, while still allowing the researchers to follow a prepared interview guide (DiCicco-Bloom & Crabtree, 2006). The format also enables flexibility to adapt the order of questions, ask follow-up questions, and explore relevant issues that emerge during the conversation, thereby generating rich and nuanced empirical material (Ambert et al., 1995). This was important for the present study, as the aim was to understand participants' experiences of AI use in relation to team learning, collaboration, and support-seeking in everyday work, rather than to obtain standardized responses.

In line with the study's abductive approach, the interview process was informed by both existing literature and insights emerging from the empirical material. The initial interview guide was developed after reviewing literature on human-AI teaming, psychological safety, team learning, and AI in the workplace. Two pilot interviews were conducted to gain a better understanding of which aspects were most relevant to the research question and to refine the interview guide. These interviews indicated that participants were more able to provide rich descriptions when questions focused on concrete work situations, interactions, and learning behaviors, rather than on broader and more abstract team constructs.

Initially, the interview guide included questions related to several team constructs, including psychological safety and team learning. Since psychological safety was considered relevant to the study, some questions were inspired by Edmondson's (1999) conceptualization of psychological safety, particularly in relation to asking questions, raising concerns, and discussing mistakes. However, as psychological safety is a group-level construct, the lack of access to intact teams limited the extent to which it could be examined directly. The pilot interviews also indicated challenges in exploring psychological safety qualitatively, as it was difficult to capture participants' underlying beliefs about whether it was safe to take interpersonal risks within the team. Therefore, psychological safety remained part of the broader theoretical framework, but the interviews focused more specifically on participants' perceptions of interpersonal risk-taking in everyday work situations.

The final interview guide focused on team learning behaviors, interpersonal risk-taking, AI use, and the role of AI in team learning processes. Questions concerning team learning behaviors were informed by Widmann and Mulder's (2025) conceptualization of team learning behaviors. Questions related to interpersonal risk-taking were inspired by Edmondson's (1999) work on psychological safety, but were formulated around concrete experiences rather than direct measurement. The guide also included questions about participants' general use of AI as well as it's role in team interaction, collaboration and learning.

All interviews were conducted in Swedish through Microsoft Teams. Conducting the interviews in Swedish enabled participants to express their experiences in their native language and provide more nuanced descriptions of their everyday work. The digital format also made participation easier for employees working in high-demand professional roles and reduced logistical constraints. With participants' consent, the interviews were audio-recorded and automatically transcribed through Microsoft Teams. The transcripts were then reviewed while listening to the recordings to ensure accuracy and to increase familiarity with the empirical material.

3.4 Data analysis

The empirical material was analysed through a thematic analysis inspired by Bryman (2016), with elements from Gioia et al.'s (2013) coding logic and Yin's (2018) approach to case study analysis. Thematic analysis was considered suitable due to its flexibility in identifying, comparing, and interpreting patterns of meaning across qualitative data. Since the study followed an abductive approach, the analysis moved iteratively between the empirical material and existing theoretical concepts, rather than being either purely inductive or deductive.

The first stage of the analysis was inspired by Gioia et al.'s (2013) emphasis on staying close to informants' own accounts in the early stages of coding. Each interview transcript was read several times to gain familiarity with the material, after which the interviews were coded individually. This was done to preserve the contextual nuances of each participant's experiences and to avoid premature aggregation across participants or companies. Thus, initial coding was primarily data-driven and focused on participants' descriptions of AI use, support-seeking, collaboration, interpersonal interaction, learning-related behaviors, and perceived interpersonal risk. Examples of initial codes included "using AI before asking a colleague," "asking AI for simple questions," "using AI to prepare before discussions," "checking AI answers with colleagues," "not wanting to disturb colleagues," and "concern about asking stupid questions."

In the second stage, the initial codes from each interview were grouped into preliminary interview-level themes. This step was used to move from isolated codes toward broader patterns within each participant's account. For example, codes such as "using AI before asking a colleague," "asking AI for simple questions," and "wanting to understand first" were grouped into a preliminary theme concerning AI as an initial support resource. Similarly, codes such as "using AI to prepare before discussions," "formulating better questions," and "checking AI answers with colleagues" were grouped into a preliminary theme concerning

AI-supported preparation for collegial learning. In this stage, the analysis remained close to the empirical material while beginning to identify recurring learning-related patterns.

In the third stage, the analysis moved from individual interviews to within-case analysis. Following Yin's (2018) case study logic, the preliminary themes were examined within each company separately before comparing the cases. This allowed the researchers to retain the contextual integrity of each case and develop an understanding of how AI-related learning processes appeared within each organisational setting. Within Company A, themes were developed around AI as a first step in clarifying uncertainties, AI-supported preparation before involving colleagues, efficiency pressures, hierarchical review structures, and concerns about asking unnecessary or overly basic questions. Within Company B, themes were developed around AI as a practical support resource, accessible collegial support, and AI as a complement to existing learning practices.

In the fourth stage, the within-case themes were compared across the two companies through cross-case synthesis. This stage was inspired by Yin's (2018) emphasis on comparing within-case patterns across cases, rather than treating cases as a set of isolated variables. The purpose was not to evaluate one company against the other, but to identify shared and contrasting patterns in how AI became integrated into team learning behaviors. During this stage, themes developed within each case were systematically compared to identify similarities and differences across the two organisational contexts. For example, initial codes such as "using AI before asking a colleague," "wanting to understand first," and "checking with colleagues afterwards" were first grouped into the interview-level theme AI as an initial support resource. These themes were then examined within each company, where Company A showed patterns related to preparation, hierarchy, and uncertainty management, while Company B showed patterns related to quick clarification, accessible collegial support, and customer-specific knowledge. Finally, the cross-case analysis developed this into the broader theme AI as a first point of contact in support-seeking.

In the final stage, the cross-case patterns were interpreted in relation to the study's theoretical framework. Existing theory on team learning behaviors, psychological safety, and sociotechnical systems functioned as sensitizing concepts, guiding the interpretation of how AI shaped support-seeking, knowledge sharing, co-construction, boundary crossing, and team activity. This stage involved elements of pattern matching and explanation building, as the emerging empirical patterns were compared with theoretical expectations about team learning as a social and interactional process. However, the aim was not to test theory in a deductive sense, but to develop an empirically grounded explanation of how AI-integrated work processes reshaped learning-related interactions within teams.

By combining Gioia-inspired coding with Yin's case study analysis logic, the study sought to remain close to participants' accounts while also developing a more abstract understanding of how AI shaped team learning behaviors across two organisational contexts.

While the interview protocol covered seven predefined team learning behaviors, the empirical material varied in depth and analytical salience across these dimensions. Four behaviors: knowledge sharing, co-construction, boundary-related knowledge access, and task-based learning, emerged as the most consistently represented in participants' accounts and therefore constitute the primary focus of the analysis. The remaining behaviors informed the interview guide and follow-up questions during data collection but did not generate sufficient empirical material for separate analytical treatment. This reflects the abductive logic of the analysis, in which analytical emphasis was guided by empirical patterns while continuously informed by the theoretical framework.

3.5 Methodological considerations

3.5.1 Trustworthiness of the Study

Validity in qualitative research concerns whether a study succeeds in capturing, representing, and interpreting the phenomenon it aims to explore, thereby ensuring that the findings meaningfully reflect participants' experiences and perspectives (Bryman & Bell, 2015). In the present study, several measures were taken to strengthen the trustworthiness of the research process and the interpretations developed from the empirical material.

First, trustworthiness was strengthened through conceptual clarification during the interviews. One challenge in the present study related to the complexity and evolving nature of AI in organisational contexts. As became evident during sampling and interviews, participants differed in how they understood and defined AI, and some initially did not recognise their own use of AI-supported tools. This conceptual ambiguity reflects the broader fragmentation of AI as a rapidly developing phenomenon and posed challenges for ensuring a consistent understanding of the phenomenon under study. To reduce ambiguity, examples of

AI applications and tools were clarified during interviews when necessary. This enabled participants to relate their experiences to a more concrete understanding of AI in their daily work practices, while still allowing room for variation in how AI was used and understood across contexts.

Second, trustworthiness was strengthened through the iterative relationship between theory and empirical material, in line with the study's abductive approach. Early interviews and pilot interviews contributed to refining the interview guide and focusing the study on concepts that participants could meaningfully reflect upon in relation to their work. For instance, while psychological safety remained theoretically relevant, team learning behaviours emerged as more empirically accessible for qualitative exploration. Rather than attempting to measure psychological safety directly, the study therefore focused on participants' descriptions of perceived interpersonal risk-taking, in relation to for example support-seeking, questioning, and knowledge sharing, in everyday work situations. This iterative refinement strengthened the alignment between the research question, empirical material, and analytical framework.

Third, the study's conceptual framing of AI-related practices as varying in degree of integration into everyday work processes contributed to strengthening validity. AI use was not treated as a uniform or fixed phenomenon, but as something that differed across individuals, tasks, and organisational contexts. This made it possible to interpret participants' accounts in a way that captured variation in how AI was embedded in work practices, without imposing a single understanding of AI adoption or use.

Fourth, transparency in the analytical process was strengthened by showing how the analysis moved from initial codes to broader themes. Inspired by Gioia et al. (2013), the analysis first stayed close to participants' own descriptions before moving toward more abstract analytical categories. Initial codes were developed into preliminary interview-level themes, which were then examined within each company and subsequently compared across cases (Yin, 2018). This process made it possible to trace how empirical observations were gradually developed into broader interpretations concerning how AI shaped team learning behaviours.

Finally, the inclusion of participants from two different Professional Service Firms, with variation in seniority, AI usage, work tasks, and team structures, contributed to the analytical depth of the study. This variation enabled the study to capture a broad range of perspectives and to identify both similarities and differences in how AI related to collaboration and team learning behaviours. At the same time, the analysis was conducted with a reflexive understanding of interview accounts. In line with Alvesson's (2003) reflexive approach to interviews, participants' accounts were not treated as direct observations of organisational reality, but as situated interpretations of their experiences. This was particularly important when analysing themes such as interpersonal risk-taking, psychological safety, and support-seeking, where participants' descriptions may reflect both everyday experiences and broader organisational norms.

3.5.2 Methodological Limitations

Despite efforts to ensure methodological rigour, several limitations should be acknowledged. First, a key limitation relates to the potential influence of socially desirable responses during interviews and the broader organisational context in which participants operate. Participants often initially described their teams as highly supportive environments where all questions were welcomed and teamwork functioned openly. However, as interviews progressed and discussions became more concrete in relation to AI use, several participants expressed hesitation about asking colleagues questions they perceived as too simple or unnecessary, instead preferring to consult AI tools first. This suggests a certain tension between formally expressed norms regarding openness and participants' lived experiences of interpersonal risk in practice.

The gradual emergence of these more nuanced reflections highlights the importance of in-depth semi-structured interviews, where follow-up questions and contextual discussion made it possible to move beyond initial, potentially idealised descriptions of teamwork practices. At the same time, it is important to acknowledge that even with this interview design, some responses may still have been shaped by organisational norms and socially reinforced expectations regarding collaboration, learning, and openness.

Participants themselves expressed how management frequently emphasised teamwork, continuous development and the importance of staying at the forefront of professional and technological change, offering multiple formal opportunities for learning. As participants operate within such organisational contexts where collaboration and knowledge sharing become a big part of formal communication and management discourse, these ideals may become partially internalised and reflected in how experiences are articulated. This does not imply deliberate misrepresentation, but rather that perceptions and descriptions of everyday work practices may be framed in relation to these organisational expectations and norms.

Consequently, participants' accounts should be understood as situated interpretations of their experiences rather than direct or fully neutral representations of behaviour. Even when not consciously intended, responses may therefore still have been subtly influenced by organisational context and norms, potentially contributing to an emphasis on idealised teamwork practices in parts of the data.

Furthermore, it is important to acknowledge a limitation related to the uneven empirical salience of the seven predefined team learning behaviours in the interview material. While the interview protocol was designed to cover all seven behaviours, four of them (knowledge sharing, co-construction, boundary-related knowledge access, and task-based learning) emerged as more consistently articulated and richly described in participants' accounts. Importantly, the unequal prominence of these behaviours in the interview data does not imply that the less frequently articulated behaviours are unaffected by the use of AI.

In addition, the evolving and fragmented nature of the AI research field presents a further limitation. AI remains a rapidly developing and inconsistently defined phenomenon in the literature, with overlapping and sometimes interchangeable terminology across studies. While this study adopts a specific framing of AI-related practices in organisational settings, this improves analytical clarity within the study but simultaneously limits direct comparability with prior research that may conceptualise AI differently or use broader or narrower definitions. As a result, situating the findings within the wider literature requires careful interpretation, as differences in conceptual scope and terminology may affect how the results align with existing studies. This challenge is further reflected in the empirical material, as participants themselves differed in how they understood and labelled AI-related tools and practices, despite clarification during interviews. This introduces a degree of residual ambiguity in the data and reinforces the difficulty of achieving full conceptual consistency across both literature and empirical accounts.

Finally, the heterogeneous sample, while beneficial for capturing a wide range of experiences, also introduced certain methodological limitations. Since participants worked in different organisational settings, roles, and team constellations, their experiences were shaped by varying contextual conditions, making direct comparisons more complex. The broad variation in AI usage and work practices may also have reduced the possibility of drawing more specific conclusions about particular professions, organisations, or types of teams. In addition, because participants differed substantially in how frequently and for what purposes they used AI, the depth and detail of the interview accounts varied, with some providing richer and more experience-based reflections than others. While this diversity enriched the empirical material and supported exploratory insights, it may also have limited the extent to which more specific patterns could be examined within a single organisational or team context.

3.5.3 Ethical considerations

Ethical considerations in this study primarily concerned informed consent, confidentiality, and the handling of sensitive empirical material. All participants were informed about the purpose of the study, the voluntary nature of participation, and their right to withdraw at any time. Participants and organisations were anonymised in transcripts and in the presentation of findings, and identifiable details were removed or generalised where necessary. Interview material was stored securely and accessed only by the researchers involved in the study.

Furthermore, given the interpretive nature of the analysis, care was taken not to overstate findings or attribute intentions to participants beyond what could be supported by the empirical material. This includes careful handling of sensitive themes such as interpersonal risk, psychological safety, and the use of AI in professional contexts, ensuring that interpretations remained grounded in participants' expressed experiences.

3.5.4 Responsible use of AI

AI was used as a supportive tool in selected parts of the research process. During the interviews, Microsoft Teams' built-in real-time transcription function, supported by Microsoft Copilot, was used to generate transcriptions of the conversations. These transcripts were subsequently reviewed manually while listening to the recordings in order to correct errors and ensure accuracy.

ChatGPT was used to support language refinement, including improving sentence structure, clarity, and grammar. DeepL translator was also used to support researchers' translation of selected quotations from Swedish into English. However, all AI-supported language suggestions and translations were critically reviewed, revised, and approved by the authors to ensure that the intended meaning was preserved. Furthermore, AI-supported tools including Google Scholar Labs and Scopus AI were used during parts of the literature search process to gain an initial overview of relevant research areas and to identify directions for further reading. These tools functioned as exploratory aids for search and orientation rather than as sources of scholarly evidence. All literature included in the thesis was subsequently independently reviewed and assessed by the authors.

4. Empirical data

4.1. Contextual findings

The empirical material was collected from employees working within two different types of Professional Service Firms (PSFs): accounting and auditing. Participants from Company B primarily worked with accounting-related services, including ongoing bookkeeping, reconciliations, VAT and tax-related tasks, monthly and annual closings, financial reporting, and other financial administration processes. Participants from Company A primarily worked within auditing, where tasks involved reviewing financial statements, assessing compliance with accounting standards and regulations, documentation processes, and supporting larger audit engagements.

Across both firms, participants described work as highly client-oriented and organised around customer-based teams. Team composition and intensity varied depending on the size and complexity of the engagement, meaning that employees often worked across parallel team constellations simultaneously. Some client engagements involved close collaboration several days per week, while others involved shorter and less frequent interactions. Participants from both firms also described work environments characterised by high workloads, deadlines, and continuous coordination across tasks, customers, and colleagues.

At surface level, participants described similar organisational structures with clear roles and responsibilities divided within teams. Despite these similarities, how this hierarchy was perceived in everyday interactions differed between the firms. In Company A, the organisational structure was perceived more explicitly, where seniority level was not only visible formally but also in social interactions. In Company B, participants instead perceived the organisation as relatively flat in everyday interactions, where access to senior colleagues and managers was generally perceived as informal and approachable despite the existence of formal organisational structures.

As mentioned in chapter 3.3.1, the initial part of the interviews regarded participants' overall experience of working within their teams, as well as several aspects related to team learning and interpersonal risk-taking. Across both firms, participants generally described their teams as supportive environments where colleagues were willing to help each other, answer questions, and share knowledge when uncertainties arose. Teamwork was therefore not only described as a formal way of organising client work, but also as an important source of everyday learning and problem-solving. Participants often emphasised that support from colleagues was particularly important when dealing with client-specific questions, unfamiliar tasks, or situations where they needed confirmation before moving forward. At the same time, participants' experiences of support-seeking appeared to be shaped by availability, time pressure, and interpersonal dynamics.

Some differences between the firms were also visible. In Company A, participants described supportive teams, but the more explicit hierarchy meant that seniority could influence how comfortable it felt to ask certain questions, particularly when employees felt that they were expected to already know the answer. In Company B, participants more often described everyday interactions as informal and approachable, where asking questions across roles and seniority levels was perceived as relatively easy. These perceptions provide an important background for understanding how AI later became integrated into existing support-seeking and learning practices.

The use and integration of AI also differed between the firms. While both firms prioritise efficiency and time-saving, their technical infrastructures and the way they handle sensitive data differ. In Company B, AI was primarily described as embedded within existing accounting and financial systems used in everyday worktasks. Through integrated automation in tools like Fortnox and Medius, AI is used extensively for OCR (Optical Character Recognition) to automatically read invoice data, such as amounts, dates, and OCR numbers. Bank integrations also allow for the automatic matching of payments. Furthermore, employees in Company B had access to regulatory support through AiDA (the AI assistant within the FAR Online regulatory framework) to navigate complex tax and accounting laws. To a lesser extent, general-purpose generative tools, such as chatGPT and Microsoft Copilot, are used within corporate accounts to draft emails, summarize training videos, and refine Excel formulas. Company B employees generally use hypothetical scenarios when asking AI questions to avoid inputting sensitive client names. While pilot projects for secure client data analysis are in development, the firm currently emphasizes caution and strict adherence to GDPR.

AI use in Company A was characterised by stronger integration and a secure internal system designed to handle sensitive information directly. Mainly, employees used the internal platform, a closed environment that grants access to models like Gemini, Claude, and GPT while ensuring data remains within the firm. A major use case is the verification of annual reports, where AI cross-references figures from different years to identify inconsistencies that humans might miss. Company A encourages the creation of custom digital agents for specific client teams. These agents are "trained" on a client's history and data to act as a digital team member. The system distinguishes between "WebSearch" (no client data allowed) and "FileSearch," a secure function where auditors can upload confidential client files for analysis. The following table summarises the differences between AI accessibility and use.

Table 3. Summary of AI use in company A and B

Category	Company A	Company B
Primary systems	Internal platform with GPT/Gemini/Claude, custom agents	Fortnox/Medius (Accounting), FAR Aida (Regulatory), MS Copilot
Handling client data	Secure "FileSearch" allows direct upload and analysis of sensitive client documents	Primarily uses hypothetical questions in chats, real data is handled within secure accounting suites
Key use cases	Auditing annual reports, bulk data analysis, and building client-specific expertise	Automation of invoice flows, regulatory lookups, and email drafting
Main perceived purpose	Enhancing audit quality and maintaining margins through high-speed data verification	Removing the "manual typing" and reducing human error in bookkeeping

4.2 Empirical findings

4.2.1 AI as a first point of contact in support-seeking

Several participants across both companies described AI as a natural first step when encountering uncertainties, questions, or certain knowledge gaps in their everyday work. While some issues were later discussed with colleagues, as explored in Section 4.2.2, other questions, particularly those described as *"quick"* and *"simple"*, were addressed solely through AI.

While participants at both companies frequently emphasised that AI could not fully replace interpersonal support-seeking, several also stated that certain social interactions had been replaced by communication with AI. While these AI interactions were able to provide participants with information, the gained knowledge appeared to be more isolated and individualised compared to learnings gained from interpersonal conversations. Audit#6 noted: "*A lot stays between me and the chat. You still share quite a lot with each other… but most of the time I think many people have their own conversations with AI, and those conversations aren't shared.*" Similarly, Audit#3 highlighted the difference between seeking support from a colleague versus from AI: *"Sometimes it can still be good to turn to the team. Because maybe I learn something from AI, but then I don't share it, since it's just me and the AI. But if I turn to the team and someone answers, then maybe a third person who has been wondering the same thing will also get answers to their questions."*

When used as a first point of contact, AI was often described as useful because of its high availability. In an often fast paced and demanding work environment, AI was frequently described as a quick, accessible, and low-threshold support resource that enabled employees to clarify uncertainties or solve smaller problems without having to wait for colleagues to become available. Accounting#2 explained: "*It's simply faster sometimes to just ask AI directly than having to wait for someone to have time*."

In addition to reducing reliance on colleagues' availability, the practice of turning to AI first was often framed as a way of reducing interruptions toward colleagues. Accounting#1 explained: "*If it's something really small [...] Then I don't start bothering someone, or well, bothering and bothering, but then I don't need to take another colleague's time when they might already be busy.*"

In Company B, AI was primarily used in situations where colleagues were perceived as busy, or less immediately accessible, reflecting considerations related more to accessibility and respect for colleagues' time than to interpersonal hesitation or reluctance to ask questions. In many cases, several participants also described feeling comfortable and generally preferring turning to colleagues even for smaller issues. AI was therefore frequently described as complementing collegial support by helping employees handle smaller questions, interpret rules, or gain quick clarification.

In Company A, participants similarly described AI as an initial support resource for work-related tasks, such as understanding regulations or specific audit processes. However, in contrast to Company B, AI use in Company A appeared more strongly connected to the formalised and hierarchical structure of their work. Several participants described using AI to avoid asking certain questions in order to uphold their own status and the power structures of the workplace. Audit#6 explained: *"Partly to avoid feeling like you're asking a stupid question. You're often very afraid, especially when you're new, of asking stupid questions or something that people expect you to already know… so it becomes easier to maybe take it to the chat instead."*

Furthermore, employees in Company A were more likely to be encouraged by colleagues to use AI as a first resource compared to participants from Company B. Audit#1 explained: *"It's also kind of encouraged like that [...] I mean, if you were to ask a question, a colleague might say something like, "Yeah, but check with the chat first?". We have an unspoken understanding that our internal chat is the first choice."* Within Company A, AI therefore appeared not only as an efficiency tool, but also as a way of navigating organisational complexity and interpersonal exposure within teams.

Finally, the replacement of certain interpersonal interactions with AI was also closely connected to efficiency demands and the perceived value of time. While participants at both companies emphasised efficiency, employees in Company A more frequently described experiencing pressure in their work and explicitly linked time to financial performance. In this context, the time-saving capabilities of AI became particularly valuable. Audit#1 explained: "*Yeah, I mean, it's really about saving time. The more efficient we become, the higher margins we can have in our budgets, and the more Company A can earn as a business*." This efficiency-oriented mindset also appeared to shape employees' reluctance to rely on collegial support for certain issues. As the same participant explained: "*Time is very valuable, and that's why it's really good that AI exists, because people care a lot about each other's time. So you try not to ask unnecessary questions, or questions that you yourself feel might be unnecessary, like "I should probably know this, but I don't." Then you don't want to waste someone else's time on it, because you feel like it's your own responsibility, or that you've somehow made a mistake.*"

In a similar way, Audit#2 described how differences in billing rates could influence who employees approached for support, explaining that more senior colleagues should not necessarily spend time reviewing smaller or less complex issues when these could be handled by someone more junior: *"Different positions come with different billing rates, they charge clients differently, so someone in the role of signing auditor probably shouldn't spend eight hours reviewing the smallest part of the company. It might be better to have someone a bit more junior check it, because ultimately it's the client who's paying for our time, so you probably start at the lower end and work your way up if there are more complicated issues."*

Audit#1 also described how this budget logic could affect learning-related interactions such as feedback: *"But then I think a lot of people shy away from it because the time you have to spend giving feedback also counts toward the client's allocation. And then you might think, 'But I don't want to spend that time on the client because it eats into my budget', since you have a set budget per team member, and a certain amount of time is expected to be spent on that client."*

Together, these accounts show that AI was not only described as a quick and accessible support resource, but also as a tool that fitted into a work context where time, budgets, and colleagues' availability were highly salient. In company A, AI therefore appeared to become a first point of contact not only because it was efficient, but also because it allowed employees to handle smaller uncertainties without immediately using colleagues' time or exposing questions they perceived as unnecessary or too basic.

4.2.2 AI as Part of the Team Learning Process

As aforementioned, beyond functioning as an independent support resource, the findings suggest that AI increasingly became part of the collaborative learning processes within both firms. Rather than participants solely going to AI with certain questions and to colleagues with others, the most common strategy to gain knowledge and answers across both Company A and B was to combine the use of both. In these instances, participants frequently described using AI prior to discussions with colleagues in order to gain some understanding, structure their thoughts, formulate questions, or validate preliminary reasoning.

In such cases, rather than replacing discussions with colleagues, participants described AI helped them prepare for those discussions. Audit#2 explained: *"It helps you a lot in gaining a basic understanding and context before asking questions, so that you can ask the right questions."* Similarly, Accounting#4 described that AI enabled them to *"build a kind of prior understanding, so that you understand your colleague's answer better and don't need to ask the same thing multiple times."* In this way, participants across both firms described AI as shaping not only access to information, but also the quality and structure of interpersonal learning interactions.

While becoming part of the learning processes at both firms, the function AI appeared to serve within these processes varied slightly depending on organisational context and interpersonal conditions surrounding support-seeking. In Company B, participants described open and informal team environments where asking questions to people of all seniority levels was normalized and support from colleagues was highly accessible. Accounting#1 explained *"I truly believe you can ask pretty much anyone a question, [...] we work in an open office landscape so you can just throw out a question to anyone.* Within this context, AI was often framed as a complementary preparatory resource that helped employees organize thoughts and formulate questions more clearly before entering discussions. Furthermore, several participants in Company B explained that AI could stimulate additional discussion and reflection within their teams. Accounting#3 expressed: "*You always gain something out of combining AI with group discussions. The more you include AI, the more things you have to discuss… it opens up for more discussions which in turn creates learning opportunities."*

In company A, participants similarly described using AI to prepare before approaching colleagues, particularly in order to gain context or formulate more precise questions. However, these descriptions more frequently appeared alongside references to hierarchical structures, and concerns about asking "*too many small questions*." Several participants emphasised that audit work in Company A was experienced as socially hierarchical, with seniority and interpersonal differences playing a prominent role in shaping everyday workplace interactions and culture.

4.2.3 Efficiency Gains and Reconfigured Learning Opportunities

Across both Company A and Company B, participants described AI-supported tools and automation as contributing to increased efficiency in everyday work processes. However, these efficiency gains were not only framed in terms of productivity. Participants across both firms frequently connected saved time to broader learning opportunities, increased exposure to complex tasks, and expanded professional development.

A recurring pattern across interviews was that AI reduced time spent on repetitive, administrative, or technical tasks, thereby enabling employees to allocate more time toward analytical work, customer interaction, or more advanced assignments. In company A, participants frequently connected efficiency gains to increased participation in more analytically complex audit work. Audit work was described as highly documentation-intensive and characterised by extensive information processing, regulation interpretation, and repetitive procedures. Participants explained that AI-supported tools helped employees navigate information, and process documentation more efficiently, reducing the amount of time spent "*getting stuck*" on smaller issues. Several participants described how this created opportunities to participate in broader and more interpretative audit reasoning together with colleagues. Audit#4 explained: "*If you save time on the administrative work, you get more time to actually understand the client and the audit itself.*" Within Company A, efficiency gains therefore appeared strongly connected to progression toward more advanced and judgment-intensive work tasks within hierarchical learning structures.

In Company B, participants similarly described how AI-supported efficiency enabled broader learning opportunities, although these opportunities were more frequently framed around customer breadth and increased task variation. Participants described how automation reduced time spent on repetitive bookkeeping activities and administrative processing, thereby creating opportunities to engage in more advanced assignments and customer-related responsibilities. Accounting#1 explained: "*You get to, as a junior, try out much more advanced tasks that you might not have had time for before*." She further connected this to broader client exposure and experiential learning: “*I can take on more clients. And you work very differently with different clients, you use different systems and sometimes work in different ways*.” Within Company B, efficiency gains therefore appeared more strongly connected to breadth of experience, expanded customer exposure, and increased operational responsibility. Participants frequently described learning through encountering different customers, industries, systems, and situations within everyday work processes. At the same time, participants across both firms emphasised that AI-supported efficiency did not eliminate the importance of interpersonal interaction or professional judgement. Learning continued to rely on collaborative reflection, practical experience, and collegial interpretation.

5. Discussion

5.1 Analysis

Across both organisations, the analysis examines how and why, AI functions as a sociotechnical mediating mechanism shaping team learning in everyday work. The chapter is structured around four interrelated team learning behaviors: knowledge sharing, co-construction, boundary-related knowledge access, and task-based learning. These behaviors are used as analytical lenses rather than discrete empirical categories, as they are deeply intertwined both theoretically and in participants' accounts of practice. The following four sections examine each dimension separately to illustrate how AI mediates different expressions of team learning behaviors, before turning to the conditions shaping these patterns. Together, these sections provide a basis for the synthesis of findings within the analysis and their broader sociotechnical implications.

5.1.1 AI-Mediated Knowledge Sharing

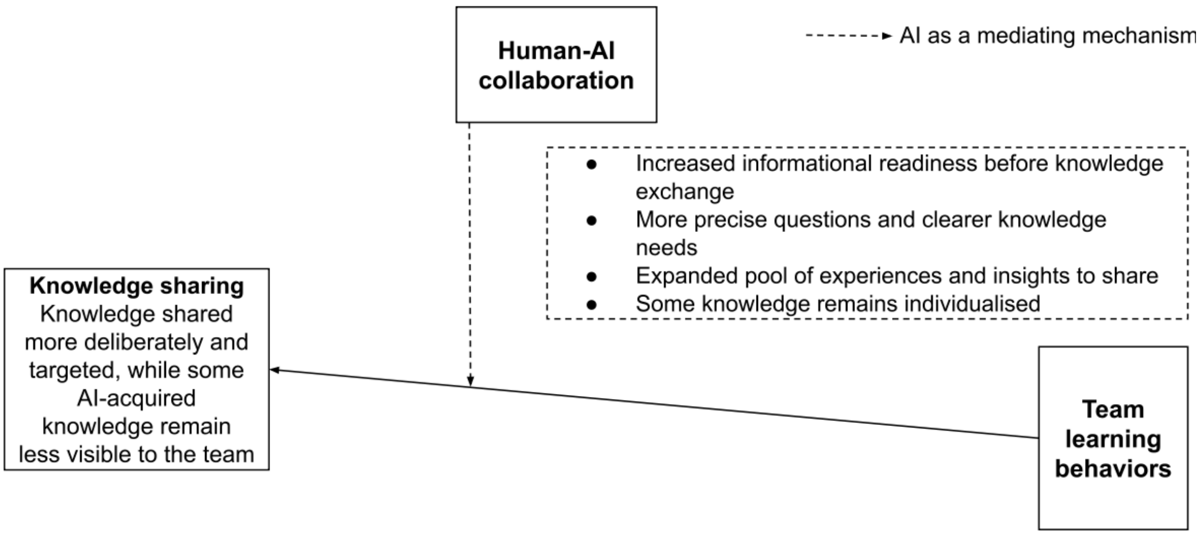
The findings suggest that the use of AI acts as a mediating mechanism in knowledge sharing, both facilitating and constraining these behaviors. Firstly, the findings suggest that AI enhances knowledge sharing by increasing employees' informational readiness prior to interpersonal interaction. Participants frequently described using AI to clarify concepts, gather relevant information, and develop a preliminary understanding before approaching colleagues for knowledge exchange. As a result, employees were often able to formulate more precise questions and communicate their knowledge needs more clearly during team interactions. Consequently, AI appears to facilitate knowledge sharing by improving employees' preparedness for them. By helping individuals clarify what they know and what they still need to learn, AI enables more targeted requests for knowledge and more efficient interactions with colleagues. In this way, AI reshapes how team members access, package, and communicate knowledge to one another, rather than changing the fundamental purpose of knowledge sharing, (Decuyper et al., 2010; Widmann & Mulder, 2025).

The findings further suggest that AI influences knowledge sharing indirectly through its effects on employees' work activities and learning opportunities. Across both organisations, participants described how AI-supported efficiency created more time to focus on complex assignments, engage with broader customer portfolios, and encounter more diverse work situations. These experiences generated new insights and knowledge that employees could subsequently share with colleagues when similar challenges emerged. An important characteristic of knowledge sharing as a team learning behavior is that its effectiveness depends not only on communication itself but also on the availability of valuable knowledge to communicate (Widmann & Mulder, 2025). In this respect, AI appears to shape knowledge sharing not only at the point of exchange but also through its influence on employees' opportunities to acquire new knowledge and experiences. AI use's influence on knowledge sharing may therefore stem partly from its ability to facilitate knowledge acquisition, expanding the pool of experiences and insights that employees can subsequently share with colleagues. As this acquisition process often involves obtaining knowledge from outside the immediate team context, it is fundamentally intertwined with the team learning behavior of boundary crossing, illustrating the interconnected nature of team learning, where behaviors are mutually reinforcing rather than analytically separate (Decuyper et al., 2010).

At the same time, the findings illustrate that the relationship between AI and knowledge sharing is not uniformly positive. While AI may increase employees' opportunities to enhance informational readiness and increase the availability of valuable knowledge to communicate, it also appears to reduce the extent to which certain knowledge is exchanged within the team. As employees resolve certain issues individually through AI tools rather than turning to colleagues, the number of occasions where knowledge is articulated and circulated within the team decreases. When employees obtain knowledge through AI without subsequently communicating it to colleagues, the knowledge remains localised at the individual level and becomes less visible to the team. Audit#3's observation that "*Maybe I learn something from AI, but then I don't share it*," and Audit#6's statement that "*A lot stays between me and the chat*" illustrates how learning may occur without entering the team's shared knowledge base. Consequently, AI introduces a new pathway through which knowledge can be acquired while simultaneously sidestepping the social interactions through which individually acquired knowledge is typically shared, discussed, and integrated into collective team knowledge.

Moreover, because knowledge sharing is a fundamentally social behavior, its value extends beyond the information exchanged (Decuyper et al., 2010; Widmann & Mulder, 2025). Everyday questions, clarifications, and requests for assistance create opportunities for colleagues to become aware of each other's expertise, develop shared understandings, and maintain common awareness of ongoing work. When these interactions are increasingly replaced by AI-mediated problem solving, teams may lose some of the informal communication processes through which shared knowledge structures are continuously maintained. The impact is therefore not limited to fewer exchanges of information, but potentially affects the collective visibility of learning and expertise within the team.

Figure 2. AI as a mediating mechanism in knowledge sharing



5.1.2 AI-Mediated Co-Construction

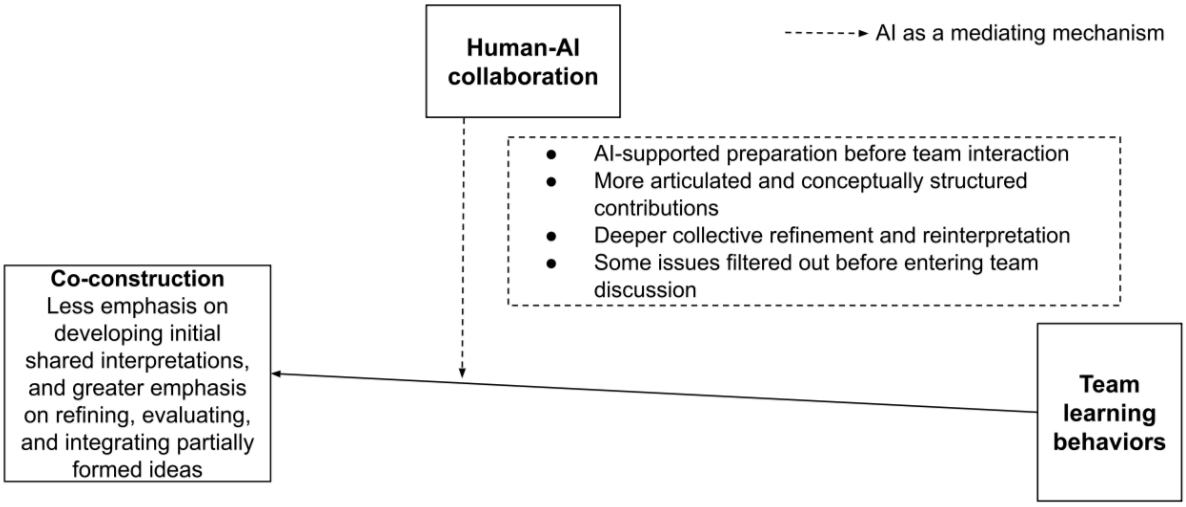
The findings furthermore suggest that the use of AI acts as a mediating mechanism in co-construction, both facilitating and constraining dimensions of the team learning process. First, AI's mediation in co-construction can be understood by its preparatory phase of interaction. In the findings, AI is not positioned as an additional "participant" in collaborative meaning-making, but as a pre-interaction mechanism that shapes what individuals bring into the co-construction process. This preparation stage becomes a key mechanism through which AI indirectly influences collective sensemaking. As a result of the AI-supported initial individual sensemaking, the ideas entering collaborative discussions are often already partially formed. This does not eliminate the need for co-construction, but rather influences the point from which team members collectively then refine, enhance, and modify ideas.

This aligns with the knowledge-sharing finding that AI improves employees' preparedness to knowledge exchange. Within co-construction, when participants arrive at interactions with greater preliminary interpretations, their contributions tend to be more articulated and conceptually structured. The use of AI therefore appears to increase the depth of co-construction, as the refining process starts off at a more developed point rather than developing foundational interpretations. As a result, interactions might progress into deeper cycles of refinement, and reinterpretation.

However, the findings also suggest that AI can constrain co-construction by shaping which issues enter collaborative discussion. When problem-solving is perceived as sufficiently completed through individual-AI interaction, employees may no longer bring these issues into interpersonal exchange. This reduces the interactional opportunities through which collective meaning-making is initiated. Since co-construction depends on interactional sequences where ideas are exposed to others' reasoning, the removal of certain issues from the collective arena directly restricts the iterative cycles through which shared unrealised meanings can emerge (Widmann & Mulder, 2025). In this sense, the use of AI introduces a filtering mechanism at the interface between individual sensemaking and co-construction, shaping which issues are escalated into the team space and which are resolved beforehand.

When co-construction does occur, AI-mediated preparation can also reshape its focus. Because collaborative work begins from a more advanced, AI-influenced starting point, attention shifts from the initial construction of meaning. Instead, attention is directed toward refining, evaluating, and integrating ideas that have already been partially developed through human-AI collaboration. Co-construction therefore becomes less oriented toward developing initial shared interpretations and more oriented toward collectively modifying and integrating interpretations that have already been partially formed through AI.

Figure 3. AI as a mediating mechanism in co-construction



5.1.3 AI-Mediated Boundary Crossing

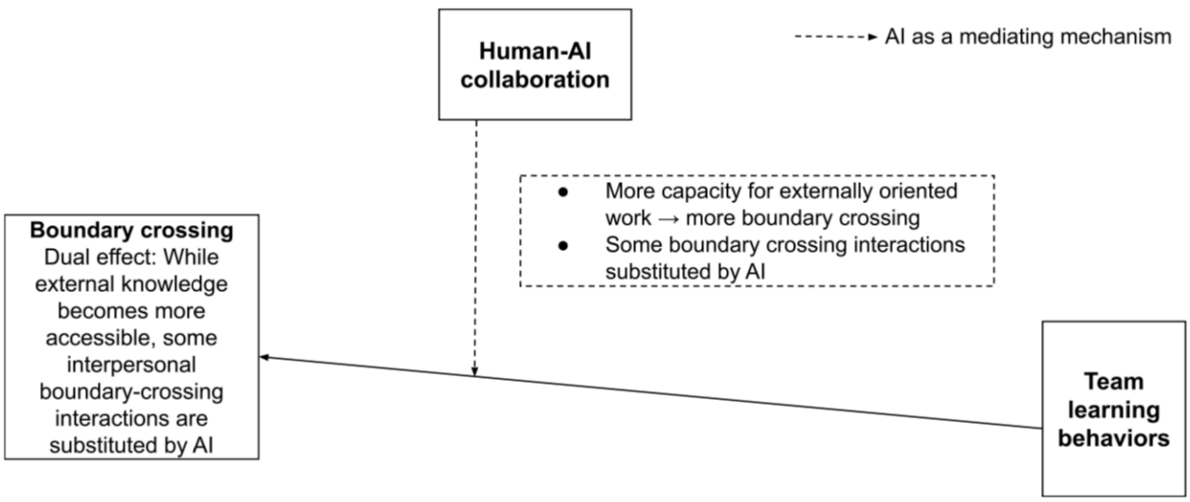
The findings indicate that the use of AI influences boundary crossing processes in team learning through two main mechanisms: an enabling effect and a substitutive effect (Decuyper et al., 2010). These mechanisms operate by reshaping how employees access knowledge from outside the team, both by increasing opportunities for interaction with external actors and by introducing AI as an alternative source of externally oriented information.

On the one hand, AI enables boundary crossing indirectly by increasing employees' capacity to engage in external interactions. As discussed in the analysis of knowledge sharing, AI-supported efficiency reduced the time spent on routine and administrative tasks, thereby freeing capacity for more complex and externally oriented work activities. In the context of boundary crossing, this translates into the traditional form of the team learning behavior as defined by Decuyper et al. (2010), with more opportunities for interaction with customers and stakeholders outside the immediate team. AI thus expands boundary crossing by reallocating employees' capacity from individual routine tasks to externally oriented interactions.

On the other hand, the findings also suggest a substitutive dynamic in relation to boundary crossing. Participants described AI as an increasingly accessible source of external-like knowledge, particularly when seeking clarification, procedural guidance, or contextual information. In these instances, AI functions as an immediately available and responsive knowledge resource that can be consulted without requiring interpersonal engagement beyond the team boundary, or more broadly at the individual level. As a result, a technologically mediated pathway for accessing external knowledge becomes embedded within everyday problem-solving practices.

From a theoretical perspective, this development does not fully align with established conceptualizations of boundary crossing. Decuyper et al. (2010) define boundary crossing as a social learning behavior characterized by interaction with actors outside the team, through which teams not only acquire knowledge, but also about exchanging and integrating it across social boundaries. Since AI does not constitute a social actor, its role cannot be understood as boundary crossing in the traditional sense. Rather, the findings suggest a form of functional substitution, whereby AI replicates some informational functions of boundary crossing interactions while bypassing the interpersonal exchanges through which social and relational learning usually occurs.

Figure 4. AI as a mediating mechanism in boundary crossing



5.1.4 AI-Mediated Team Activity

The findings further suggest that the use of AI has implications for team activity. In line with the earlier discussion on AI-mediated knowledge sharing, co-construction. AI does not replace these behaviors, but instead reshapes how learning is embedded in ongoing work, shifting the balance between individual preparation and interpersonal engagement during task performance.

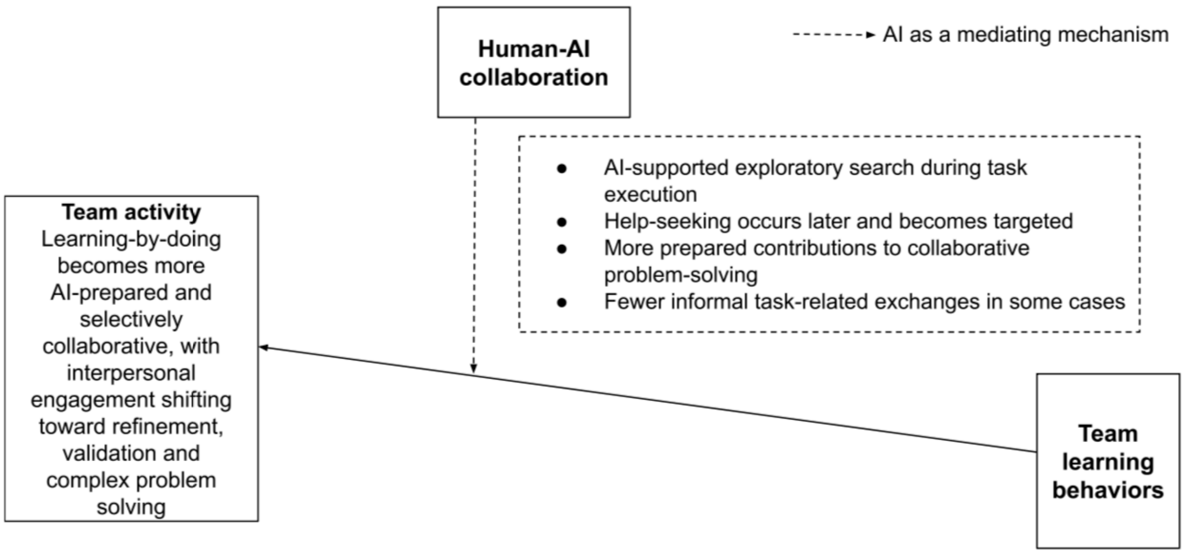
First, the findings indicate that AI partly transforms team activity processes involving the collaborative search for new information or solutions within the team. Participants frequently described using AI to obtain information, clarify procedures, and generate initial solutions during task execution. In continuity with the earlier finding that AI enhances employees' informational readiness prior to interaction, AI here functions as an immediate search resource that allows individuals to conduct a substantial part of exploratory search independently. Whereas exploratory search would traditionally involve consulting colleagues or jointly investigating solutions, AI enables employees to enter collaborative situations with pre-formed insights, thereby reducing the need for initial collective search, while simultaneously increasing the level of preparation brought into it.

Furthermore, AI influences helping behavior by changing when and how colleagues are involved in problem-solving. As also reflected in the co-construction process, where AI shapes the starting point of collaborative meaning-making, help-seeking tends to occur later in the problem-solving process. Employees often resolve initial uncertainties through AI before engaging colleagues, meaning that interpersonal support becomes more focused on refinement, validation, or exception handling rather than basic clarification. This reduces the frequency of early-stage interruptions during task execution, while simultaneously reconfiguring helping behavior toward more targeted and higher-level contributions within the team.

In addition, the findings suggest that AI affects performance monitoring within team activity. Participants described how AI-supported preparation enabled them to enter collaborative situations with a clearer understanding of task status and potential solutions. This echoes the earlier observation that AI strengthens employees' ability to structure and articulate their knowledge needs prior to interaction, which in turn improves coordination during execution. As a result, monitoring becomes less about jointly identifying what is happening in real time and more about evaluating and aligning pre-developed understandings of task progress.

Finally, the findings indicate potential implications for keeping up to date within teams. As also suggested in the analysis of AI-mediated knowledge sharing, where AI can reduce micro-interactions that normally circulate emerging insights, the increasing reliance on AI for individual problem-solving may reduce informal exchanges that traditionally sustain shared situational awareness. When employees resolve issues independently through AI, fewer of these experiences surface in everyday interaction, limiting opportunities for colleagues to remain continuously updated on each other's work and learning processes. In this way, the substitutive dynamics identified in boundary crossing are also reflected at the level of daily team activity, where AI increasingly becomes an alternative pathway for obtaining task-relevant information that would otherwise be socially shared.

Figure 5. AI as a mediating mechanism in team activity



5.1.5 Conditions shaping AI-mediated Team Learning

While the previous sections have shown how AI-mediated knowledge sharing, co-construction, boundary crossing, and team activity, these changes cannot be explained by AI use alone. Rather, the findings suggest that AI-mediated team learning behaviors emerged through the interaction between AI's technical availability and the social and organisational conditions in which work was carried out. In line with a sociotechnical perspective, the use of AI did not shape team learning behaviors as an isolated tool, but became meaningful through the work conditions that made AI use more or less relevant in specific situations.

Three conditions were particularly important: time and efficiency pressure, accessibility of support, and perceived interpersonal risk-taking. Importantly, the findings illustrate that these conditions were not neutral or evenly distributed across companies, but were themselves shaped by organisational structures and workplace norms that influenced who could seek help, when, and from whom. These conditions shaped whether employees turned to AI, colleagues, or a combination of both when encountering uncertainty in their work. They also help explain why the same visible behavior, such as using AI before asking a colleague, could have different meanings across the two companies.

Time and efficiency pressure as conditions shaping interaction

A central condition shaping AI-mediated learning is the persistent experience of time pressure in everyday work. Across both firms, participants described tightly scheduled workflows, deadlines, and continuous task switching. Within such environments, the choice between seeking support from a colleague or consulting AI is not neutral, but evaluated in relation to immediacy and interruption costs.

AI was repeatedly described as "faster" and "always available," making it a first point of contact in situations where uncertainty needed to be resolved quickly. This reflects a shift in how learning is organized over time: interpersonal interaction requires coordinating availability between people, while AI does not depend on team schedules or mutual timing. As a result, AI reduces the effort required to obtain support or information, which makes it a particularly attractive alternative under time-constrained conditions. This finding aligns with sociotechnical arguments that technologies become embedded in work practices by reshaping how work is organized and performed within specific organisational contexts (Sawyer & Jarrahi, 2014).

Beyond the individual level, time pressure is also shaped by broader efficiency logics that characterize both companies, though in slightly different forms. In Company A, efficiency is explicitly tied to billing structures, budgets, and margin considerations. Here, time is not only scarce but economically quantified, which reinforces a strong rationale for minimizing interruptions to colleagues. Participants described that questions perceived as "small" or "non-essential" were often handled independently, and some also described instances where colleagues responded to requests for help by asking whether AI had been consulted first. In Company B, efficiency pressures are less explicitly financial in everyday discourse, but still present through workload management and the general expectation of responsiveness. In this sense, AI becomes positioned as a mechanism for handling low-complexity uncertainties individually, thereby reserving interpersonal interaction for more complex or value-added discussions.

This budgeting and client-based logic may also put earlier findings into perspective and contextualise why team learning behaviours such as team reflexivity, constructive conflict, and storage and retrieval behaviours did not prominently emerge in interviews. Participants described how work time is closely tied to client-specific budgets, where hours are effectively "*charged*" against particular engagements. Within this framing, time spent on activities that are not directly perceived as contributing to immediate client value generation, such as reflecting on practices, discussing ways of working, or engaging in broader feedback and coordination, can be seen as drawing away from the budgeted time allocated to the client. As a result, these forms of learning are not simply additional activities, but may be experienced as competing with billable work that is ultimately funded by the client, thereby making it less legitimate to engage in such reflection during working hours.

Accessibility as a sociotechnical constraint and enabler

A second condition shaping AI-mediated learning is the perceived accessibility of support. Accessibility here refers not only to technological availability, but also to social and organisational access to colleagues as knowledge resources.

Across both firms, participants emphasized that colleagues are generally supportive and willing to help. However, accessibility is dynamically shaped by workload, physical proximity, and organisational structure. When colleagues are perceived as busy or not immediately available, AI becomes a functionally equivalent but more accessible alternative. This creates an important difference between AI and interpersonal support: while interpersonal support is relational and contingent, AI support is immediate and non-relational. This changes how employees access knowledge and support in everyday work. Instead of synchronizing with social availability, employees increasingly interact with a system that is continuously accessible. Consistent with STS theory, this illustrates how changes in technical arrangements can alter patterns of interaction and interdependence within the broader work system (Trist & Bamforth, 1951; Cherns, 1976).

Yet accessibility also differs meaningfully between the two cases. In Company B, relatively flat structures and informal communication norms reduce the "*distance*" between employees and more senior colleagues, making interpersonal support more readily accessible. In Company A, despite formal availability of colleagues, accessibility is moderated by hierarchy and perceived role distance. Thus, even when colleagues are technically accessible, they may not be psychologically or socially accessible in the moment of uncertainty. Consequently, AI does not only become a substitute when colleagues are unavailable, but also when interpersonal access is perceived as socially costly. Accessibility therefore operates as both a structural and perceptual condition that channels learning behaviors toward AI.

Perceived interpersonal risk-taking

Building on this, a third condition shaping AI-mediated team learning is perceived interpersonal risk-taking. Consistent with Edmondson's (1999; 2003) work on psychological safety, the findings suggest that asking questions, expressing uncertainty, or seeking confirmation involves varying degrees of social exposure.

In this study, this condition appears particularly salient in Company A, where hierarchical structures and professional expectations intensify concerns about competence signaling. Several participants explicitly described avoiding certain questions in order to not appear inexperienced or to avoid asking something they "*should already know*." In these cases, AI functions not only as an efficiency tool but as a mechanism for reducing interpersonal risk. It allows employees to resolve uncertainty without engaging in interactions that risk exposing lack of competence. In STS terms, AI becomes part of the social regulation of work: it does not eliminate interpersonal risk, but redistributes it by shifting learning from public interaction to private sensemaking. This is particularly important because team learning behaviors such as co-construction often depend precisely on the willingness to expose uncertainty in social settings.

In line with the concept of psychological safety, these dynamics illustrate how individuals continuously assess whether engaging colleagues may be perceived as appropriate within the social and relational context of the team, which in turn shapes when and how employees turn to AI as an alternative channel for resolving uncertainty.

In Company B, interpersonal risk-taking is less pronounced due to more informal norms and easier access across roles. However, even in this context, as mentioned in regards to availability and accessibility, AI is still used to avoid unnecessary interruptions or to respect colleagues' time.

Organisational structure as a contextual factor

Building on this, organisational structure emerges as a contextual factor that shapes how the above mechanisms manifest in practice. Importantly, organisational structure does not directly determine AI use; rather, it interacts with time pressure, accessibility, and interpersonal risk to shape when AI becomes the preferred entry point into learning processes.

In Company A, organisational hierarchy, with clearly differentiated roles and associated expectations for interaction and deference, in some cases amplifies the substitution of interpersonal support with AI. AI is used not only because it is faster, but because it allows employees to navigate structured authority relations without immediate exposure to colleagues. The "AI first" logic here is therefore jointly produced by efficiency pressures, budget awareness, and hierarchical sensitivity. AI becomes a socially safe intermediary that allows employees to prepare, validate, or resolve questions before entering upward interaction.

In Company B, by contrast, similar "AI first" behavior emerges from a different configuration of conditions. Here, perceived flatter structures and more accessible colleagues reduce hierarchical barriers, meaning that AI use is less about avoiding power distance and more about convenience, immediacy, and reducing interruptions. The same observable behavior, turning first to AI, thus emerges from different underlying mechanisms across contexts.

This variation illustrates that similar outcomes can emerge from different combinations of social and technical conditions. AI adoption in team learning is therefore not driven by a single dominant mechanism but by context-specific combinations of structural constraints and interpersonal norms.

Synthesis: conditions shaping AI-mediated learning

Taken together, time and efficiency pressures, accessibility, and perceived interpersonal risk do not operate as isolated predictors of AI use. Instead, they create a set of conditions that shape when employees turn to AI, when they seek support from colleagues, and when learning involves both.

These conditions help explain why AI becomes embedded as an intermediary in team learning processes rather than simply as a tool or replacement for interaction. In line with STS theory, the findings suggest that AI becomes integrated into team learning through its interaction with existing social arrangements, norms, and work practices rather than through its technical capabilities alone (Trist & Bamforth, 1951; Cherns, 1976; Sawyer & Jarrahi, 2014). AI is drawn into the learning system precisely because it reduces the time and effort involved in seeking support, increases accessibility, and mitigates interpersonal exposure under conditions where time, hierarchy, and performance pressures make interpersonal interaction more consequential. AI's role as a preparatory and filtering device is not inherent to the technology itself, but emerges because employees operate within environments where efficiency, accessibility constraints, and interpersonal risk considerations make it advantageous for employees to work through uncertainty independently before involving colleagues. In this sense, AI-mediated team learning is not simply a technological effect, but the outcome of a continuously negotiated balance between social exposure and ease of access within contemporary knowledge work systems.

5.1.6 AI as a Sociotechnical Reconfiguration of Team Learning Behaviors

Across the four team learning behaviors, a consistent pattern emerges in how AI becomes embedded within everyday learning processes. In line with previous research suggesting that team learning behaviors are highly interdependent and collectively constitute a broader learning process (Decuyper et al., 2010; Widmann & Mulder, 2025), the findings illustrate that AI influences not only individual learning behaviors but also the relationships between them. In particular, AI appears to shape how uncertainty is processed and moves between individual and collective levels of work.

Taken together, the patterns demonstrate a reconfiguration of how team learning unfolds as a process. Drawing on the team learning framework (Decuyper et al., 2010; Widmann & Mulder, 2025), learning behaviors continue to occur, but their sequencing, timing, and interdependence appear to be altered. Rather than uncertainty directly triggering interpersonal processes such as asking questions, discussing interpretations, or jointly developing solutions, AI increasingly functions as an intermediary resource through which employees first engage in individual sensemaking before deciding whether further collaboration is required. As a result, learning-related interactions often occur at a later stage of the problem-solving process and are shaped by prior AI-supported preparation.

From a sociotechnical systems perspective (Trist & Bamforth, 1951; Cherns, 1976; Sawyer & Jarrahi, 2014), these findings indicate that AI becomes part of the joint arrangement of social and technical elements through which work and learning are organised. The effects observed in team learning cannot be understood as consequences of the technology alone, but emerge through its interaction with organisational conditions such as time pressure, accessibility of colleagues, efficiency expectations, and perceived interpersonal risk. Within these conditions, AI functions as a readily available point of entry into problem-solving, influencing how employees move between individual sensemaking and interpersonal collaboration.

Importantly, AI does not replace team learning behaviors, nor does it operate as an autonomous participant in learning processes. Instead, it becomes integrated into the sociotechnical infrastructure through which these behaviors are enacted. In doing so, AI appears to both prepare and filter learning-related interaction. It prepares employees for collaboration by enabling more informed and structured participation in discussions, while simultaneously filtering which uncertainties enter collective learning processes, as some are addressed individually before interpersonal interaction becomes necessary.

Overall, the findings suggest that the impact of AI on team learning is less about the emergence of entirely new learning behaviors and more about the reconfiguration of existing ones. Rather than functioning as a persistent intermediate step in a strictly linear sense, AI introduces a flexible intermediary layer between uncertainty and collaboration that reshapes the pathways through which team learning unfolds. TLBs thus become increasingly distributed across social and technological resources, with human interaction and AI-supported sensemaking becoming closely intertwined in the production of collective understanding.

5.2 Conclusion

This study set out to explore how the use of AI in work processes shapes team learning behaviors within Professional Service Firms (PSFs). Drawing on a qualitative multiple-case study of employees in audit and accounting firms, the findings show that AI has become embedded in everyday work practices and increasingly shapes how learning unfolds within teams. Rather than replacing collaboration, AI functions as an intermediary layer between individual uncertainty and interpersonal interaction, supporting employees in gaining orientation, clarifying problems, and developing preliminary understanding before engaging colleagues.

The study extends existing research on team learning behaviors by showing that these processes are increasingly distributed across sequences of individual human-AI interaction and subsequent interpersonal collaboration. In this sense, AI does not simply add to or reduce team learning, but redistributes parts of the learning process by shifting initial exploration, information gathering, and sensemaking into individual AI-supported activity before entering the collective domain.

Empirically, AI was found to reshape four team learning behaviors. It enhanced knowledge sharing by increasing informational readiness, while sometimes limiting the visibility of individually acquired insights. It supported co-construction by enabling more developed contributions, while reducing some early-stage joint idea development. Furthermore, the use of AI both enhanced and partially substituted aspects of boundary crossing by enabling more opportunities to acquire external informational inputs, while replacing some of the need for direct interpersonal engagement across organisational and professional boundaries. Finally, the use of AI also influenced team activity by expanding opportunities for learning through efficiency gains, while reducing some routine collaborative interactions.

Importantly, these effects were shaped by contextual conditions, including time and efficacy pressure, accessibility of support, and perceived interpersonal risk-taking, all of which influenced whether employees turned to AI, colleagues, or both. In the client-oriented and time-sensitive environment of PSFs, AI became particularly valuable for managing uncertainty and efficiency demands, but did not replace the need for collegial judgement and contextual interpretation in more complex situations. Notably, the use of AI did not make learning individualised. Instead, AI-supported sensemaking consistently preceded interpersonal validation and deeper collaborative learning, and colleagues remained central for interpretation, professional judgement, and contextual understanding.

In conclusion, the use of AI in Professional Service Firms shapes team learning behaviors in several ways, reconfiguring the relationship between individual and collective learning processes. AI becomes embedded in sociotechnical systems where learning unfolds through a combination of individual human-AI interaction and interpersonal collaboration. Rather than strengthening or weakening team learning, AI reshapes its structure, timing, and relational dynamics in everyday professional work.

5.3 Contributions

5.3.1 Theoretical contributions

The study contributes by empirically supporting a sociotechnical understanding of AI in team-based work. Rather than showing AI as an isolated technological tool with uniform effects, the findings indicate that its role in team learning is shaped by the interaction between technological possibilities and existing social conditions, such as work structure, accessibility of colleagues, hierarchy, and perceived interpersonal risk-taking. This is consistent with the sociotechnical systems perspective, which emphasizes that technology and social systems are mutually interdependent and must be understood together. In this study, AI did not simply enter the work process as a neutral support tool, but became integrated into already established patterns of collaboration, support-seeking, and learning. The contribution therefore lies in showing how AI reshapes team learning not only through its technical functions, but through the way these functions are interpreted, used, and embedded within specific social and organisational contexts.

Theoretically, this study furthermore contributes by showing how team learning behaviors may need to be reconsidered when AI becomes integrated into existing work processes. Traditional conceptualizations of team learning behaviors are grounded in social and interpersonal learning, where learning occurs through interaction between team members. However, the findings of this study suggest that AI can alter this process by becoming an additional source of information, interpretation, and problem-solving within everyday work. In some cases, AI supported learning in human-AI dyads, where employees used AI to retrieve information, explore ideas, clarify uncertainties, or test possible solutions before involving colleagues. This indicates that AI may partly replace certain interpersonal learning behaviors. At the same time, AI also became embedded within existing team learning behaviors by shaping how, when, and with what quality these behaviors occurred. In this way, AI did not simply replace team learning, but changed the balance within team learning behaviors by shifting some activities from initial meaning-making toward evaluation, refinement, and validation. The study therefore contributes by showing that AI can both substitute and reconfigure team learning behaviors, creating a more hybrid form of learning in which individual AI-supported sensemaking and interpersonal team learning coexist.

As this study adopts a qualitative approach and explores individual-level perceptions of team constructs, psychological safety could not be measured directly in the traditional sense (Newman et al., 2017). However, the findings suggest that perceived psychological safety may help explain why AI becomes integrated into team learning processes differently across work contexts. While participants from Company B generally appeared more comfortable engaging in interpersonal support-seeking despite access to AI, participants from Company A more often described considerations related to appearing inexperienced or incompetent when deciding whether to ask AI or a colleague. This indicates that AI does not shape team learning behaviors in isolation, but in relation to perceived interpersonal risk-taking. In doing so, the study contributes by showing how interpersonal risk may influence whether AI primarily complements collegial learning or becomes a lower-risk intermediary in support-seeking. This partly confirms Edmondson (1999), explaining that psychological safety is a crucial facilitator of team learning behaviors.

Finally, the study contributes to the understanding of team learning behaviors in AI-integrated work processes by showing not only how these behaviors are reshaped, but also why they unfold in particular ways. The findings indicate that AI-mediated team learning behaviors are shaped by contextual conditions such as time and efficiency pressures, accessibility of support, and perceived interpersonal risk-taking. These conditions are particularly salient in Professional Service Firms, where learning-related interaction takes place within client-oriented, time-sensitive, and performance-driven work processes.

5.3.2 Practical contributions

In contemporary organisations, where AI is increasingly implemented into existing work processes, this study contributes to a practical understanding of how AI may reshape important team processes. The findings show that AI should not be understood as a separate tool, independent from the social systems in which it is used. This means that AI implementation should not only be evaluated in terms of productivity, efficiency, or task performance, but also in relation to how it influences the social conditions through which teams learn, share knowledge, and develop shared understanding.

This is particularly important because team learning behaviors have been associated with outcomes such as team performance, innovation, adaptation, and knowledge development. While many organisations seek to leverage the efficiency gains that AI offers, the findings suggest that such gains may become counterproductive if they unintentionally reduce opportunities for interpersonal learning, knowledge sharing, and collective sensemaking. For managers, this implies that AI-supported work practices should be followed by active reflection on which learning interactions are strengthened, redirected, or potentially lost when employees increasingly use AI in their work.

The study also offers practical implications for how organisations support employees' learning and development. AI may help employees prepare better questions, access information faster, and work more independently. However, organisations should be attentive to whether AI use reduces the visibility of uncertainty, questions, and learning needs within teams. This is especially relevant for junior employees, whose professional development often depends not only on receiving answers, but also on observing colleagues' reasoning, participating in discussions, and learning how judgement is developed in practice. organisations may therefore need to create deliberate spaces for discussion, reflection, feedback, and knowledge sharing to ensure that efficiency gains do not come at the expense of collective learning and development.

5.4 Limitations of the Study

Several limitations should be considered when interpreting the conclusion of this study. First, the study is based on participants' self-reported experiences and perceptions of AI use and team learning behaviors. Consequently, the findings reflect how employees interpret and describe their work practices rather than direct observations of behavior. Participants may not always be fully aware of how AI influences their interactions with colleagues, and their accounts may also be shaped by organisational norms and expectations regarding collaboration, learning, and technology use. While the semi-structured interview format enabled in-depth exploration and follow-up questions, the findings should therefore be understood as participants' interpretations of their experiences rather than objective representations of team processes.

In addition, the study focuses on individual experiences rather than complete teams. As a result, it was not possible to examine team learning behaviors or psychological safety as shared team-level phenomena. Although participants provided rich descriptions of collaboration and support-seeking within their teams, the study cannot determine whether these perceptions were collectively shared by other team members. Future studies including multiple members from the same teams could provide a more comprehensive understanding of how AI influences team dynamics at the collective level.

Furthermore, the study was conducted within Professional Service Firms operating in audit and accounting-related contexts. These organisations are characterized by knowledge-intensive work, strong efficiency pressures, high levels of expertise, and increasing investments in AI technologies. While this context provided a relevant setting for exploring AI-integrated learning processes, the findings may not be directly transferable to other organisational settings with different task characteristics, structures, or technological maturity. The role of AI in shaping team learning behaviors may vary across industries, occupations, and organisational environments.

Finally, AI remains a rapidly evolving phenomenon. Both the capabilities of AI systems and organisational practices surrounding their use continue to develop at a rapid pace. The findings therefore capture perceptions and experiences at a particular point in time and should be interpreted in relation to the current stage of AI adoption within the participating organisations. As AI technologies become increasingly integrated into everyday work processes, the relationship between AI, collaboration, and team learning behaviors may evolve further.

5.5 Future Research

The findings of this study suggest several directions for future research. Further studies could examine team learning behaviors at the collective level by including several members from the same teams. Since both team learning behaviors and psychological safety are commonly understood as phenomena emerging through interaction, studies of complete teams could provide deeper insight into how learning-related interaction is shared, negotiated, and developed over time. Observational or longitudinal designs would be particularly valuable for capturing how support-seeking, knowledge sharing, co-construction, and interpersonal risk-taking unfold in everyday work rather than only through retrospective accounts.

Future research could also explore team learning behaviors across a wider range of organisational and professional contexts. The present study focused on Professional Service Firms operating within audit and accounting, where work is shaped by expertise, client orientation, regulation, time pressure, and collaboration. Other contexts may involve different forms of interdependence, professional judgement, hierarchy, or learning conditions. Comparative studies across industries and occupations could therefore develop a more nuanced understanding of how work context shapes the relationship between technology-supported work practices and team learning.

Another promising direction concerns the different forms through which technology becomes integrated into learning-related work. Participants in this study described varying degrees of integration, ranging from occasional use of general-purpose tools to more embedded organisation-specific systems. Future studies could examine how different levels of integration, organisational guidelines, and managerial expectations influence whether technology-supported work becomes a complement to interpersonal learning, a preparation stage before collaboration, or a partial substitute for certain learning interactions.

Future research could also examine team learning behaviors that were less visible in the present study. While knowledge sharing, co-construction, boundary crossing, and team activity were most clearly represented in participants' accounts, team reflexivity, constructive conflict, and storage and retrieval were less prominent. Further studies could explore whether these behaviors are less affected by AI-supported work practices, less common in time-pressured professional settings, or more difficult to capture through interview-based methods. This would contribute to a more complete understanding of how all seven team learning behaviors are enacted in contemporary work environments.

Finally, future research could investigate the long-term implications for learning and professional development. Several participants described how AI-supported work enabled faster access to information, quicker problem-solving, and more independent task execution.

However, questions remain regarding how such changes affect the development of expertise, professional judgement, and learning from colleagues over time. This is particularly relevant for junior employees in knowledge-intensive professions, whose development often depends on repeated practice, observation, feedback, and participation in collective problem-solving. Taken together, future research could deepen understanding of how team learning behaviors evolve as work practices become increasingly supported by AI, and how organisations can preserve collective learning while benefiting from new forms of technological support.

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Appendixes

Appendix A: Information letter and consent form

Information Letter for Participation in Interview

Thank you for considering participating in an interview about your experiences of using AI in your work.

This study is part of a master's thesis conducted within the Master's programme in Management at Lund University School of Economics and Management. The purpose of the study is to explore how employees at Professional Service Firms perceive AI-integrated work processes with a focus on aspects such as collaboration and interactions in teams as well as team learning.

The interview will take approximately 60 minutes and will focus on your experiences of AI use and teamwork. One researcher will lead the interview, while both researchers will be present. The interview can be conducted either in person or digitally, depending on your preference.

Participation is entirely voluntary. You may decline to answer any question and may withdraw your participation at any time before or during the interview, without providing a reason.

With your consent, the interview will be audio-recorded to ensure accurate transcription and analysis. The recordings will only be accessed by the researchers, stored securely, and deleted after the completion of the study. All material will be anonymized, and no identifiable information will be included in the final thesis. The name of your employing company will not be included and the results will be presented in a way that ensures that individual participants cannot be identified.

Before the interview, you will be asked to sign a consent form confirming your participation.

If you have any questions or would like further information, please feel free to contact us.

Victoria Johnsson,

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Consent to Participate in Study

This study is part of a master's thesis exploring how employees at Professional Service Firms perceive AI-integrated work processes.

I confirm that I have read and understood the information provided about the study and have had the opportunity to ask questions.

I understand that my participation is voluntary and that I may decline to answer any question or withdraw at any time without providing a reason.

I consent to the interview being audio-recorded and understand that the material will be anonymized, handled confidentially, and deleted after the completion of the study.

I agree to participate in this study.

Place and date: ___________________________

Name (first and last): _____________________

Signature: ________________________________

Appendix B: Semi-Structured Interview Guide

The interview guide was originally written in Swedish, the English translated version is presented below.

1. Introduction and background
    - Brief introduction to the study, including information about anonymity, confidentiality, voluntary participation, and the participant's right to withdraw at any time.
    - Guiding questions:
        - Could you briefly describe the company you work for and your role within the organisation?
        - How long have you worked in your current role?
        - What are your main work tasks and responsibilities?

2. Work context and team structure
    - Guiding questions:
        - How is your work organised in teams?
            - *Probe: team size, roles, seniority levels, team leaders, project-based or client-based teams*

- Can you describe what it is like to work and collaborate within your team?
    - *Probe: atmosphere, relationships, communication, and differences between teams*
- How would you describe the leadership and role distribution within your team?

3. Team learning and collaboration

- Guiding questions:
    - How do you usually share knowledge, insights, or experiences within your team?
    - How do you ask colleagues for help or support when you are uncertain about something?
    - How does your team handle situations where members have different views on a problem or solution?
    - Can you describe how your team discusses both successful work and difficulties or mistakes?
    - How does feedback usually take place within or across teams?
    - To what extent do you reflect on or evaluate work processes together?

Interpersonal risk-taking

- Guiding questions:
    - Do you feel that there is room to be open and honest within your team? Why or why not?
    - How does it feel to ask colleagues questions or request help?
    - Can you describe a situation where you made a mistake or were uncertain about something?
        - *Probe: how the participant reacted, whether they shared it with others, and how the team responded*
    - Are there situations where it feels easier or harder to ask questions or share uncertainty?

4. AI use in daily work

- Guiding questions:
    - How is AI used in your daily work?
        - *Probe: tools, systems, tasks, frequency, and purpose*
    - Can you describe a typical work task where AI is involved?
    - Is AI use mainly encouraged by the organisation, initiated by yourself, or both?
    - Are there guidelines or rules for how AI should be used?
    - How has AI use in your work developed over time?

6. AI, collaboration and team learning

- Guiding questions:

- When you are uncertain about something, how do you decide whether to ask a colleague or use AI?
- Are there certain types of questions or tasks where you prefer AI over colleagues, or the other way around?
- Has AI changed the types of questions team members ask each other?
- Is there knowledge that was previously shared between colleagues but is now accessed through AI?
- Has AI changed the need to consult colleagues or experts outside your immediate team?
- Do you experience that learning takes place more collectively or more individually since AI became part of the work?
- Are there situations where AI makes work more individual rather than collaborative?
- How do you decide when AI is sufficient and when human expertise is needed?
- What positive/negative effects do you associate with AI use work?
- How do you think AI will affect your work and team collaboration in the future?