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Evolving Expertise in the Age of AI: How Professionals Working with Artificial Intelligence Redefine Their Roles

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ABSTRACT

The growing integration of artificial intelligence (AI) into professional work raises important questions about how roles evolve in AI-enabled environments. While prior research has examined the impact of AI on tasks and decision-making, less attention has been given to how professionals interpret and enact their roles in everyday work. This study addresses this gap by exploring how professionals involved in the deployment and organizational integration of AI systems redefine their roles as AI becomes embedded in organizational practices.

The study adopts a qualitative multiple-case design based on semi-structured interviews with professionals working in AI-intensive organizations. Drawing on sociotechnical systems theory, the analysis examines how role evolution emerges through the interaction between human actors and AI systems.

The findings show that AI is experienced not merely as a tool, but as an integrated part of daily work that supports idea generation, content production, and analysis. Human actors continue to play a critical role in assessing, directing and taking accountability for AI-assisted work. Professional roles are still structurally solid, but how they are carried out on a daily basis has changed, moving from task execution to coordination and supervision. Accountability still remains human-centered, but it is becoming more complicated as expertise increasingly focuses on evaluating and analyzing AI-generated content.

This paper contributes by applying sociotechnical systems theory to modern AI contexts and provides an empirically supported explanation of role evolution in AI-enabled work.

KEYWORDS: Artificial Intelligence (AI), Professional roles, Human-AI Collaboration, Expertise Reconfiguration, Sociotechnical systems, Role enactment

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TIIVISTELMÄ

Tekoälyn (AI) kasvava integroituminen asiantuntijatyöhön herättää keskeisiä kysymyksiä siitä, miten ammatilliset roolit kehittyvät tekoälyä hyödyntävissä työympäristöissä. Aiemmat tutkimukset ovat tarkastelleet tekoälyn vaikutuksia tehtäviin ja päätöksentekoon. Vähemmän huomiota on kiinnitetty siihen, miten ammattilaiset tulkitsevat ja toteuttavat roolejaan arjen työssä. Tämä tutkimus vastaa tähän tutkimusaukkoon tarkastelemalla, miten tekoälyjärjestelmien käyttöönottoon ja integrointiin osallistuvat asiantuntijat määrittelevät roolinsa uudelleen, kun tekoäly vakiintuu osaksi organisaatioiden käytäntöjä.

Tutkimuksessa käytetään aineistoa, joka koostuu puolistrukturoiduista haastatteluista tekoälyintensiivisissä organisaatioissa työskentelevien asiantuntijoiden kanssa. Analyysi pohjautuu sosioteknisten järjestelmien teoriaan ja tarkastelee, miten roolien kehittyminen rakentuu ihmistoimijoiden ja tekoälyjärjestelmien välisessä vuorovaikutuksessa.

Tulokset osoittavat, että tekoälyä ei koeta pelkkänä työkaluna, vaan integroituneena osana päivittäistä työtä, tukien ideointia, sisällöntuotantoa ja analyysiä. Ihmisillä säilyy keskeinen rooli tekoälyavusteisen työn arvioinnissa, ohjaamisessa ja vastuun kantamisessa. Ammatilliset roolit ovat rakenteellisesti edelleen melko vakiintuneita. Niiden päivittäinen toteutus on kuitenkin muuttunut tehtävien suorittamisesta kohti koordinointia ja valvontaa. Vastuu säilyy edelleen ihmiskeskeisenä, mutta sen luonne monimutkaistuu, kun asiantuntijuus painottuu yhä enemmän tekoälyn tuottaman sisällön arviointiin ja analysointiin.

Tutkimuksen panos näkyy soveltamalla sosioteknisten järjestelmien teoriaa nykyaikaisiin tekoälykonteksteihin. Tutkimus myös tarjoaa empiirisesti perustellun selityksen ammatillisten roolien kehittymisestä tekoälyä hyödyntävässä työssä.

AVAINSANAT: Artificial Intelligence (AI), Professional roles, Human-AI Collaboration, Expertise Reconfiguration, Sociotechnical systems, Role enactment

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1. INTRODUCTION

1.1. Motivation for the study

Professionals in a range of knowledge-intensive areas are seeing a growing influence on their daily work because of artificial intelligence. AI is starting to integrate daily tasks and decision-making situations at an individual level. This means that professionals have to interpret algorithmic outputs, choose how to apply them and take responsibility for the outcomes. What AI can do is not the only concern as it becomes incorporated into professional work, but also how people adjust their judgment, accountability and role enactment when AI systems influence decision-making situations (Jarrahi, 2018; Faraj, Pachidi, & Sayegh, 2018).

Professionals whose work involves deploying AI systems are most affected by these individual-level changes. The variety of activities that algorithms can assist has increased due to developments in machine learning, especially in activities that involve classification and prediction (Brynjolfsson & Mitchell, 2017). These changes have an impact on the work that professionals do. The analytical aspects of work are more and more being taken over by AI systems. Humans are still responsible for problem definition, context interpretation and managing the limitations of algorithmic results. Professionals often work in human-AI hybrids in these situations, which means that results are produced by combining human judgment with algorithmic computation (Rai, Constantinides, & Sarker, 2019).

These developments raise questions about individual professional expertise and role enactment. According to research, AI-enabled work systems may change how expertise is expressed and valued, by dividing cognitive tasks between humans and computers (Faraj et al., 2018). As AI systems influence decisions, professionals may need to reevaluate what is considered relevant expertise, how their contribution is measured and how responsibility should be distributed. People’s experiences, opinions and interactions in daily work are what makes role evolution happen. This means that it would not be sufficient enough to concentrate on organizations as the main unit of research, because it does not capture these changes.

The discussion on technological change has mostly focused on general labor market trends or big occupational shifts. These studies have still provided important information about how technology changes work (Autor, 2015). Such perspectives offer important background information. However, they don’t talk about how professionals, especially those who work closely with AI systems, experience role change in AI-intensive environments. The relationship between technology and work activities has long been highlighted by sociotechnical research, meaning that technological development has to be studied by how it’s perceived and implemented within specific work contexts (Orlikowski, 2007). This emphasizes how important it is to research how people understand and enact changing role responsibilities in environments where AI is being incorporated more and more into everyday professional work.

The goal of this thesis is to gain a deeper understanding of these dynamics at an individual level. This study explores how individuals understand AI-driven change, negotiate their roles in connection with AI systems and organizational expectations, and understand responsibility and expertise in AI-enabled work by focusing on professionals involved in the deployment and organizational integration of AI systems in organizational contexts. Researching these problems at the level of individual role enactment offers observations that enrich more general explanations of technological change and a grounded perspective on how AI changes professional work in practice (Jarrahi, 2018; Faraj et al., 2018).

1.2. Research gap

Research on AI and the future of work has grown a lot. There are still some aspects that are not understood well enough. There are three gaps that stand out.

Majority of current research focuses on general theoretical models of human-AI collaboration or macro-level labor market outcomes (e.g., automation, augmentation, hybrid intelligence). These models offer useful conceptual frameworks, but they still often ignore the real-world experiences of professionals whose work is the closest related to AI systems. For example, Rai et al. (2019: iii) find that "AI-enabled hybrids create new organizational forms,". Still, there isn't much empirical research on how these hybrids change expert roles. Davenport and Kirby (2016: 84) also state that "augmentation is the most promising path forward for knowledge workers,". They also don't offer any proof of how augmentation works for technical professionals whose roles continue to involve AI capabilities.

Existing research on human-AI collaboration focuses mostly on managers, analysts or professionals who don't work in the technological field. There is less research on professionals involved in the deployment and organizational integration of AI systems in organizational contexts. However, their work is likely to be the most impacted by AI's developing abilities. Previous literature has consistently acknowledged this gap. For instance, "future research should investigate how AI transforms the work practices and identities of digital experts who interact most closely with these systems," according to Benbya et al. (2020: 46). Also, Faraj et al. (2018: 67) point out that "we know little about how professionals navigate changing boundaries of expertise in AI-intensive environments,". This highlights the need for empirical research that focuses on expert-level adaptation.

According to sociotechnical systems theory, technological change has a direct connection to social and organizational processes. There is still little empirical research done on how AI-driven changes affect professional roles, responsibilities and perceived value. The use of AI in the modern day creates new kinds of sociotechnical impact that has not been common in previous technological eras. Trist and Bamforth (1951: 4) have still noted that "technical innovation inevitably brings new social arrangements". Recent studies specifically call for more research on how AI’s technological capabilities link to the changes of professionals role structures. For example, Dellermann et al. (2021: 159) recommend research on "the microfoundations of expertise in hybrid human–AI systems". Shrestha et al. (2021: 203) believe that "future research should explore how human roles evolve as AI takes on more complex analytical tasks."

Even with these suggestions, there is still little empirical research done on how AI professionals understand their evolving roles. This presents an important gap in our knowledge of organizational transformation that is enabled by AI.

1.3. Research problem and theoretical contribution

These observations lead to the central research problem of this thesis:

How do professionals responsible for deploying AI systems redefine their roles as AI becomes integrated into everyday work?

This question reflects the struggle between quickly developing AI technologies, and how human expertise is needed to evolve in order to successfully integrate these technologies into organizational work processes. The professionals involved in deploying AI systems work at the intersection of human judgment, organizational expectations and technical capability. Because of this, they are an especially relevant group for examining how roles change in AI-enabled environments. Deployment is understood broadly in this study. This way, it allows the examination of both the technical implementation of AI systems and the organizational processes used to incorporate these technologies into everyday work. So, the focus is on professionals involved in the deployment and organizational use of AI systems. So the focus is not on individuals who are only involved in technical development. The focus on role definition presents a structured approach for analyzing how work practices change in AI-enabled environments. Even though the study also examines changes in expertise and responsibility, they are analyzed as related aspects of role transformation, instead of separate phenomenas.

Using a theoretical lens to analyze the relationship between technological capabilities and human interpretation is essential in order to understand this challenge. Because of this, the thesis uses sociotechnical systems theory as its theoretical lens. This lens provides a strong foundation for analyzing role evolution in situations where humans and AI systems collaborate on everyday work tasks, by understanding work systems as created together by social and technical elements.

This study makes the following main theoretical contributions. It analyzes how professionals involved in the deployment and organizational integration of AI systems reinterpret what is considered meaningful human contribution as AI becomes integrated in everyday work, which adds value to the literature on expertise and professional roles in technological environments. It also offers empirical insight into how professionals negotiate boundaries, responsibilities and legitimacy, which improves knowledge of human-AI collaboration at the expert level. This explains how human judgment and AI outputs interact in actual organizations. The study also expands on sociotechnical systems theory by applying it to the context of modern AI. It does so by demonstrating how roles evolve in work environments where technology is adaptive and more capable of participating in cognitive activities.

The study also offers insight into how organizations can support professionals involved in the deployment and organizational integration of AI systems. This is especially relevant from a managerial perspective when technologies are changing rapidly. The findings provide insights for redesigning roles, expertise and responsibilities in AI-intensive environments. It also discusses how to maintain expert motivation and a sense of professional contribution as AI capabilities are advancing, and how to structure teams when AI becomes more involved in work processes. The findings of this study can benefit organizations adopting AI, HR leaders, consulting firms and authorities interested in AI governance and talent development.

1.4. Thesis structure

There are five chapters in this thesis. Chapter 1 presents the research topic, research question and contributions. Chapter 2 reviews literature on AI and professional work and develops the sociotechnical conceptual framework that guides the study. The research design, case selection, data collection and analysis are all described in chapter 3. Chapter 4 presents the empirical findings, organized around the framework's four analytical aspects. Chapter 5 discusses the findings in relation to current literature and finishes with theoretical and managerial implications, suggestions for future research and limitations of the study.

2. LITERATURE REVIEW

2.1. AI and the Changing Nature of Professional Work

Artificial intelligence (AI) means a collection of computing technologies that allow systems to learn from data, make predictions or classifications, and assist in decision-making in specific work areas. AI is usually understood as a type of limited artificial intelligence in organizational study. Basically, this refers to systems that are meant to carry out specific tasks, instead of having human-like intelligence (Jordan & Mitchell, 2015; Kaplan & Haenlein, 2019). Modern AI systems, especially those built on machine learning, are more and more being used to assist with cognitive and analytical tasks in the workplace. This is why they are very relevant to the study of professional work and expertise (Shrestha et al., 2019).

Artificial intelligence has become a major technological advancement that is influencing modern work processes, especially in knowledge-intensive and expert areas (Autor, 2015; Brynjolfsson & Mitchell, 2017). In the past, periods of digitalization and automation were mostly targeting only routine and measurable tasks. Recent developments in AI expand the impact of technology on complicated cognitive tasks like prediction, classification and analytical judgment unlike ever before (Brynjolfsson & Mitchell, 2017; Jarrahi, 2018). These advancements show how AI is changing the nature of professional work while also automating tasks (Brynjolfsson & Mitchell, 2017; Jarrahi, 2018). As a result, it has become harder to tell the difference between contributions made by humans and machines to work. This is why professionals have to interact more actively with algorithmic outputs, and also maintain responsibility for interpretation and final decision-making (Jarrahi, 2018; Shrestha et al., 2019).

Modern AI systems use data to find patterns and representations. They do not use preset rules. This allows them to participate in more difficult analytical tasks like forecasting, legal analysis, diagnostics and strategic planning (Kaplan & Haenlein, 2019; Shrestha et al., 2019).

The usual division between human expertise and technological support becomes challenged because of these capabilities (Shrestha et al., 2019; Faraj et al., 2018). This challenge happens because professionals are increasingly relying on AI-generated insight, when they are still responsible for the outcome of these insights. This means that AI does not just automate tasks. It is getting integrated into the cognitive core of professional work.

Earlier studies have discussed how AI redistributes cognitive tasks between humans and technological systems. This changes decision-making and professional work methods (Brynjolfsson & Mitchell, 2017; Rai, Constantinides, & Sarker, 2019). Some studies focus on the automation of predictive aspects of work (Brynjolfsson & Mitchell, 2017). Some studies show the rise of human-AI collaboration, where professionals and AI systems work together to produce joint results (Rai et al., 2019; Shrestha et al., 2019). These insights show that AI changes how human work is done, instead of just replacing it (Rai et al., 2019; Shrestha et al., 2019). The rise of AI repositions human expertise, but it does not eliminate the need for it. For example, human expertise may be needed less in task execution and more in interpretation, evaluation and analysis of AI-generated outputs (Faraj et al., 2018).

Professional work will be significantly impacted by these developments. Professional expertise is no longer defined only by the ability to carry out analytical, predictive and classificatory tasks, because AI systems are increasingly supporting these tasks. Instead, expertise is increasingly defined by the ability to judge, contextualize and integrate AI-supported insights into existing work practices (Faraj et al., 2018; Beck & Young, 2005). This means that expertise becomes divided across humans and machines, and professional value is found in the ability to supervise and manage this divide instead of just task execution. As stated previously, this explains that human expertise is not disappearing, but being redefined around being able to work with AI effectively (Faraj et al., 2018; Shrestha et al., 2019).

AI also reshapes how professional roles are defined and enacted (Rai et al., 2019; Shrestha et al., 2019). AI systems are becoming more integrated into decision-making situations. It means that professionals, especially those involved in the deployment of AI, take on more responsibilities that go beyond just technical implementation. These expanded responsibilities could include advising stakeholders, explanations between technical and non-technical actors, and making sure AI systems are being used correctly in specific situations. Professionals have to also manage new forms of collaboration with AI systems, because they are becoming more involved in joint task performance (Rai et al., 2019; Shrestha et al., 2019). This supports the idea that professional work is becoming more relational (Faraj et al., 2018; Rai et al., 2019). It involves ongoing interaction between human judgement and algorithmic output.

There are new organizational and cognitive demands when working with AI systems. Professionals must monitor system behavior, manage uncertainty and be alert for any mistakes or biases that may be integrated in these models (Elish, 2019; Faraj et al., 2018). These new demands may cause concern about accountability and increase role ambiguity. This becomes clear in situations where AI systems assist decision-making but do not make the actual decision. It creates uncertainty around responsibility and increases role ambiguity (Elish, 2019; Faraj et al., 2018).

So, according to research, AI transforms professional work by redefining how expertise, roles and responsibility are enacted in practical application, instead of replacing the work itself (Brynjolfsson & Mitchell, 2017; Rai et al., 2019; Shrestha et al., 2019). These studies show a shift towards a more integrated and interactive type of human-AI work, instead of a particular direction. These changes are especially important for professionals who work closely with AI systems. They highlight the importance of examining how these individuals understand and adapt to their evolving roles in AI-enabled work environments (Rai et al., 2019; Shrestha et al., 2019).

This study recognizes between the connected but analytically different concepts of professional role, expertise and responsibility. Professional roles are the expected tasks, behaviors and activities associated with an individual in organizational settings (Katz & Kahn, 1978; Biddle, 1986). Expertise refers to the development and application of knowledge, skills and judgment, especially in situations involving interpretation and decision-making (Faraj et al., 2018). Responsibility describes the accountability associated with actions and decisions in these roles, especially if outcomes are influenced by both human and technological contributions (Elish, 2019).

Even though these elements are theoretically separate, previous studies indicate that they are closely connected in technology-enabled work (Rai et al., 2019; Shrestha et al., 2019; Faraj et al., 2018). The expertise needed to complete these tasks is being reshaped by changes in task performance, such as the incorporation of AI, which also affects how responsibility is assigned and enacted in reality (Rai et al., 2019; Shrestha et al., 2019). At the same time, as forms of expertise and accountability evolve, it influences how professionals interpret and enact their roles, which highlights the mutually beneficial relationship between these dimensions.

The main analytical lens in this thesis is professional role redefinition. Changes in expertise and responsibility are analyzed as interrelated dimensions that make role transformation evident in AI-enabled work situations. Section 2.3 presents a conceptual framework that is based on this related perspective.

2.1.1. Role Change and Role Ambiguity in Technology-Intensive Work

According to research on professional work, roles are not simply stable positions that do not change, but they are socially formed patterns of expectations, responsibilities and behaviors that evolve over time (Katz & Kahn, 1978; Biddle, 1986). Role theory emphasizes that roles influence how individuals understand what is expected of them and how they should act within organizational settings (Katz & Kahn, 1978; Biddle, 1986). Technological advancement becomes especially significant when it challenges these already established expectations. This results in changes to task boundaries, leadership structures and responsibility distribution, which in turn destabilize professional roles (Ilgen & Hollenbeck, 1991; Ashforth et al., 2000). These two perspectives explain that professional roles are constantly shifting and sensitive to changes brought on by techological change.

A key insight from role theory is that role change is usually seen as increased role ambiguity and role conflict instead of role replacement or elimination (Ilgen & Hollenbeck, 1991; Ashforth, Kreiner, & Fugate, 2000). Role ambiguity happens when individuals don't have clear information about their expectations, responsibilities or performance standards. Role conflict happens when conflicting demands are made on the same role (Ilgen & Hollenbeck, 1991; Ashforth, Kreiner, & Fugate, 2000). If technological capabilities evolve faster than how organizational role definitions can adapt, it creates this role ambiguity in technology-intensive environments (Ashforth et al., 2000; Bechky, 2003). This means that professionals have to take on new responsibilities without giving up their current ones. As a result, this creates uncertainty about priorities, authority and accountability (Ilgen & Hollenbeck, 1991; Ashforth et al., 2000). This shows that role ambiguity is a common outcome when technological change evolves faster than formal role definitions.

Earlier studies highlight that technological development is one of the main causes for role ambiguity in professional work (Ashforth, Kreiner, & Fugate, 2000; Bechky, 2003). Organizations often find it difficult to redefine roles as a response to emerging technologies (Ashforth et al., 2000; Bechky, 2003). Professionals participate in interpretive processes to try and decide how their roles should be enacted in changing conditions, instead of being guided by specific job redesign (Weick, 1995; Orlikowski, 2007). This sensemaking process is very prominent in knowledge-intensive fields, where work mainly relies on judgment, discretion and implicit expertise (Alvesson, 2001; Faraj, Pachidi, & Sayegh, 2018). Role expectations become more flexible and contentious as a result, which highlights how role enactment becomes an evolving interpretive process instead of a set organizational structure.

Technological change also concerns jurisdictions and boundaries between professions, tasks and forms of authority (Abbott, 1988; Bechky, 2003). According to Abbott's (1998) theory of professions, professional groups keep their legitimacy by asserting their authority over specific tasks and forms of expertise. This authority can be challenged when technologies allow new actors or technological systems to do things that used to need professional expertise (Abbott, 1988; Bechky, 2003). These challenges do not mean that there will be professional decline. Instead of professional decline, they usually lead to boundary work. Boundary work means that professionals try to redefine, defend, or expand their area of expertise (Abbott, 1988; Gieryn, 1983; Bechky, 2003). These studies show that technological change does not eliminate professional roles. It does however change how they are defined and maintained.

If technology gets involved in the cognitive tasks of professional work, boundary work becomes especially important (Abbott, 1988; Bechky, 2003). When this happens, professionals may focus on the parts of their jobs that are still hard to automate. These tasks could include making judgments, ethical reasoning, or interacting with clients (Bechky, 2003; Ashforth et al., 2000). They might also emphasize that technologically assisted tasks need expert supervision (Bechky, 2003; Ashforth et al., 2000). This allows professionals to maintain legitimacy when they are adapting to evolving technology (Abbott, 1988; Bechky, 2003). These negotiations are usually informal and situational, and they happen in everyday work. They do not happen through clear organizational instructions (Bechky, 2003). This is how professionals reshape their roles when technological change happens, instead of just adapting to the change.

This means that roles do not change in a linear way in technology-intensive environments. When technology divides tasks between humans and machines, professionals experience role expansion, role fragmentation or role hybridization (Ashforth et al., 2000; Bechky, 2003). Role expansion means that new responsibilities get added into already existing roles. With role expansion, usually the workload does not get reduced. Role fragmentation means that tasks are seperated across different actors or systems. This can blur responsibility and accountability. Role hybridization means that roles that combine technical, advising, and coordinative features emerge. This requires professionals to navigate multiple different logics at the same time (Ashforth et al., 2000; Bechky, 2003).

Professional roles play a huge part in meaning and self-definition. It makes these dynamics closely related to identity work (Pratt, Rockmann, & Kaufmann, 2006). Professionals can experience identity tension when technology changes role expectations. Identity work happens because the parts of the professionals' work that they used to value are changing or are not important anymore (Pratt et al., 2006). Professionals do identity work to balance the changing work demands with their sense of professional self (Ashforth et al., 2000; Pratt et al., 2006). This usually means that they redefine what meaningful contribution means when work environments are evolving.

Role ambiguity and what comes with it is not always negative. Uncertainty can be challenging, but it can also create opportunities for role innovation and professional growth (Ashforth et al., 2000; Pratt et al., 2006). Earlier studies disucss that in order for professionals to successfully navigate technological change, they have to actively shape their roles and not just passively adapt to the external changes (Ashforth et al., 2000; Bechky, 2003). This concept relates with sociotechnical methods because they consider roles as emergent and continuously negotiated accomplishments, as opposed to set organizational structures (Orlikowski, 2007; Leonardi, 2011).

These role dynamics become more obvious in AI-enabled work environments. AI systems directly interact with the cognitive core of many professional roles, because they increasingly assist tasks including analysis, prediction, and judgment (Brynjolfsson &

Mitchell, 2017; Shrestha et al., 2019). That is why professionals working with AI must decide which aspects of their work remain exclusively human, which can be assigned to AI systems and how responsibility should be distributed when results are produced jointly (Rai et al., 2019; Shrestha et al., 2019). These negotiations usually happen when there are no clear organizational instructions, which increases role ambiguity and requires professionals to rely on their own interpretations (Elish, 2019; Faraj et al., 2018).

According to research on role change, role ambiguity and boundary work, the evolution of professional roles together with technological change is a socially rooted interpretive process. Roles evolve through ongoing negotiation, sensemaking, and enactment in practice. They are not determined only by technological abilities (Ashforth et al., 2000; Bechky, 2003; Pratt et al., 2006; Orlikowski, 2007). As this study examines how professionals involved in the deployment and organizational integration of AI systems interpret and redefine their roles as AI becomes integrated into everyday work, this insight provides an important foundation. The study extends established role theory into the context of modern AI-enabled work environments by focusing on role enactment at the individual level.

2.1.2. Sensemaking and Professional Identity in AI-Enabled Work

Technological change does not affect only tasks and workflows. It also changes how professionals understand their roles, responsibilities, and identities (Ashforth, Kreiner, & Fugate, 2000; Pratt, Rockmann, & Kaufmann, 2006). When technological development affects the core of how professional expertise is enacted, individuals participate in interpretive processes to understand what these changes mean for their work and themselves (Weick, 1995; Orlikowski, 2007). Sensemaking is known as the ongoing process where individuals create meaning in situations defined by ambiguity, disturbance or uncertainty (Weick, 1995). These circumstances are common in technology-intensive work environments, because evolving technological capabilities usually evolve faster than already established role expectations and professional norms (Faraj, Pachidi, & Sayegh, 2018; Jarrahi, 2018).

This section focuses on AI-enabled work, but it is important to pay attention to these interpretive processes in order to understand how professionals respond to these changes. Sensemaking is a helpful framework for examining how individuals interpret and adapt to evolving work conditions. Particularly in situations where the effects of technology on roles, expertise and responsibility are still somewhat unclear (Weick, 1995; Faraj et al., 2018).

According to research on professional identity, roles are important sources of meaning and self-definition in addition to being functional positions. Professional identity is formed by the repeated enactment of roles and through common understandings of what competent, legitimate, and valuable work means (Pratt et al., 2006; Ashforth et al., 2000). When evolving technologies change professional tasks, it can compromise these established identity foundations by changing what activities are valued, visible or recognized as expert work (Bechky, 2003; Faraj et al., 2018). If previously important aspects of professional roles are changed or assigned to technological systems, they can experience identity tension (Pratt et al., 2006).

Research on technological change indicates that these identity tensions usually lead to active sensemaking and identity work, because professionals try to maintain a clear sense of self as these changing conditions are happening (Pratt et al., 2006; Ashforth et al., 2000). Professionals usually try to interpret technological change in ways that allow them to keep professional legitimacy, instead of just accepting new ways of working (Bechky, 2003; Ashforth et al., 2000). This can show as emphasizing more those aspects of work that remain very human, like making decisions or working with other people. It can also mean that we change the way we look at technology-assisted tasks as needing expert supervision and not just being done (Bechky, 2003; Ashforth et al., 2000).

Sensemaking is especially important in situations where responsibility and accountability are unclear. Professionals have to interpret how responsibility should be distributed between humans and systems when technologies support or impact decision-making(Rai, Constantinides, & Sarker, 2019; Elish, 2019). This ambiguity is especially noticeable in AI-enabled work, because results can be hard to explain (Brynjolfsson & Mitchell, 2017; Shrestha et al., 2019). In these situations, professionals participate in ongoing sensemaking to decide when to trust AI systems, when to get involved and how to justify decisions influenced by algorithmic recommendations (Weick, 1995; Jarrahi, 2018).

The research also emphasizes how responsibility in technology-mediated work is redistributed and negotiated in sociotechnical systems. So, it is not just being passed from humans to machines (Rai et al., 2019; Orlikowski, 2007). Elish's (2019) idea of "moral crumple zones" shows how even if automated systems play a significant role in decision-making, humans would still remain at the center of accountability. As professionals have to balance formal accountability with little control over algorithmic behavior, it amplifies role and identity tension (Elish, 2019; Rai et al., 2019).

These challenges affect particularly those professionals who work closely with AI systems. AI is increasingly assisting with analytical and predictive tasks. This means that professionals can feel that their authority is being redefined. At the same time, professionals are expected to explain, justify and regulate the use of AI in organizations (Brynjolfsson & Mitchell, 2017; Shrestha et al., 2019). This puts them at the middle of technical systems and organizational stakeholders. This requires ongoing sensemaking about their own roles and also about how others should trust and understand AI (Jarrahi, 2018; Faraj et al., 2018).

Sensemaking and identity work are ongoing processes. They are not one-time responses. Professionals have to constantly reevaluate how they understand role boundaries, expertise, and responsibility as AI systems are developing and organizational expectations changing (Weick, 1995; Orlikowski, 2007). This recurrent dynamic is consistent with sociotechnical perspectives that understands roles as emerging and constantly challenged (Orlikowski, 2007; Leonardi, 2011).

According to research on sensemaking, professional identity and responsibility, AI changes professional work through task redistribution, but also through deeper interpretive processes (Weick, 1995; Pratt et al., 2006; Rai et al., 2019). During AI-enabled change, professionals are constantly trying to find meaning in what their role actually entails, how expertise should be shown and who is responsible for what. In AI-enabled work, professionals have to constantly evaluate how evolving technological abilities change their roles, expertise and responsibilities. That is why these sensemaking processes are especially relevant in this field. This provides an important foundation for this study, which examines how professionals involved in the deployment and organizational integration of AI systems make sense of and redefine their roles as AI becomes integrated into everyday work practices.

2.2. Sociotechnical Systems Theory and Role Evolution

Sociotechnical systems theory provides an excellent perspective for examining how work and professional roles evolve in the contexts of technological change (Trist & Bamforth, 1951; Orlikowski, 2000). The sociotechnical approach originates from early studies of industrial work systems. It highlights that work outcomes are a result from the combined interaction of social and technical factors, not just from either technology or human action alone (Trist & Bamforth, 1951). This perspective emphasizes that technologies are not outside influences that drive organizational outcomes. Instead, they are enacted through the social structures, roles, and practices in how work is performed (Orlikowski, 2000, 2007).

According to sociotechnical systems theory, effective work systems need alignment between technical systems and social organization (Trist & Bamforth, 1951). However, further studies have gone beyond this idea of "alignment" to highlight how dynamic and recurring this relationship is (Orlikowski, 2000; Leonardi, 2011). Studies have shown that technologies both shape and are shaped by human action, interpretation, and organizational context, especially in knowledge-intensive work environments (Barley, 1986; Orlikowski, 2000, 2007). This perspective challenges the common ”problematic” views of technology, because it emphasizes that the effects of technological change depends on how technologies are interpreted, applied and integrated into everyday work practices.

When looking at professional roles rom a sociotechnical perspective, they are not fixed structures. They are evolving achievements that are constantly enacted and negotiated in practice (Orlikowski, 2007; Leonardi, 2011). Technological advancements, like AI, do not directly redefine roles. Instead of redefining roles, they change the circumstances where roles are executed (Barley, 1986; Orlikowski, 2000). This means that there can be changes in how tasks are divided between humans and technologies, how expertise is used, and how responsibility is assigned and enacted (Rai, Constantinides, & Sarker, 2019). From this perspective, role evolution can be seen as a sociotechnical process. In this process, changes in technology, expertise and responsibility are all equally important.

Technological systems continue to integrate more in tasks including analysis, prediction, and decision support in AI-enabled work environments. That is why this perspective is especially relevant (Rai, Constantinides, & Sarker, 2019). As these technological advancements are becoming more integrated into their everyday work, professionals have to constantly negotiate how to engage with AI systems, use their expertise, and maintain accountability for results (Jarrahi, 2018; Rai et al., 2019). AI is not replacing human roles, but it is changing how roles are enacted. It changes how roles are executed by redistributing tasks, redefining expertise, and it also complicates responsibility (Rai et al., 2019; Shrestha et al., 2019).

Sociotechnical systems theory offers this study a useful theoretical foundation. Sociotechnical systems theory helps us understand how professional roles develop through ongoing interactions between humans and technology. Instead of seeing roles as fixed, this perspective shows that what we do and the tools we use shape each other over time. (Orlikowski, 2007; Leonardi, 2011). This theory helps us see how professionals involved in the deployment and organizational integration of AI systems redefine their roles as technology keeps changing. It focuses on how roles, expertise, and responsibility interact in AI-enabled work systems.

2.2.1. Origins and Core Assumptions of Sociotechnical Systems theory

Sociotechnical systems theory emerged out of research in the mid-1900s at the Tavistock Institute (Trist & Bamforth, 1951; Trist, 1981). Researchers wanted to know why new technologies didn’t always make work better or more efficient. (Trist & Bamforth, 1951). Trist and Bamforth’s (1951) seminal study of coal mining revealed that you can’t look at technical changes alone. You also have to consider the social side of work. They found that when you introduce new technology without adjusting work organizations as well, it can disrupt established roles, coordination patterns, and sources of meaning. Sometimes, these changes can even lead to unintended and worse outcomes.

One of the key ideas in sociotechnical systems theory is that social and technical elements are closely connected and they make up work systems together. You can not really understand one element without thinking about the other (Trist & Bamforth, 1951; Orlikowski, 2000). Instead of assuming that technology alone decides outcomes, this theory points out that outcomes emerge from the way technical arrangements, human actors, and organizational structures all interact (Trist & Bamforth, 1951; Leonardi, 2011). This challenges the belief that technology shapes everything on its own, and instead it shows that the way technology affects work depends on how it is interpreted, enacted, and integrated into practice (Orlikowski, 2000, 2007).

Over time, organizations started to focus more on knowledge-intensive and professional work. Because of this shift, researchers started to use sociotechnical ideas to examine how technologies reshape roles, authority, and expertise (Barley, 1986; Orlikowski, 2000). Barley's (1986) study of CT scanners in radiology departments found that new technologies can actually reorganize professional roles, mostly by changing who controls information and interpretive authority. What is interesting in Barley's research is that it showed that the same technologies did not have the same effects everywhere. It depended on how the professionals involved adapted to and enacted them in practice. This supports the sociotechnical view that technology doesn't automatically dictate roles, but they emerge through the way professionals interact with new systems in their everyday work.

Other researchers have developed these ideas more by showing that roles and organizational structures are always changing. Barley and Tolbert (1997) argued that people shape and reshape their roles everyday as they respond to changing technologies and what is expected of them at work. In this view, roles are not fixed. They are shaped through interaction between social practices and technical conditions (Barley & Tolbert, 1997; Orlikowski, 2007). This has direct implications for understanding role evolution, because when technology changes, roles change too. However, roles do not change through direct replacement, but they change through human interpretation and enactment.

In information systems research, sociotechnical systems theory has been expanded by ideas that emphasize how closely technology and everyday work are linked. Orlikowski (2000, 2007) describes the use of technology as an essential part of how organizations are structured. Leonardi (2011, 2012) shows that while technological features can both enable and limit certain actions, it doesn't take away from human agency. These perspectives build on sociotechnical thinking, because they emphasize that technology and social practices shape each other, and they are not independent from each other.

In short, sociotechnical systems theory sees work systems as constantly changing environments where roles, expertise, and responsibility emerge through the way social and technical elements interact (Trist & Bamforth, 1951; Orlikowski, 2007). According to this theory, technological capabilities do not directly determine outcomes. Instead, they reshape how professionals enact their roles, use their expertise, and take on responsibility as work systems keep evolving (Leonardi, 2011; Rai, Constantinides, & Sarker, 2019). This is especially useful for understanding how work changes in AI-enabled work environments.

2.2.2. Core Concepts of Sociotechnical Systems Theory

Sociotechnical systems theory has a set of core concepts that help explain how people and technology work together (Trist & Bamforth, 1951; Orlikowski, 2007). Instead of treating technologies, roles or organizational structures as separate elements, the theory focuses on how they are all connected and always changing. It emphasizes how roles emerge through real-life actions and relationships (Orlikowski, 2000; Leonardi, 2011). These concepts are especially useful for analyzing how professional roles evolve in technology-intensive environments, because they show how roles, expertise, and responsibility are constantly shaped by ongoing interaction with technological systems (Barley, 1986; Orlikowski, 2007).

Table 1 summarizes the key concepts from sociotechnical and related organizational literature that guide the analytical framework of this thesis.

Table 1. Core Concepts of Sociotechnical Systems Theory

Concept	Definition	Reference
Sociotechnical system	A work system composed of interdependent social and technical elements whose	Trist & Bamforth (1951); Trist (1981)

	interaction jointly produces outcomes	
Joint optimization	The principle that effective work systems require alignment between social organization and technical arrangements	Trist & Bamforth (1951); Cummings (1978)
Agency	The capacity to influence action, understood as emerging through interaction between humans and technologies rather than residing solely in either	Orlikowski (2007); Leonardi (2011)
Sociomateriality	The inseparability of social practices and material artefacts in the enactment of work	Orlikowski (2007); Cecez-Kecmanovic et al. (2014)
Distributed cognition	A view of cognition as extending across people, artefacts, and organizational arrangements rather than residing solely in individuals	Hutchins (1995); Faraj et al. (2018)
Role enactment	The idea that professional roles are continuously produced and reproduced through practice rather than fixed by formal structures	Barley (1986); Barley & Tolbert (1997)
Emergence	The notion that work outcomes and role configurations arise	Orlikowski (2000); Leonardi (2011)

	unpredictably through ongoing interaction within sociotechnical systems	

These concepts are based on sociotechnical systems theory. They emphasize that professional work can not be understood by examining only technology or social structures on their own (Trist & Bamforth, 1951; Orlikowski, 2000). Instead, roles, expertise and responsibility develop as people interact with technical systems in specific organizational contexts (Leonardi, 2011; Barley & Tolbert, 1997).

These concepts also provide the conceptual link to the analytical focus of this study. Specifically, role enactment explains how professional roles are always being shaped by what they do in real-life situations (Orlikowski, 2007; Barley & Tolbert, 1997). Distributed cognition explains how expertise is more and more being shared between humans and technological systems (Hutchins, 1995; Faraj, Pachidi, & Sayegh, 2018). Agency and emergence help explain how responsibility is negotiated in situations where outcomes are produced together (Leonardi, 2011; Rai, Constantinides, & Sarker, 2019).

Together, these concepts give us the theoretical vocabulary we need for the analysis of this study. The analysis explores how professionals involved in the deployment and organizational integration of AI systems redefine their roles in AI-enabled work environments.

2.2.3. Empirical Applications of Sociotechnical Systems Theory in Studies of Work and Roles

Researchers have often used sociotechnical systems theory to study how new technologies actually change the way people work, their professional roles, and how organizations are set up (Trist & Bamforth, 1951; Barley, 1986; Orlikowski, 2000). Sociotechnical studies focus on how roles and responsibilities develop through situational interactions between human actors and technical systems. In these studies, it is not assumed that technology development creates similar outcomes (Orlikowski, 2000, 2007; Leonardi, 2011). This collection of research offers important insights into how professional work is affected byt the introduction of new technology into complex organizational contexts.

Sociotechnical thinking was earlier mainly empirically applied on industrial and technical work systems. It illustrates how technological changes usually had unexpected effects on authority relations, coordination systems, and role structures (Trist & Bamforth, 1951). These studies produced important insights that have continued to be essential for later research. Technological advancement changes work by redistributing tasks, responsibilities, and sources of expertise across sociotechnical systems, not by replacing roles.

This perspective has been expanded by more studies to knowledge-intensive and professional fields. In these studies, the implications for roles and competence are more noticeable (Barley, 1986; Orlikowski, 2000). Barley's (1986) research of CT scanners in radiology departments showed how new technology can change professional roles by altering access to information and interpretive authority. Barley supported the sociotechnical claim that role change is enacted rather than determined, by demonstrating how these technologies may result in different role configurations based on how professionals modify what they do.

Additional research saw roles as ongoing achievements that come from the repeated interaction between organizational expectations and contextual behavior (Barley & Tolbert, 1997; Ashforth, Kreiner, & Fugate, 2000). According to this perspective, technologies change roles by changing the conditions where actors negotiate responsibilities, boundaries, and authority. Studies that use this perspective show that when technology is evolving and there are not clear instructions from their organizations, professionals have to often figure things out as they go. It leads them to participate in boundary work, coordination, and interpretation of new situations (Bechky, 2003; Ashforth et al., 2000).

The concept of sociomateriality highlights that social practices and technological innovations are inseparable in the enactment of work. This has further developed sociotechnical perspectives in the information systems literature (Orlikowski, 2000, 2007; Cecez-Kecmanovic et al., 2014). Related research shows how technological features both provide and restrict activity, while still requiring human initiative and interpretation (Leonardi, 2011, 2012). These studies show that technological effects on work and roles are not due to the technology itself, but they result from ongoing interaction in practice.

More recent empirical research has expanded sociotechnical perspectives in order to examine distributed cognition and coordination in technology-intensive work systems. This research highlights how the enactment of expertise and responsibility is being reshaped, because analytical and interpretive tasks are increasingly being shared across people, artefacts, and organizational routines (Hutchins, 1995; Faraj et al., 2018). From this perspective, professional expertise comes from an individual's ability to successfully collaborate with other actors and technology systems.

Studies that apply sociotechnical systems theory consistently show that technological change reshapes professional work by reconfigurating roles, expertise, and responsibility (Barley, 1986; Orlikowski, 2000; Rai, Constantinides, & Sarker, 2019). Technologies do not produce the same outcomes, but they change how tasks are distributed, how authority is exercised, and how accountability is enacted in practice. These insights provide a strong empirical foundation for using sociotechnical systems theory as the analytical lens of this study.

2.3. Synthesis: A Sociotechnical Framework for Analyzing Professional Role Evolution in AI-Enabled Work

This section develops a conceptual framework for understanding how professional roles evolve in AI-enabled work environments. This is done by bringing together the two literature streams that were discussed above. The first stream focused on earlier studies about how AI is reshaping professional work, including changes in expertise, collaboration styles and what's expected of different roles. The second stream introduced sociotechnical systems theory as a theoretical lens, which helps explain how social and technical elements interact to create work and roles (Orlikowski, 2007; Leonardi, 2011).

The framework that is created in this chapter looks at how professional roles change over time. It does not view role change as something that happens automatically when technological change is introduced, but as a process that happens through ongoing interactions. It focuses on how professional roles are shaped through the interaction between technological capabilities, work practices, expertise, and responsibility in organizational contexts (Barley, 1986; Orlikowski, 2007). By focusing on these real-world interactions, the framework highlights that role changes do not just happen by adopting new tools, but they are enacted and negotiated in practice.

The framework uses a sociotechnical perspective that emphasizes enactment, interpretation, and emergence. It does not view AI as something that automatically changes professional roles. Instead, it sees professional roles as something that is always being created and adjusted as professionals interact with AI systems in their everyday work. This way of thinking fits with earlier sociotechnical research, which shows that technologies change work differently and depending on how professionals use it in real situations (Barley, 1986; Orlikowski, 2007; Leonardi, 2011).

Building on this perspective, the framework breaks things down into four connected analytical dimensions: technological enactment, role enactment, expertise reconfiguration, and responsibility negotiation. These dimensions all influence each other and they keep evolving through ongoing interaction. For example, when the way technology is used changes, it can shift how professionals perform their roles, how they use their expertise and how responsibility is seen. At the same time, changes in expertise and responsibility can also affect how roles and technologies are enacted in practice.

This framework shows that the way professional roles change in AI-enabled work environments is an ongoing and evolving process. It views the four dimensions as all connected to each other, rather than linearly structured. This gives us a clear yet adaptable framework to look at how professionals involved in the deployment and organizational integration of AI systems interpret and redefine their roles in changing sociotechnical environments.

This study centers on three key dimensions: role, expertise, and responsibility. These dimensions help explain how work is performed (role), how value is created and assessed (expertise), and how accountability is handled in environments where AI plays a part in the process (responsibility). They are especially relevant for professionals involved in the deployment and organizational integration of AI systems, since their work focuses on turning technological capabilities into real-world practices. Unlike typical users of AI, these professionals are deeply involved in the implementation, integration, and governance of AI technologies in organizational processes. This means that they perform and coordinate tasks (role), evaluate and use knowledge on AI-generated outputs (expertise), and navigate accountability in situations where algorithmic systems play a role in decision-making (responsibility).

2.3.1. Purpose of the Framework

The purpose of this conceptual framework is to provide a way to analyze how professionals involved in the deployment and organizational integration of AI systems interpret, negotiate, and enact their changing roles in organizational contexts. It is designed to support qualitative research by highlighting the main areas through which the evolution of professional roles can be studied in practice.

The framework focuses on how the interplay between technology, expertise, and responsibility leads to shifts in professional roles in AI-enabled work. It guides the analysis of how professionals interpret AI systems, integrate them into their work, and adapt their roles as tasks and organizational expectations change.

Specifically, the framework makes it possible to analyze:

- how professionals enact and integrate AI into their everyday work practices
- the transition of work processes from direct execution to AI-supported task coordination
- how expertise is used by evaluating, interpreting, and guiding AI outputs
- how responsibility and authority are negotiated when humans and AI work together to generate results

The framework helps make sense of empirical data because it focuses on how these interconnected dimensions influence each other. At the same time, it remains flexible and sensitive to the specific context and evolving dynamics of each situation. This way, the framework supports the main goal of the study: to explain how professional roles are redefined through ongoing interaction with AI systems in sociotechnical work environments.

2.3.2. Core Analytical Dimensions

The framework is grounded in sociotechnical systems theory and the research on professional work. It sees that changes in professional roles are shaped by four dimensions that are closely connected and influence each other. Every dimension highlights a different, but related, aspect of how professionals interact with AI systems, and how their roles are enacted, perceived, and redefined in everyday practice.

"Technological enactment" describes how professionals actually use AI systems in their daily work. This dimension does not focus only on technical features. It includes how professionals interpret what AI can do, set up and adjust the systems, and integrate them into their regular routines. It also covers how they judge the outputs that AI provides, decide when to trust or ignore AI recommendations, and change their work habits in response to how the system behaves (Orlikowski, 2007; Leonardi, 2011).

The way technology is put in to use, so technological enactment, shapes the environment where professional perform their roles. As AI systems become a part of everyday work, they start to influence how tasks are organized, how work is coordinated, and how decisions get made. This means that there is a direct connection between how technology is used and how roles are enacted: the choices professionals make about integrating AI have a real impact on the way their roles evolve.

Role enactment refers to how professionals actually perform and reinterpret their roles as AI becomes a part of their work routines. From a sociotechnical perspective, roles are not just fixed positions. They are continually developed and redefined through practice (Barley & Tolbert, 1997). This dimension looks at how responsibilities might grow, shrink, or shift over time. It also considers how the lines between technical and non-technical work can change, and how professionals interact with others in their organizations. In other words, changes in how technology is enacted are closely linked to how professional roles are enacted in practice.

"Expertise reconfiguration" refers to how the definition and base of professional expertise change in AI-enabled environments. As AI takes on more analytical and predictive tasks, expertise becomes something that is shared between technology and human professionals (Faraj et al., 2018). This dimension looks at how professionals rethink what counts as valuable knowledge (Faraj et al., 2018; Bechky, 2003), how they explain the value they bring alongside AI systems, and how they maintain their professional legitimacy even when some of their main responsibilities become partly automated. Changes in role enactment are closely connected to shifts in how expertise is applied and recognized.

In sociotechnical systems, responsibility negotiation is about figuring out who is accountable and who has authority when working with AI. Professionals often have to work out who is responsible for certain outcomes, and how to handle mistakes or ethical concerns when AI plays a role in making decisions (Jarrahi, 2018). This dimension looks at how professionals make sense of their responsibilities when it comes to AI-generated outputs, and how they deal with the challenges that come from balancing organizational expectations and the limitations of technology (Jarrahi, 2018; Elish, 2019). Changes in expertise and role enactment have a direct impact on how responsibility is understood and enacted.

These four dimensions are all closely connected and they influence each other. The way technology is used shapes how roles are performed, which in turn affects how expertise is applied and how responsibility is negotiated. At the same time, professionals' changing views about what counts as expertise and who is responsible also shape how they interact with AI and enact their roles. This constant interaction highlights the sociotechnical perspective that professional roles evolve through ongoing interaction rather than following a predictable path.

2.3.3. The Conceptual Model

Figure 1 presents the conceptual framework that is developed in this study. The framework sees the evolution of professional roles as something that emerges overtime from the ongoing interaction between social and technical elements in AI-enabled work systems. In this view, AI systems are treated as technical elements that become part of everyday work practices. The organizational environment includes institutional norms, expectations, and governance structures. These structures influence how roles take shape, but they do not strictly determine them.

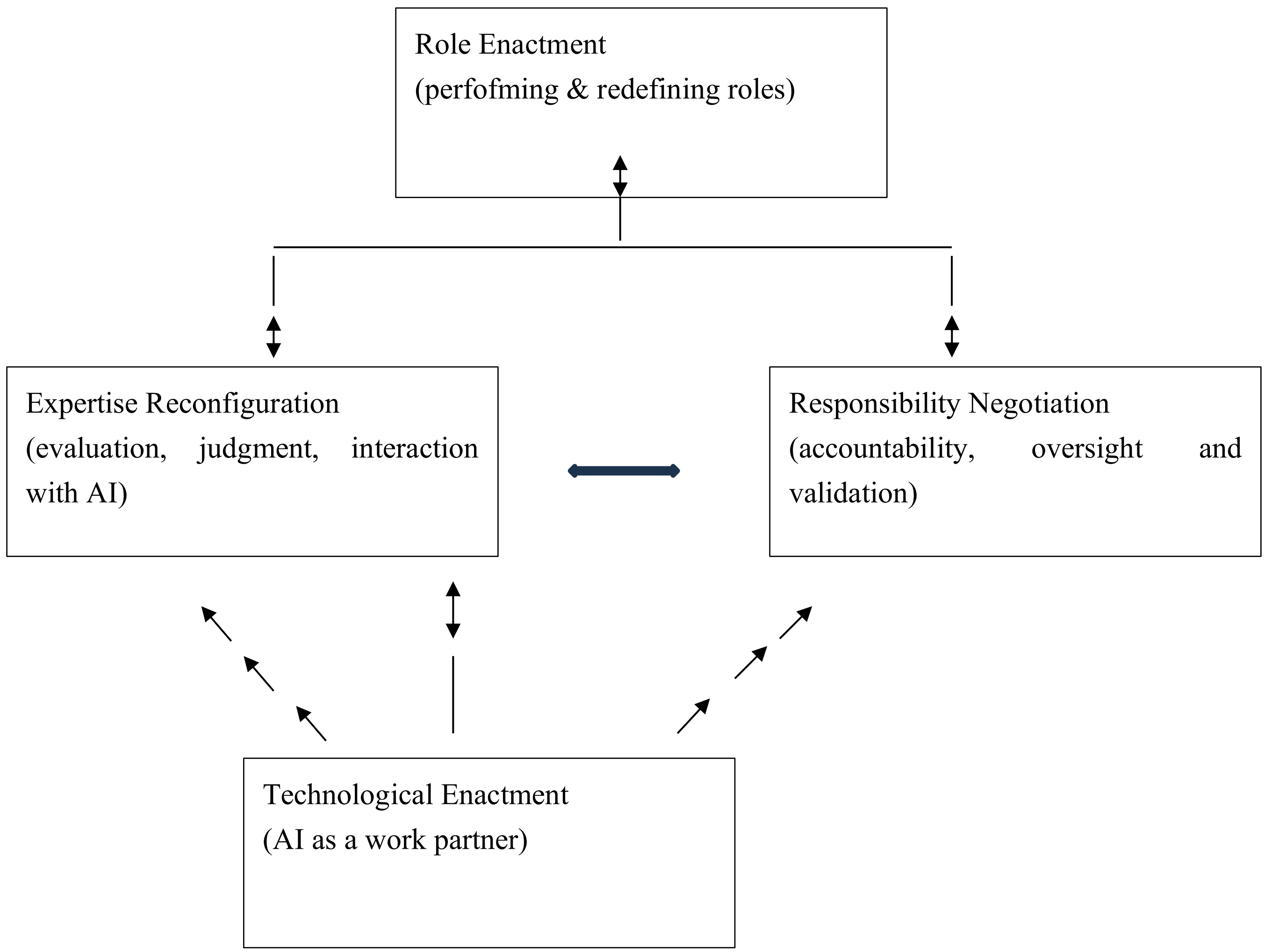

Figure 1. Conceptual framework of AI-enabled professional work

At the core of the framework are four key sociotechnical processes: technological enactment, role enactment, expertise reconfiguration, and responsibility negotiation. These processes represent how professionals make sense of and bring AI systems into their work, carry out and reshape their roles, rethink what expertise means, and work out questions of accountability and authority. All of these dimensions interact to shape how professional roles evolve. Role evolution is seen as a dynamic process, where professionals continually redefine how their roles are enacted, how they use their expertise, and how they understand responsibility as things change over time.

The framework sees the evolution of professional roles as a dynamic, ongoing process rather than a straightforward outcome. Changes in roles are understood as something that emerges from the way professionals actually use and work with AI systems in specific organizational contexts. This means that role changes do not happen as a direct result of technology capabilities alone. This approach is consistent with sociotechnical research, which shows that technologies reshape work through everyday actions and experiences, not through automatic or predetermined effects (Barley, 1986; Orlikowski, 2007; Leonardi, 2011).

The conceptual model includes a feedback loop to show that the relationship between professional roles and AI is ongoing and mutually influential. As professionals' responsibilities shift and their understanding of expertise are changing, it influences how they approach and use AI technologies in the future. This cyclical process highlights how technology and professional roles develop together over time, and they each influence the other in a continuous and co-evolving way.

The framework brings together AI as the empirical context and sociotechnical systems theory as the analytical lens. By doing so, it provides a clear structure for examining how professional roles evolve in AI-enabled work environments. Importantly, the model does not assume that there is only one way for roles to evolve. Instead, it recognizes that different patterns of change can emerge, and it depends on how professionals work with new technologies, respond to organizational demands, and navigate their roles and responsibilities in practice (Barley, 1986; Orlikowski, 2007).

3. METHODOLOGY

This chapter explains the methodological choices that support the study and how the research was designed and conducted. It describes the research strategy and design, the case selection process, data collection methods, data analysis procedures, and ethical considerations. These sections demonstrate the methodological rigor of the study and provide transparency on how the empirical material was created and analyzed.

3.1. Research strategy and research design

This section presents the research strategy and design that are used in this study. It explains the philosophical and methodological foundations that guide the research approach, and it justifies the choice of a qualitative multiple-case study design for examining professional role evolution in AI-enabled work contexts.

3.1.1. Research Approach

This study adopts a qualitative research approach in order to examine how professionals involved in the deployment and organizational use of AI systems redefine their roles as AI becomes embedded in everyday work. Qualitative research is especially suitable for this study, because the aim is to understand meanings, experiences, and sensemaking processes, not to test predefined hypotheses (Creswell & Poth, 2018). A qualitative approach allows in-depth interaction with participants' perspectives, as professional role evolution involves subjective interpretations of role, expertise, and responsibility.

The study is based on an interpretive research framework, which assumes that human interaction and interpretation shape social reality. From this perspective, professional roles are not fixed or objectively given. Instead, they are continuously enacted through practice and through interaction in specific organizational contexts (Orlikowski, 2000; Walsham, 1995). This epistemological perspective aligns closely with sociotechnical systems theory. It views that work outcomes are emergent from the interaction between social and technical elements, not as deterministic effects of technology.

3.1.2. Research Design: Qualitative Multiple-Case Study

The study uses a qualitative multiple-case study design to examine the evolution of professional roles in AI-enabled work environments. Case study research is relevant when the research goal is to examine modern phenomena in their real-life context, and when the boundaries between the phenomenon and its context are not clearly defined (Yin, 2018). A case-based approach is especially suitable in this study, because professional role evolution can not be properly separated from the organizational and technological contexts where AI is deployed.

A multiple-case design is chosen in order to allow analytical comparison across different organizational contexts, and to improve the reliability of the findings. Studying multiple cases makes it possible for the researcher to find common patterns and context-specific differences in how professionals interpret and enact their roles (Eisenhardt, 1989). This study does not aim for statistical generalization. It aims for analytical generalization by developing theoretically formed insights that build on the already existing sociotechnical understandings of work and roles (Yin, 2018).

The cases are chosen using theoretical sampling logic. This means that cases are chosen because of their relevance to the research question, not for the purpose of representativeness (Eisenhardt, 1989). All of the chosen organizations are actively engaged in the deployment of AI systems. This ensures that participants have direct experience of working in AI-intensive environments. This design allows a detailed analysis of how professional roles evolve in different organizational settings, and still remains grounded in a common empirical phenomenon.

3.1.3. Alignment with the Conceptual Framework

The sociotechnical conceptual framework that was created in section 2.3 informs the research design. The framework identifies technological enactment, role enactment, expertise reconfiguration, and responsibility negotiation as key analytical dimensions for examining professional role evolution. The multiple-case design allows these dimensions to be explored in different organizational contexts. This makes it possible for the study to capture how sociotechnical interactions actually take place.

This study combines an interpretive qualitative approach with a multiple-case design. This combination makes it well-suited to explore how professional roles change in ongoing and cyclical ways. By using these methods, the study is able to provide a rich, theory-driven and evidence-based explanation of how professionals involved in the deployment and organizational integration of AI systems redefine their roles in changing sociotechnical work environments.

3.2. Case selection and research content

This section presents the empirical context of this study and explains why the particular cases were selected. It explains how the case organizations were selected, gives an overview of each case, and introduces the interview participants. The cases were chosen for their theoretical relevance rather than statistical representativeness. It allows for a deep examination of how professional roles evolve in AI-enabled work contexts.

3.2.1. Case Selection Criteria

The study uses theoretical sampling to choose cases that are especially suitable for addressing the research question (Eisenhardt, 1989). The cases were chosen because they are highly relevant to the topic that is being studied, not for the purpose of representativeness. The organizations that were selected meet three criteria.

All organizations are actively engaged in the deployment of artificial intelligence systems in organizational or client-facing contexts. In other words, AI is not just a technology they are testing out, but it is an important part of everyday work. These organizations employ professionals who are directly responsible for deploying AI systems in organizational or client-facing contexts. These individuals work at the crossroads of technical systems and organizational decision-making, which makes their experiences especially relevant for studying how roles change. The cases are different in terms of organizational focus and their level of experience with AI, which allows for comparison in different AI adoption contexts.

Using a multiple-case design makes it possible to compare how different organizations approach the same challenges, while still being based on a shared empirical setting. The study looks for patterns in how professionals understand and enact their roles in environments where AI plays a major part.The study aims to identify recurring themes in professional role evolution by examining the similarities and differences between cases (Yin, 2018).

3.2.2. Overview of Case Organizations

The empirical material for this study comes from four organizations that work in the field of artificial intelligence. Each of these organizations is actively involved in the deployment of AI systems in organizational or client-facing contexts. This means that AI is a regular part of everyday work practices, and not something that is limited to experimental development. These organizations were selected because they represent environments where AI is a central focus, and where professional roles are likely to evolve as a result.

Table 2. Overview of Case Organizations and AI Deployment Context

Company Alias	Organizational Focus	Approx. Size	AI Deployment Context	Nature of Deployment
Company1	AI consulting services	Small-medium	Client-facing AI solutions	Deployment and integration in client organizations
Company2	AI and data solutions	Small-medium	Organizational AI Systems	Deployment of AI models into operational use
Company3	AI-based software products	Small	Productized AI Systems	Deployment of AI-enabled products
Company4	Applied AI startup	Small	Organizational AI Applications	Deployment and adaptation of AI solutions

Note: Organizational size is reported in approximate terms due to limited availability of public data.

These organizations offer a rich empirical context for examining how professionals actually work with AI technologies in their daily work. Even though the organizations are different in focus and structure, each case involves ongoing interaction between human expertise and AI systems. This makes them well-suited for comparing and analyzing different approaches to professional role evolution.

3.2.3. Overview of Interviewees

The interview participants were selected because they are directly involved in the deployment and organizational use of AI systems. The participants have different formal roles, like AI Lead, AI Engineer, CEO, COO, and Co-founder. Despite their different job titles, all of them play an active part in how AI systems are introduced, adapted, and used in organizational contexts.

Table 3. Overview of Interviewees

Interview Code	Company Alias	Role	Experience with AI Deployment	Interview duration
I1	Company1	AI Lead	Client AI Deployment	29 minutes
I2	Company1	AI Engineer	Client AI Deployment	25 minutes
I3	Company2	CEO	AI System Deployment	18 minutes
I4	Company3	COO	AI-enabled product Deployment	17 minutes
I5	Company4	Co-founder	Applied AI Deployment	24 minutes

This variety in roles was seen as an important strength for the analysis. The deployment of AI systems in AI-intensive environments is not just about handling the technical implementation. It includes many different activities that are needed to integrate AI into everyday work practices. That is why the interviewees were selected to represent different, but complementary, perspectives on how AI becomes part of an organization.

Participants in technical roles shared their experiences with designing, implementing, and validating AI-supported systems. Meanwhile, participants in leadership and founder roles provided perspectives into how AI fits into broader organizational processes, decision-making, and client-facing work. By including both viewpoints, the study was able to explore how professional roles change across the many different ways that AI is introduced and used in organizations.

3.2.4. Case Relevance for the Research Question

The interviewees selected for this study are a strong fit for the research question, which looks at how professionals who deploy AI systems redefine their roles as AI becomes integrated into everyday work. In this study, deployment is understood boradly, not just as technical implementation, but as the entire process of bringing AI systems into organizational contexts. This includes the practical work of integrating AI into workflows, interpreting its outputs and shaping how it is used in decision-making and everyday tasks. By taking this broader view, the study is able to include both technical and managerial perspectives, since people in senior roles often play a key part in deciding how AI is put into practice and used within their organizations.

From this perspective, what matters about the interviewees isn’t just whether they are directly involved in building AI systems. Their value comes from their active role in how AI systems are actually put to use in organizations. The selected interviewees handle tasks like setting up AI-supported solutions, evaluating their outputs, translating technical capabilities into practical application, and helping to integrate AI into everyday work processes.

This approach fits well with the sociotechnical perspective that guides this study. It emphasizes that real technological change occurs through the ongoing interaction between technical systems and the social and organizational practices they are part of. Because the interviewees are deeply involved in these interactions, they are especially well positioned to shed light on the research question.

3.3. Data collection

This section outlines the methods used to collect data for the study. The primary source of data comes from semi-structured interviews with professionals involved in the deployment and organizational integration of AI systems. To add context and support the interpretation of these findings, secondary data sources were also used.

3.3.1. Primary Data: Semi-Structured Interviews

The primary data for this study were collected through semi-structured interviews with professionals involved in the deployment and organizational use of AI systems. Semi-structured interviews are well suited for qualitative research because it encourages participants to share their experiences, interpretations, and thought processes, while still giving the interviewer room to explore new topics as they come up (Kvale & Brinkmann, 2015). This method is particularly well-suited for examining how professional roles change over time, as it lets participants talk in their own words about shifts in their responsibilities, expertise, and interactions with AI systems.

The sociotechnical conceptual framework created in section 2.3 formed the foundation for the interview guide. The guide was organized around four broad themes: (1) participants' role and responsibilities in deploying AI, (2) their everyday interaction with AI systems, (3) changes they noticed in expertise and accountability, and (4) how they interpret and adapt their roles over time. While these themes gave the interviews some structure, the conversations remained flexible so that participants could discuss topics they felt were especially important.

All interviews were conducted remotely and each lasted about 30 minutes. With participants' consent, the interviews were audio-recorded and then transcribed word-for-word for analysis. To protect the interviewees' privacy, their names have been anonymized and they are referred to by interview codes (for example, I1–I5) throughout the thesis.

3.3.2. Secondary Data Sources

Secondary data was collected to help interpret the interview findings and to give context about the case organizations. Most of this information came from publicly available sources, such as company websites, service descriptions, blog posts, press releases, and other online materials that describe the organizations' AI activities, offerings, and areas of focus.

The purpose of these materials was to help the researcher gain a clear understanding of each organization's business focus, AI deployment context, and public positioning before and during the interview analysis. The purpose is not for them to serve as a primary source of analysis. So, the secondary data made it easier to become familiar with the empirical setting. It also allowed a more informed interpretation of interviewees' experiences.

In some situations, the secondary data were also used to contextualize specific things said in interviews (Yin, 2018). For example, it helped to contextualize statements about organizations' AI-related products, services, or deployment environments. However, the study's analytical focus remained on the interview material. The secondary data served more as a contextual support, not as an empirical dataset on its own.

3.4. Data analysis

The empirical data were analyzed using an iterative qualitative analysis approach. This approach combines inductive coding with theoretically informed interpretation. The analysis was inspired by the Gioia methodology (Gioia et al., 2013), but it still stayed sensitive to the study's sociotechnical systems (STS) perspective.

The analysis started with a careful reading of the interview transcripts to become thoroughly familiar with the data. During this stage, the focus was on how participants described their daily work with AI, how their roles were changing, and their views on responsibility and expertise. The initial coding aimed to capture these stories using language that closely matched how the participants themselves spoke. This approach led to a set of first-order concepts that reflected how interviewees themselves interpreted their experiences. For example, participants described AI as a "tool," a "sparring partner," or an "assistant," and they highlighted things like increased speed, the importance of critical evaluation, and how AI was becoming part of their everyday routines.

After identifying these first-order concepts, the next step was to compare and group them into more abstract, second-order themes. This phase involved moving beyond simply describing what was said, and began to focus on finding patterns in how participants thought about their roles and their interactions with AI. This process revealed recurrent themes in the data, like the growing importance of evaluation and judgment in expert work, the shift from task execution to coordination of AI-supported processes, and the importance of human responsibility even with the growing use of AI systems. Themes were redefined and adjusted throughout the analysis by consistent movement between the empirical material and the emerging interpretations.

Then, the four dimensions of the study's analytical framework—technological enactment, role enactment, expertise reconfiguration, and responsibility negotiation—were used to explain the themes that were found. This framework was used as a focusing lens to help support the interpretation of how human roles and technological capabilities are co-constructed in practice. So, the framework was not used in a strict deductive manner. This made it possible for the analysis to be grounded in the empirical data, and also connect the findings to a more broad theoretical discussion.

The study does not use a formal cross-case analysis design. Still, the analysis involved systematic comparison between participants to find recurring patterns and variations in how AI is experienced in different roles and contexts. This comparative aspect made it possible to support the development of strong themes, and still preserved the variety of perspectives found in the data.

The coding process was carried out repeatedly to improve analytical rigor. This means there were multiple returns to the data to ensure that interpretations stayed rooted in the empirical material. Emerging themes were regularly compared against the data to ensure consistency and prevent over-interpretation of participant comments. Attention was paid to maintain participants' meanings while developing analytical significance.

Figure 2 presents the resulting data structure, which illustrates the progression from first-order concepts to second-order themes and aggregate dimensions.

Table 4. Data structure

1st Order Concepts	**2nd Order Themes**	**Aggregate Dimensions**
"AI gives suggestions, but I decide what to use"	AI as a supportive tool	**Technological enactment**
"It helps generate ideas faster"	AI as a generative collaborator	
"Sometimes it feels like working with a partner"	Human–AI interaction in work processes	
"You still guide what it produces"		
"My work is faster now"	Shift in day-to-day work practices	**Role enactment**
"I don't do everything manually anymore"	Increased autonomy and speed	
"You manage the process more than execute everything"	Coordination of AI-supported work	
"It changes how I approach tasks"		

"You need to know if the output is actually good"	Evaluation over execution	**Expertise reconfiguration**
"Anyone can generate content, but not everyone can evaluate it"	Judgment and critical thinking	
"Experience matters more in judging results"	Knowing what 'good' looks like	
"It's about understanding quality, not just producing"		
"At the end of the day, I am responsible"	Human accountability	**Responsibility negotiation**
"You can't blame the AI"	Validation of AI outputs	
"You need to check everything it produces"	Distributed but human-centered responsibility	
"Responsibility doesn't disappear, it changes"		

3.5. Ethical Considerations

Ethical considerations were carefully addressed throughout the research process, like university guidelines and already established qualitative research ethics. Participation in the study was voluntary. All the interviewees were informed about the purpose of the research, the use of the data, and their right to withdraw at any time.

All interviewees were anonymized in the thesis, and any identifying information was removed from transcripts and reporting to protect participant confidentiality. Interview data was securely stored and used only for academic research purposes. There were no major ethical risks expected because the interviews were professional in nature and focused on work practices, not private information.

The study follows established guidelines for responsible qualitative research. This means that participants' perspectives are represented respectfully, informed consent was obtained, and confidentiality is maintained in the whole research process (Kvale & Brinkmann, 2015).

4. FINDINGS

4.1. Technological Enactment: AI as a Reconfigured Work Partner

The data shows that AI is seen as an active and integral part of daily work, rather than just a static tool. In every case, participants described interacting with AI on a regular basis, often in ways that blur the line between simply using a tool and actually collaborating with it. This is especially important for professionals who are involved in the deployment and organizational integration of AI systems, because their roles involve not only using AI themselves, but also actively shaping how it gets integrated in everyday work processes.

Participants in both Company 1 and Company 2 emphasized how deeply AI is embedded in their daily workflows. One interviewee said that “it’s such an integrated part of my daily work… it’s basically there all the time” (I1). Another participant from Company 2 highlighted just how common AI has become, saying that "it's used even more than email" (I3). These comments highlight that, for many professionals, AI is starting to function more like a basic part of the work infrastructure, rather than something separate or optional. This indicates that professionals are working in environments shaped by AI, rather than using AI as an external tool. This also reflects the position of these professionals who are using AI, but also integrating it into everyday workflows.

However, the way all participants talked about interacting with AI resembled collaboration. In Company 1 a participant described AI as “a kind of sparring partner… a first critical eye” (I1). This means that AI is used to support idea generation and early-stage evaluation. From this perspective, AI is also used to co-develop ideas and explore alternative solutions in addition to executing tasks. Additionally, participants talked about interacting with AI systems iteratively and improving outputs through back-and-forth interaction. This implies that AI interaction is not a one direction input-output use, but it is an ongoing process. This means that the way tasks are approached and completed are changing.

Even though participants described using AI in a collaborative way, they still made a clear distinction between AI-generated outputs and final work products. In all interviews, AI was mostly used to generate drafts, structures, or preliminary analyses. These drafts were then developed more and validated by the human user. For example, one participant explained that "AI produces the content, but the final work is done by a human who ensures the quality" (I4). This shows that human judgement plays an important part in refining and validating AI-generated outputs. Even when AI generates the first output, the final outcome still depends on human evaluation and decision-making.

One recurring theme that came up in all the companies was that AI was especially useful in tasks that involve repetition, scale, or rapid iteration. One participant from Company 2 talked about how they assign repetitive analytical tasks, like processing lists or analyzing large sets of keywords, to AI systems, but they still keep a close eye on the results. This approach shows a clear divide in labor. AI is relied on for handling tasks that require speed and the ability to work at scale, while humans focus on interpreting the results and making decisions. As a result, the way work is organized shifts. AI takes on the heavy lifting, and humans remain responsible for giving meaning and direction.

Participants also pointed out that AI has its limitations. For example, if its outputs are used without careful review, they can sometimes turn out generic or low in quality. In Company 3, this was described as a situation where "the content can become a bit messy or unclear" (I4) if there is not sufficient human refinement. Because of these limitations, working with AI involves ongoing monitoring and adjustment. It's not just about handing tasks over to the system. It's an active process that requires human involvement.

In all the cases, AI is seen as a kind of hybrid work partner that combines the aspects of a collaborator and a tool. It helps generate ideas, content, and analysis, but it still depends on humans for direction and quality control. With this reconfiguration, AI becomes an active but still controlled participant in professional work, rather than serving as a passive tool.

4.2. Role Enactment: Stability and Transformation of Professional Roles

The findings highlight how complex the changes to professional roles are in organizations that are adopting AI. Rather than showing a uniform shift in roles, the data suggests that while the official definitions of roles stay mostly the same, the way the work gets done is changing quite a bit. The main focus is on role enactment, but these changes are closely linked to shifts in expertise and responsibility. This is elaborated on more in the following sections.

All participants emphasized that the core purpose of their roles have not really changed. For example, interviewees from Company 1 said their main responsibilities, such as designing and implementing solutions, have stayed the same. What's different now are the tools and processes they use to accomplish these tasks. As one participant explained, "the core of what I do hasn't really changed, it's just how I do it now" (I1). Also the interviewees in leadership positions in Company 2, Company 3 and Company 4 said that the structure of their roles has remained largely unchanged. Especially when it comes to decision-making authority and overall accountability. What has changed, however, is that tasks that used to require coordination with others can now often be handled more independently thanks to AI. This changes how roles are enacted on a daily basis.

Even though participants felt their formal roles were stable, they all described significant changes in how they actually do their work. One major shift is that professionals can now complete more tasks on their own. An interviewee in Company 4 noted that "I don't necessarily need to ask other people for help anymore. I can give tasks to AI instead" (I5). This highlights how AI is enabling greater individual autonomy, especially for those involved in deploying AI. Their jobs now involve not just using AI tools, but also organizing and overseeing how AI-driven work happens.

Another change participants pointed out is how important it is to coordinate and guide work that involves AI. All professionals described moving away from doing tasks directly themselves, towards overseeing processes where AI generates intermediate outputs. This often means starting tasks, checking the results AI produces, and deciding whether those results are good enough to use. As a participant from Company 3 put it, “AI produces the content, but the final work is done by a human who ensures the quality” (I4). In other words, the day-to-day focus of these roles is shifting from doing all the hands-on work to supervising and coordinating how the work gets done with AI’s help. The role itself hasn’t fundamentally changed, but the emphasis has moved from performing tasks to managing the overall process.

At the same time, new aspects of professional roles are emerging that go beyond traditional task boundaries. Participants from Company 3 and Company 4 talked about advising their colleagues or clients on how best to use AI and managing expectations about what AI can and cannot do. This involves explaining the possibilities and the limitations of AI systems, especially when there’s a mismatch between what people think AI can do and what is actually possible. One interviewee explained, “expertise means being able to explain what is realistic and what is not, and what kind of risks are involved” (I4). This points to a new aspect that is emerging in professional roles, where individuals have to act as translators between technological systems and organizational or client needs.

How participants experienced these role changes depended on their positions and professional context. Those in more technical roles described AI as being deeply embedded into their daily work, which has changed the way they approach and complete tasks. In contrast, participants in senior leadership positions said that while AI has increased the speed and efficiency of their work, it hasn’t really changed the core nature of their roles.These findings reveal that role transformation is not uniform. Instead, it is shaped by the specific responsibilities and position of the individual in the organization. Individuals involved in more hands-on work experience deeper changes than those operating at a more strategic level.

A key insight here is that AI does not fundamentally change professional roles when it comes to formal responsibilities. Instead, it transforms how these roles are enacted in practice, and introduces new forms of autonomy, coordination, and mediation. This results in a reconfiguration of professional work that is structurally subtle but significant when it comes to execution.

4.3. Expertise Reconfiguration

The findings in all cases reveal a significant reconfiguration of what defines expertise in AI-supported work. The importance of expertise is not reduced because of the integration of AI. Expertise shifts from task execution toward evaluation, interpretation, and judgment. These changes in expertise also influence how professionals perceive their roles and their value in organizational contexts. This links expertise reconfiguration to broader changes in how professional work is understood.

All participants said that AI is very effective at generating outputs such as text, code, or analytical suggestions. Even though it is effective at generating these outputs, participants emphasized that these outputs need continuous human oversight to ensure quality and relevance. As a result, expertise is not primarily associated with producing work from scratch anymore. It is now more closely linked to the ability to critically assess and refine AI-generated outputs. So the core of expertise moves away from production towards judgment. Knowing what to trust becomes more important than knowing how to create. A participant in Company 1 described this shift as moving away from “having the right answer” toward the ability to “quickly go through options and see what actually makes sense” (I1).

Critical thinking is becoming an increasingly important aspect of this reconfiguration. All participants said that they need to constantly question AI outputs, identify potential errors, and assess if relevant information may be missing. An interviewee in Company 2 emphasized that “you don’t outsource the output completely. You still need to know what good looks like and be able to tell what is hallucination and what isn’t” (I3). This adds a new layer of cognitive work that did not exist in the same way before AI was used. It means that expertise now involves continuously questioning outputs generated by AI systems, and not just producing or retrieving information.

In addition to this evaluation aspect, expertise now also involves the ability to effectively interact with AI systems. This includes for example creating the correct prompts, guiding the generation process, and repeatedly improving outputs through discussion. A participant in Company 1 explained that “generating ideas with AI is very cheap and fast, but it also produces a lot of low-quality output” (I1). This means that expertise involves the ability to navigate an abundance of information.

A common pattern in all companies is the importance of domain knowledge as a requirement for effective use of AI. Participants consistently emphasized that if you do not have a strong understanding of the subject matter, it is difficult to recognize errors or misleading outputs. An interviewee from Company 1 explained that “it requires a really deep understanding of the topic. If you don’t have that, the AI can go wrong and you might not even notice it” (I1). This highlights the important role of expertise in identifying potential issues in AI-generated outputs. Rather than replacing the need for domain knowledge, AI actually makes expertise even more important. Its presence enhances what AI can do, while its absence increases the risk of mistakes. When professionals have strong expertise, AI becomes a more valuable tool. But in areas where expertise is lacking, the risk of making a mistake increases significantly.

Several participants also noted a shift toward more abstract forms of expertise, like judgment and “knowing what good looks like.” Being able to judge the quality of AI outputs has become especially important in contexts like content creation or decision-making. One participant in Company 2 emphasized that “you need to know what good looks like yourself" (I3). This highlights that judgement is essential in evaluating AI-generated outputs. This type of expertise isn't so much about technical skills, but about assessing if the outcome meets broader goals and standards.

Being able to tell the difference between what AI can realistically do and what it can't was also seen as an important part of expertise. A participants from Company 3 talked about the need to judge what's possible with AI and to clearly communicate those limits to others. As one interviewee put it, "expertise means being able to explain what is realistic and what is not, and what kind of risks are involved" (I4). This kind of expertise involves understanding both the strengths and weaknesses of AI systems, and also being aware of the risks that come with using them.

This study shows that expertise in AI-supported work increasingly involves the ability to guide, evaluate, and contextualize AI outputs. AI does not reduce the need for expertise. Instead, it shifts the focus towards more complex cognitive capabilities. These capabilities include critical thinking, judgment, and the ability to operate effectively in environments defined by fast output production and uncertainty.

4.4. Responsibility Negotiation

The findings in all cases show that responsibility remains firmly with human actors, even with the integration of AI into professional work. Even though this idea is consistently shared, the way responsibility is understood and experienced becomes more complex in AI-supported contexts. These changes in expertise also influence how professionals view their roles and their value in organizational contexts. This reflects broader changes in how professional work is understood.

In all cases, participants emphasized that AI itself cannot be considered responsible for outcomes. Instead, responsibility remains with the individual or organization making the final decision. A participant in Company 2 emphasized that “humans are responsible, of course. AI isn’t really an entity that you could hold accountable or put in jail” (I3). The same perspective was shared in all roles, from technical experts to senior leaders. It shows a shared understanding that responsibility cannot be delegated to AI systems. Even when AI plays an active role in producing outcomes, accountability ultimately remains with human actors.

At the same time, bringing AI into the workflow introduces new types of responsibility, especially around how AI outputs are used and validated. All participants emphasized that they are responsible not just for their own decisions, but also for results that come from working with AI. This means they often have to take ownership of work they didn’t create entirely themselves, but that they have reviewed or approved. One interviewee explained, “in the end, the responsibility is on the person using the AI. You need to have enough understanding of the topic to apply source criticism and think about whether it’s actually correct” (I2). So, responsibility becomes more about validating and assessing outputs, rather than simply being the author. This shift is especially important for those responsible for deploying AI, because they remain ultimately accountable for how AI systems are used in practice.

Several participants described the need for greater vigilance and careful oversight when working with AI. All interviewees recognized that AI systems can generate information that sounds convincing but isn’t always correct. Because of this, users have to actively check and judge the reliability of AI outputs before using them. A participant in Company 3 put it this way: “we see all the time that the quality varies and that there is a lot of hallucination, so it doesn’t make sense to let AI make decisions at that level” (I4). This adds another layer of responsibility. Professionals have to make sure that AI-generated content is accurate and relevant before it is used. So, rather than reducing responsibility, using AI actually increases it.

Participants also pointed out the broader implications of using AI systems in organizations. It was frequently stated that no matter how advanced the systems become, responsibility ultimately stays with humans. The data shows that while the way AI systems are designed and implemented may shape how responsibility is enacted in practice, it does not replace individual accountability. Instead, it complicates how responsibility is understood in sociotechnical work systems.

Responsibility was also seen as being more situational and personal. Participants pointed out that, while organizations might provide general guidelines for using AI, it's ultimately up to each individual to decide how these tools are actually applied. One participant explained, "this is similar to cybersecurity. A company can provide guidelines, but in the end only you decide whether you click a link or not. The same applies to AI tools. You can't outsource that responsibility" (I4). This highlights how individual judgment and awareness remain central to managing the risks that come with using AI.

Even with these complexities, participants kept a clear boundary: AI supports decision-making but it does not make decisions. In all the cases, it was made clear that no matter how integrated AI becomes, responsibility still remains with human actors.

The findings show that responsibility in AI-supported work is not reduced, but it actually becomes more expanded and redistributed. Instead of removing accountability, AI changes the way it looks, as it requires ongoing human judgment for things like validation, oversight, and making sure the technology is used appropriately. While the nature of accountability shifts, it remains firmly with humans. This makes the concept of responsibility in sociotechnical work environments more dynamic and layered than before.

4.5. Synthesis of Findings

Taken together, the findings of this study show how integrating AI into professional work changes the way technology, roles, expertise, and responsibility all connect and interact.

Each of the four dimensions, technological enactment, role enactment, expertise reconfiguration, and responsibility negotiation, captures a different aspect of this transformation. While each dimension captures a different aspect, they are all closely linked and together they provide a clear picture of what it is like to work with AI.

When it comes to technological enactment, AI is not experienced as just a passive tool. Instead, it takes on an active role in daily work, and it helps with things like generating ideas, creating content, and performing analytical tasks. Even so, this involvement is always guided and controlled by human professionals. This means that AI becomes a kind of hybrid work partner that blends the aspects of both a tool and a collaborator. This shift in how technology is used sets the stage for other changes in the workplace to happen.

In terms of role enactment, the formal responsibilities that are tied to professional roles haven't been completely redefined. Instead, what's really changing is how these roles are carried out in daily work. The findings show that while the main goals of each role remain the same, the way people do their jobs is evolving. They have more independence, can get things done faster, and spend more time coordinating work that's AI has assisted. So, while the basic structure of roles is stable, the practical changes are significant.

In expertise reconfiguration, the changes happening in the workplace are closely linked to a shift in what counts as expertise. As AI is taking on a larger role in producing work, professional expertise is now less about creating outputs from scratch and more about evaluating, interpreting, and providing direction for what AI generates. Professionals have to sort through large amounts of AI-created material, judge its quality, and decide what's actually useful. This puts a stronger emphasis on higher-level cognitive skills like good judgment, critical thinking, and the ability to recognize what truly makes for high-quality results.

With responsibility negotiation, the ultimate responsibility still rests with humans, even as AI becomes a bigger part of daily work. . What changes is that responsibility becomes more complex and layered. Professionals aren't just responsible for their own decisions anymore, but they also have to review and sign off on what AI produces. At the same time, how responsibility is handled depends on how AI is actually used within the organization. This highlights that while accountability may be more widely distributed, it remains centered on human judgment within sociotechnical systems.

These findings show that AI does not replace human roles. Instead, it changes how those roles are put into practice in a sociotechnical environment. A recurring theme in all four dimensions is the emergence of a human-in-the-loop dynamic. In this setup, AI systems help generate ideas and support work, but humans are the ones who evaluate, guide, and stay accountable for the outcomes. This dynamic shows that the focus shifts from directly doing all the tasks to managing and coordinating work that involves AI.

Looking back at the conceptual framework that was introduced in section 2.3, the findings both confirm and expand on the importance of the four analytical dimensions. The results make it clear that technological enactment, role enactment, expertise reconfiguration, and responsibility negotiation don't happen in isolation, but they are closely connected in real-world practice. For example, when AI becomes better at generating outputs, it directly affects what counts as expertise and how responsibility is handled. This reinforces just how interconnected sociotechnical systems really are.

The findings extend the framework even further by showing that integrating AI brings changes to each of these dimensions, and also shows a broader shift in professional work toward coordination. Professionals are no longer only focusing on carrying out tasks by themselves. They are spending more time managing, evaluating, and shaping processes that involve the support of AI. This highlights just how important human agency remains, even as workplaces become more automated. Humans are still needed to guide and make sense of how AI is used.

This study offers a deeper understanding of professional roles in AI-enabled environments. It shows that AI's impact isn't simply about replacing humans or automating work. Instead, it's about transforming how work is done, how it's evaluated, and how it's managed. The future of professional work isn't about losing human expertise. It's about reconfiguring that expertise to work alongside even more capable technological systems.

5. DISCUSSION

This chapter discusses the study's findings and connects them to the existing literature and the sociotechnical conceptual framework that was developed in Chapter 2.The goal is to interpret the empirical results and highlight the study's theoretical contributions to research on artificial intelligence, professional work, and sociotechnical systems.

The findings show that bringing AI into professional settings doesn't simply automate tasks or replace human roles. Instead, AI transforms how work is carried out through a set of interconnected sociotechnical processes that involve technological enactment, role enactment, expertise reconfiguration, and responsibility negotiation. These processes show how the interactions between humans, AI systems, and organizational environments drive the ongoing evolution of professional roles in AI-enabled environments.

This study responds to recent calls in the literature for more concrete and practical insights into how AI is changing professional roles and expertise, by exploring these dynamics through real-world examples (e.g., Faraj et al., 2018; Benbya et al., 2020). The study does not focus on broad labor market trends or abstract models of how humans and AI work together. Instead, the findings give insight into how professionals involved in the deployment and organizational integration of AI systems actually interpret and enact their roles in everyday settings. This approach offers a deeper understanding of how AI is reshaping professional work at the individual level.

The chapter goes on to discuss the theoretical implications of these findings, explore what they mean for managers, suggest directions for future research, and address the study's limitations.

5.1. Theoretical implications

This study adds on to the literature on artificial intelligence and professional work, and sociotechnical systems theory. By looking at how professionals involved in the deployment and organizational integration of AI systems actually interpret and enact their roles, the findings build on existing research in three key ways.

The study contributes to our understanding of AI and professional work by offering real-world insights into how roles change in daily practice. Previous research has often explained AI's impact using concepts like automation and augmentation (e.g., Davenport & Kirby, 2016; Brynjolfsson & Mitchell, 2017). This describes how specific tasks might shift from humans to machines. While these frameworks help explain task-level changes, they don't always capture how professionals themselves experience and make sense of these changes in their everyday work.

The findings from this study show that AI doesn't just automate or enhance certain tasks, but it actually changes how work is carried out. While professional roles may look the same on paper, what changes is their everyday execution. This extends prior research because it shows that role change in AI-enabled settings is often subtle and rooted in daily practice, rather than changing formal role definitions. This means that the study does not focus on task-centric perspectives, but it highlights the importance of looking at how roles are enacted as an ongoing, context-dependent process.

The study also adds to literature on expertise in technology-rich environments by demonstrating how AI changes the basis of expertise. Earlier research has suggested that AI may shift cognitive tasks between humans and machines (Faraj et al., 2018). However, there has not been much real-world evidence on how this shift affects the nature of expertise itself. The findings show that expertise is now increasingly defined by the ability to evaluate, interpret, and guide the results that are produced by AI. Expertise is not defined by simply being able to produce outputs on your own.

This shift shows that expertise is moving away from just doing tasks toward making informed judgments. Professionals now add value by assessing the quality of AI outputs, putting them into the right context, and making informed decisions even when things are uncertain. By focusing on the essential role of human judgment in managing AI-supported work, the study deepens our understanding of distributed cognition. Rather than reducing the importance of expertise, AI makes it a more reflective and evaluative skill.

The study also brings something new to sociotechnical systems theory by applying it to modern AI-enabled workplaces. Sociotechnical research has long pointed out that the interaction between social and technical elements shapes roles and work practices (Trist & Bamforth, 1951; Orlikowski, 2007). However, there hasn’t been much real-world research on how this process happens in environments where technology is adaptive, data-driven, and capable of producing outputs that used to be the domain of human experts.

The findings show that a ”human-in-the-loop” dynamic is central to how people and technology interact in AI-enabled settings. This means that while AI systems generate outputs it’s up to humans to evaluate, guide, and take responsibility for the final results. This setup shows that, even though authority is shared, it isn’t equal. AI helps carry out tasks, but humans still hold the final say and remain accountable. The study advances sociotechnical theory by showing how role enactment, expertise, and responsibility are shaped together in environments where technology isn’t fixed, but is constantly generating new possibilities and evolving over time.

5.2. Managerial implications

The findings of this study have several practical implications for organizations that are integrating AI into professional work, especially in roles that are related to the deployment and use of AI systems. The introduction of AI changes the way work gets done on a daily basis, instead of simply changing the formal job descriptions. This suggests that organizations should not treat AI adoption only as a technical implementation project. Instead, adopting AI should be seen as a broader shift that affects work practices and professional roles (Brynjolfsson & Mitchell, 2017; Faraj et al., 2018).

One important implication is how organizations support their employees when they are adjusting to new ways of working. As the findings show, professionals are moving away from doing tasks themselves toward coordinating, evaluating, and guiding processes that involve AI. This shift requires more than just technical skills. It calls for the ability to interpret AI outputs, judge their quality, and use them appropriately in context. Organizations should focus not only on improving employees' technical skills, but also on strengthening their evaluative and critical thinking abilities. In practice, this could mean giving employees space to try out AI tools, reflect on how they use them, and develop shared guidelines for using AI effectively and responsibly.

The findings also highlight the continued importance of domain expertise in AI-supported work. AI systems can generate large amounts of outputs quickly. Their value still mostly depends on the user's ability to recognize what is relevant, accurate, and meaningful. This supports the idea that AI does not replace expertise, but it shifts its focus toward interpretation and judgment (Faraj et al., 2018). For organizations this means that investments in AI should also mean continuing to invest in domain knowledge and professional expertise. Reducing expertise because of automation could potentially make it more difficult to employ AI effectively.

Another implication has to do with responsibility and accountability. It became clear in all the interviews that even though AI is becoming more and more involved in generating outputs, responsibility still remains with human actors. Professionals need to validate and take ownership of outputs that are not fully produced by themselves as responsibility is becoming more complex. This means that it is important for organizations to clearly define expectations for the use of AI, and to set guidelines for validation, oversight, and decision-making (Elish, 2019; Jarrahi, 2018). Without this clarity, employees can experience uncertainty about their responsibilities regarding outputs generated by AI.

The results suggest that AI adoption may change how work is divided in organizations. Traditional collaboration may change because individuals are becoming more capable of completing tasks independently with the support of AI. While using AI can boost efficiency and give individuals more autonomy, it may also reduce opportunities for sharing knowledge and working through problems together. Because of this, organizations should carefully consider how to balance gains in individual productivity with the ongoing need for teamwork, collaboration, and learning within groups.

The findings indicate that successfully integrating AI into professional work isn't just about having the right technology. It also depends on how organizations help people adapt their roles, build new expertise, and manage responsibility as work changes. From a sociotechnical perspective, managing this kind of transition means paying close attention to both the technical side and the human, social aspects of work.

5.3. Suggestions for future research

This study provides insight into how professionals experience changes in their roles when working with AI, but it also opens up several opportunities for further research. For example, it would be valuable to explore how these dynamics might play out in different industries or types of organizations. Future studies could build on these findings by looking at a broader mix of workplaces, including larger companies or more traditional sectors where AI adoption may look quite different.

In addition, there's a need to understand how professional roles develop long term. The findings here suggest that many of the changes are still in progress and haven't fully settled yet. It would be especially useful to study how these roles continue to evolve as AI systems become more advanced and more deeply embedded in the everyday work of organizations. Long-term research could help determine if the patterns that are observed in this study are simply short-term adjustments, or if they represent lasting changes in professional work.

There’s also an opportunity to take a closer look at the differences between different roles. In this study, participants came from both technical and leadership backgrounds, so their experiences weren’t exactly the same. Future research could focus more on specific types of roles to better understand how AI impacts different forms of expertise and responsibility.

The findings also highlight the importance of judgment and evaluation in AI-supported work, but does not go into detail on how these skills are actually developed. Further studies could explore how professionals learn to work effectively with AI, how these evaluative skills are built in practice, and what kinds of training or organizational support are most helpful.

Future studies could explore the broader organizational and societal effects of these changes. While this study centers on individual experiences, shifts in expertise and responsibility could have wider impacts on organizational structures, decision-making, and accountability. Looking at these bigger-picture questions could give a deeper understanding of how AI is changing work beyond just the individual level.

5.4. Limitations

This study has various limitations that should be kept in mind when interpreting the findings. One limitation has to do with the size and makeup of the sample. Since the study is based on a small number of interviews, it limits how much these findings can be generalized to other settings. The main goal of the study is to provide analytical insights, rather than statistical generalizations. Still, having a larger and more diverse group of participants would likely have offered an even broader range of perspectives.

Another limitation involves the selection of interviewees. All interviewees were involved in deploying or using AI systems, and they represented a mix of technical and leadership positions. Even though this variety added valuable perspectives, most participants were in senior or managerial roles, like CEOs, COOs, or founders. These individuals are typically more involved in setting strategy and overseeing how AI is integrated into the organization, rather than interacting with AI systems on a daily basis. As a result, the findings may reflect more of an organizational and strategic viewpoint, making it harder to gain detailed insights into how operational-level professionals use AI in their everyday work.

Another limitation is that the study relies on self-reported data, which can introduce certain biases. When participants talk about their own experiences, their accounts might not always match what actually happens in practice. For example, people might highlight some parts of their work and downplay others, or describe their roles in ways they think are expected. Using additional sources of data or observations could have helped provide a more well-rounded view.

The study also focuses on organizations that are already actively using AI. Because of this, the findings might not capture the challenges faced by organizations that are just starting out with AI, where uncertainty and resistance to change are often more common. As a result, the study mostly reflects experiences in environments where AI is already part of established work routines.

This study looks at how professional roles are evolving at a particular moment in time. Because AI technologies are advancing so rapidly, the dynamics described here may continue to change in the future. The findings should be viewed as a snapshot of current developments, rather than as a final state.

It is also worth noting that AI tools (such as ChatGPT) were used during the writing process. These tools helped with language editing, improving clarity and readability, and summarizing or simplifying draft text. However, they were not used to create original research content, conduct analysis, or shape the study's findings or conclusions. All interpretations, theoretical insights, and analysis were conducted independently by the author.

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