JÖNKÖPING UNIVERSITY
Jönköping International Business School

Drowning in the Flood or Surfing on the Wave? Skill Development in the Era of AI

A Single Case Study on AI-related Skill Development

MASTER THESIS WITHIN: Global Management (M.Sc.)

NUMBER OF CREDITS: 30

PROGRAMME OF STUDY: Global Management

AUTHORS: Jorina Margret Baltzereit and Katharina Ebner

JÖNKÖPING: May 2025

Master Thesis in Business Administration

Title: Drowning in the Flood or Surfing on the Wave?
Skill Development in the Era of AI.
A Single Case Study on AI-related Skill Development

Authors: Jorina Margret Baltzereit and Katharina Ebner

Tutor: Anup Banerjee, Ph. D.

Date: 2025-05-19

Key terms: Artificial Intelligence, Skills, Skill Development, Workplace Learning, Formal Learning, Informal Learning

---

Abstract

Background: Artificial Intelligence (AI) is rapidly transforming workplaces and reshaping skill requirements. As tasks become more automated or augmented, employees require technical, human and conceptual skills to work with and alongside AI. While this shift has sparked growing interest in skill development, little is known about how workplace learning influences employees' AI-related skill development.

Purpose: Our thesis aims to answer the following research question: *How does workplace learning influence employees' AI-related skill development?* By analyzing formal and informal learning initiatives in an organizational setting within the Information and Communication Technology (ICT) industry, we aim to offer both theoretical and practical insights. We also provide practical guidance for companies through introducing a conceptual framework that builds upon the sociotechnical systems (STS) theory.

Method: We conduct a qualitative single case study guided by a relativist ontology and a social constructionist epistemology. Data is collected through 15 semi-structured interviews with employees across departments, complemented by three observations and the analysis of secondary data. Grounded analysis is applied to inductively code and interpret the data. Triangulation of interviews, observations and secondary data enhances the credibility and depth of our findings.

Conclusion: Our findings reveal that formal learning provides a foundation for the development of AI-related skills, but often lacks depth, role-relevance and accessibility. Informal learning, in contrast, plays a central role in influencing employees to experiment, collaborate and adapt their skills to evolving AI tools. Rather than a fixed endpoint, AI-related skill development emerges as an ongoing process. The influence of workplace learning is multifaceted and shaped by individual engagement, organizational initiatives and contextual factors. By applying the STS perspective, our study highlights workplace learning as a dynamic mechanism that balances the transformation of employees' skills with technological change through AI.

Acknowledgements

We would like to begin by expressing our appreciation to our supervisor, Anup Banerjee, for his continuous guidance, critical feedback and encouragement throughout the research process. His insights were essential in helping us sharpen our focus and strengthen the quality of our work.

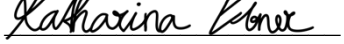
We are also deeply thankful to all participants who generously shared their time and insights during interviews and observations. Their willingness to engage with us provided essential contributions to the depth and richness of our empirical material. It was a privilege to gain insights into their work and experiences.

We would also like to express our sincere gratitude to our main contact within the company, whose openness and commitment greatly facilitated our data collection. His active support in gathering participants for the interviews and observations, as well as his ongoing assistance throughout the process, was invaluable to the success of our thesis.

Lastly, we extend our genuine thanks to our families and friends for their constant support, patience and encouragement throughout this journey.

Working on this thesis together has been an exciting and meaningful experience and we hope our passion for the topic is reflected in the pages that follow.

Jönköping, 19th of May 2025



Jorina Margret Baltzereit

Katharina Ebner

Declaration

We hereby declare that this thesis represents our own work.

We confirm that we obtained the necessary ethical approvals (e.g. GDPR) and acknowledged our obligations and the rights of the participants involved in the research.

We read and followed Jönköping University's current research ethics guidelines regarding the use of Artificial Intelligence (AI) tools, as outlined in the Course Guide. During the preparation of this work, we used the following AI tools for the following purposes:

- **Grammarly**: Used to correct grammar, spelling and sentence structure.
- **DeepL**: Used to translate and refine sentences to enhance academic language.
- **ChatGPT**: Used as a tool for feedback on grammar and spelling, idea generation and clarification of technical questions.

As authors, we critically reviewed and edited the content as needed and take full responsibility for the content and findings presented in our thesis.

Jönköping, 19th of May 2025

Jorina Margret Baltzereit

Katharina Ebner

Table of Contents

1. Introduction 1
1.1. Background 1
1.2. Problem Discussion 4
1.3. Purpose 5
2. Literature Review 7
2.1. Approach to Literature Review 7
2.2. AI and Workplace Transformation 12
2.3. Skills in the AI-impacted Workplace 14
2.4. Workplace Learning 17
2.4.1. Formal Learning 18
2.4.2. Informal Learning 19
2.5. Linking AI, Skills and Workplace Learning 20
2.6. Summary of Literature Review 22
3. Methodology 23
3.1. Research Philosophy 23
3.2. Research Design 24
3.3. Research Strategy 26
3.3.1. Single Case Study Rationale 26
3.3.2. Single Case Study Selection 28
3.3.3. Single Case Study Context 28
3.4. Methods 30
3.4.1. Data Collection 30
3.4.1.1. Primary Data 31
3.4.1.2. Secondary Data 36
3.4.1.3. Triangulation 37
3.4.2. Data Analysis 38
3.4.3. Data Quality 40
3.4.3.1. Credibility 41
3.4.3.2. Transferability 41
3.4.3.3. Dependability 41
3.4.3.4. Confirmability 42
3.4.4. Ethical Considerations 42
4. Empirical Findings 44

4.1. Adoption of AI in the Workplace 44
4.1.1. Integrating AI into Work 44
4.1.2. Critical Reflections on the Use of AI 47
4.2. Transformation of Knowledge and Skills through AI 50
4.2.1. Building Foundational AI Knowledge 50
4.2.2. Evolving Skill Requirements due to AI 52
4.3. Dynamics within Workplace Learning 55
4.3.1. Opportunities within Formal Learning 55
4.3.2. Opportunities within Informal Learning 59
4.4. Summary of Empirical Findings 62
5. Discussion 63
5.1. Discussion of Findings on AI Literature 63
5.2. Discussion of Findings on Skills Literature 65
5.3. Discussion of Findings on Workplace Learning Literature 66
5.4. Conceptual Framework 68
6. Conclusion 71
6.1. Answer to the Research Question 71
6.2. Theoretical Implications 72
6.3. Societal Implications 73
6.4. Practical Implications 74
6.5. Limitations 75
6.6. Future Research 76
7. Reference List 77
Appendices 83

Figures

Figure 1: Literature Review Approach (own figure)..... 11
Figure 2: Coding Structure Overview (own figure)..... 40
Figure 3: Conceptual Framework (own figure)..... 68

Tables

Table 1: Keywords in Boolean Search Format (own table)..... 8
Table 2: Boolean Search Rounds (own table)..... 9
Table 3: Interview Overview (own table)..... 32
Table 4: Observation Overview (own table)..... 36
Table 5: Secondary Data Overview (own table)..... 37

1. Introduction

This chapter provides an overview of the background, the research problem and the purpose of our study. First, we highlight current research on AI, skills and workplace learning. Second, we discuss the research problem and outline the identified research gap. Third, we present our study's purpose and conclude by posing the research question along with the scope and delimitations of our thesis.

1.1. Background

"We estimate that 14% of existing jobs could disappear as a result of automation in the next 15-20 years, and another 32% are likely to change radically […]." (OECD, 2019a)

As stated by the Organization for Economic Cooperation and Development (OECD), a considerable portion of today's workforce will need to further develop their skills – or risk falling behind in the job market. At the center of this transformation is Artificial Intelligence (AI), a machine-driven system, capable of functioning at varying levels of autonomy, that is increasingly reshaping workplaces, redefining job roles and substantially altering the skills required in organizational contexts (European Parliament and Council of the European Union, 2024; Tamayo et al., 2023). Discussions about the future of work brought two differing opinions forward. While critics argue that AI will lead to widespread job losses by replacing human workers, others contend that it will generate new employment opportunities by creating demand for roles in AI development, maintenance and oversight (Jaiswal et al., 2021).

These shifts are particularly relevant in technology-intensive industries, where AI can enhance operational efficiency and support data-driven decision-making (OECD, 2019a). Across industries such as Information and Communication Technology (ICT), AI adoption is becoming essential not only for competitiveness but also for regulatory compliance in increasingly digitalized environments (OECD, 2019a). In response to the growing integration of AI and the associated risks, the EU AI Act introduces a regulatory framework to ensure transparent and responsible AI usage (European Parliament and Council of the European Union, 2024). Notably, Article 4 emphasizes AI literacy, requiring organizations to ensure that employees receive adequate training to understand both the operation and broader impacts of AI systems (European Parliament and Council of the European Union, 2024). As these technologies are

fundamentally modifying current workplaces, shifting skill requirements emerge due to the implementation of AI (Rinta-Kahila et al., 2023; Zirar et al., 2023).

Skills are learned abilities that allow individuals to achieve certain objectives or tasks (Katz, 1974; OECD, 2019b). Analyzing the development and future projections of the World Economic Forum's (WEF) *top core skills*, which illustrate the most frequently cited skills across sectors and jobs (WEF, 2016), reveals a visible change in workplace skill demands over the past decade. In 2015, the top three skills were (1) complex problem-solving, (2) coordinating with others, and (3) people management (Gray, 2016; WEF, 2016). A decade later, in 2025, the focus has shifted toward (1) analytical thinking, (2) resilience, flexibility, agility as well as (3) leadership and social influence (WEF, 2025). From 2025 until 2030, the fastest-growing skills are expected to be (1) AI and big data, (2) networks and cybersecurity, and (3) technological literacy (WEF, 2025). These skill evolutions appear relatively stable across industries and show that employees should continuously adapt and balance a set of different skills involving technical, human and conceptual skills (WEF, 2025; Zirar et al., 2023).

Technical skills, which refer to utilizing specific tools and processes, have increased emphasis on data proficiency and AI competencies. Notably, technical skill requirements vary by occupation, while special AI knowledge, such as machine learning, is in high demand for ICT roles, AI literacy and profound digital skills remain crucial for the broader workforce (Alekseeva et al., 2021; Jaiswal et al., 2021; OECD, 2023; Stephany & Teutloff, 2024). Human skills, such as interpersonal competencies and collaboration, remain critical as they distinguish humans from AI systems (Sanders & Wood, 2023), while conceptual skills involve interpreting complex interrelations and today require strong analytical thinking (Jaiswal et al., 2021; Sanders & Wood, 2023; WEF, 2016; Zirar et al., 2023).

Given these rapid workplace and skill changes, organizations across industries are acknowledging the importance of employee skill development through workplace learning (Sanders & Wood, 2023; Tamayo et al., 2023; WEF, 2025). The success of these skill development strategies highly depends on company-wide knowledge, shared responsibility and commitment to ensure the identification of skill gaps and the facilitation of workplace learning (Tamayo et al., 2024; Zirar et al., 2023). Workplace learning encompasses both formal and informal learning, each playing an important role in skill development (Clardy, 2018; Manuti et al., 2015). Formal learning refers to structured, planned training programs, often conducted in educational settings or through employer-led courses (Manuti et al., 2015; OECD, 2019a;

Sparr et al., 2017). In contrast, informal learning occurs within daily work activities, for instance, through problem-solving, collaboration, mentoring or experiential learning (Manuti et al., 2015; Watkins & Marsick, 2023).

Skill development may involve upskilling or reskilling, whereby upskilling involves obtaining new skills for a current job, while reskilling refers to acquiring new skills to perform a different role (Jaiswal et al., 2021; Li, 2024). According to the WEF (2025), 77% of employers surveyed worldwide, consider up- and reskilling as the most frequently implemented workforce learning strategy in response to AI adoption in the upcoming years. This trend is particularly noticeable in the ICT industry, where AI plays a central role in business transformation. As an industry that heavily depends on AI for automation, cybersecurity and software development, the ICT industry experiences an especially high demand for AI-related skills.

In the context of our thesis, the term *AI-related skills* encompasses not only technical competencies but also human and conceptual skills, which are essential for working with and alongside AI. By *working with and alongside AI*, we refer to the ability to interact with AI systems, leverage their capabilities and collaborate in a way that integrates AI-related skills within an increasingly digitalized workplace. Notably, 99% of ICT companies identify AI as main driver for business transformation, highlighting the industry's reliance on AI to enhance innovation and competitiveness. Consequently, 87% of employers in this industry, 10% more than the global average, view up- and reskilling as prioritized strategy to enable their workforce to work with and alongside AI (WEF, 2025).

Viewing these background aspects under the light of academic research reveals that as AI continues to reshape workplaces, the ability to adapt through skill development becomes increasingly substantial. Ensuring that employees are equipped with the necessary skills is crucial to maintaining both individual employability and organizational competitiveness in the evolving digital environment. In this context, the emergence of AI can be seen as a powerful wave. While some adapt to these changes, others risk being overwhelmed by its force. Workplace learning, in particular, plays a central role in shaping the way employees navigate those changing waters and develop the AI-related skills needed to surf the wave (Rajaram & Tinguely, 2024).

1.2. Problem Discussion

The WEF Future Job Report 2025 and the OECD Employment Outlook 2023 emphasize the growing importance of researching the impact of AI adoption on workforce skills, underpinning the need for skill development strategies (OECD, 2023; WEF, 2025). Similarly, academic literature confirms that research centered around AI, skills and workplace learning has notably increased in recent years, reflecting AI's impact on workplaces and skill demands (Davenport & Ronanki, 2018; Hillebrand et al., 2025; Jaiswal et al., 2021; Zirar et al., 2023). Within this growing body of literature, three interlinked research streams have emerged.

First, AI as a driver of ongoing workplace transformation has been widely explored (Davenport & Ronanki, 2018; Hillebrand et al., 2025), with literature centering around the way AI has altered job tasks, organizational processes and business requirements (Anthony et al., 2023; Krakowski et al., 2023). Second, growing attention has been paid to the evolving skill demands in AI-impacted workplaces (Chuang, 2024; Jaiswal et al., 2021; Sanders & Wood, 2023; Sousa & Wilks, 2018; Zirar et al., 2023), with studies and institutional reports identifying which skills become redundant and which competencies increase in relevance (Chuang, 2021; Jaiswal et al., 2021; OECD, 2023; WEF, 2025). Third, the role of workplace learning in supporting skill development is widely acknowledged (Clardy, 2018; Manuti et al., 2015). Research argues that both, formal and informal learning are not mutually exclusive but inherently connected and substantial impact factors for skill development in organizations (Clardy, 2018; Manuti et al., 2015). Therefore, as AI continues to transform workplaces, researchers suggest that skill development should be pursued in tandem with technological transformation, to ensure a synergistic human-AI coexistence in organizations (Chuang, 2024; Tamayo et al., 2023; Zirar et al., 2023).

Highlighting this development, one area that requires particular attention is the influence of workplace learning on AI-related skill development. Workplace learning literature acknowledges that both formal and informal learning contribute to skill development (Manuti et al., 2015). However, research on the influence of workplace learning on the development of AI-related skills is scarce. Zirar et al. (2023) specifically highlight the need for future research to investigate adequate training strategies for enabling employees to develop required skills in AI-impacted workplaces. Engström et al. (2024) further point towards a gap in the way workplace learning processes are shaped through AI adoption. Their findings suggest that employees' engagement with AI technologies in the workplace plays an important role in the

development of relevant skills. However, they emphasize that little is known about the way organizations can create conditions that foster such exploratory learning beyond formal training offers. Thus, the authors stress that future research is needed to investigate not only suitable training strategies but also the way workplace learning supports the development of AI-related skills (Engström et al., 2024). Furthermore, Li and Yeo (2024) highlight that AI changes the way in which learning occurs in organizations. Thereby, the authors accentuate that further investigations are required to explore the influential relationship between workplace learning, AI adoption and employee skill development. This call to action is further underlined by insights from practice-oriented literature, which highlights that many organizations struggle to develop effective up- and reskilling strategies regarding rapidly changing skill demands (Goel et al., 2022; Tamayo et al., 2023). As Goel et al. (2022) highlight, besides growing awareness of the need to further develop skills due to technological changes driven by AI, organizational skill development efforts often remain fragmented. Additionally, these academic gaps and suggestions are reinforced by the OECD (2023), stressing that more research on AI, organizational skill development initiatives and employee training is needed. However, research providing insights into workplace learning in the context of AI-related skills remains insufficiently explored.

Bringing these perspectives together reveals a critical gap at the intersection of AI, skills and workplace learning. While AI's impact on tasks and skill requirements is considerable, the influence of workplace learning on employees' AI-related skill development requires more exploration.

1.3. Purpose

Our thesis aims to explore the influence of workplace learning on employees' AI-related skill development. Specifically, we contribute to this academic and professional discussion in three ways. First, we advance the current research landscape. While previous studies focus on AI, skills and workplace learning rather separately, our research concentrates on the intersection of these three discussions by examining the influence of workplace learning on AI-related skill development. Second, we provide practical insights for businesses. Organizations that want to support AI-related skill development through workplace learning gain insights into the influence of learning initiatives and where to focus efforts on. Third, we provide a conceptual framework, illustrating the influence of workplace learning on employees' AI-related skill development. This framework offers practical guidance for organizations but also a theoretical

foundation for future research. In line with this research aim, our thesis seeks to answer the following research question:

How does workplace learning influence employees' AI-related skill development?

To define our thesis scope and delimitations, we decompose the key components of the research question. Regarding *workplace learning,* our study focuses on formal and informal workplace learning that is used for skill development related to AI. *Workplace* in this context refers to the environment in which employees perform their job roles, encompassing both physical and digital spaces impacted by AI adoption. *Influence* refers to the ways in which workplace learning shapes employees' AI-related skill development. Regarding *employees*, the unit of analysis is the employee and their individual learning experiences and outcomes. Therefore, we analyze the individual workers and exclude teams, departments and the organization as a whole entity. To explore this influence, we conduct a qualitative single case study. Concerning *AI-related*, our research focuses on technical, human and conceptual skills. This involves skills directly related to AI tool usage, but also complementary skills necessary to work alongside AI. Our analysis of *skill development* encompasses both the learning of new skills and the strengthening of existing skills to enhance current job performance.

2. Literature Review

This chapter reviews literature on AI's impact on work, skill development and workplace learning. First, we outline the approach to the literature review, explaining the selection and analysis of relevant sources. Second, we analyze AI's impact on workplaces and required skills. Third, we discuss the manner in which learning occurs in workplaces. Fourth, we present a summary of the literature review.

2.1. Approach to Literature Review

To establish a theoretical foundation for our study, we conduct a structured literature review. While not a systematic literature review, we apply a systematic search strategy to ensure transparency in identifying relevant studies. This review aims to assess and synthesize existing research on work transformation under the impact of AI, skills related to AI and formal and informal workplace learning. By analyzing prior studies, we aim to reflect on theoretical frameworks and empirical findings relevant to our research. To ensure a structured search process, we identify key terms and phrases that center around the core aspects of our research focus. The selected keywords are combined to obtain a wide range of the most relevant sources. The exact terms used in the search process are showcased in Table 1.

Keywords in Boolean Search Format
AI
"Artificial Intelligence" OR "AI"
Skills
"Skill*" OR "Competenc*" OR "Skillset" OR "Expertise*" OR "Abilit*" OR "Proficienc*" OR "Know-how*" OR "Qualification*" OR "Aptitude*" OR "Mastery"
Specific Skills
"Digital Litera*" OR "Tech* Savv*" OR "Critical Think*" OR "Analytical Think*" OR "Problem Solv*" OR "Adaptability" OR "Tech*" OR "Conceptual" OR "Cognitiv*"
Skill Development
"Skill* Development" OR "Competenc* Development" OR "Reskilling" OR "Upskilling" OR "Future Skill*" OR "Skill* Training*" OR "Retraining" OR "Uptraining"

Workplace Learning
"Workplace Learning" OR "Formal Learning" OR "Informal Learning"
Drivers, Aims and Challenges
"Driver*" OR "Aim*" OR "Challenge*" OR "Barrier*" OR "Hurdle*" OR "Success*" OR "Goal*" OR "Difficult*" OR "Problem*" OR "Struggle*" OR "Weakness*" OR "Gap*" OR "Obstacle*" OR "Constrain*" OR "Complication*" OR "Issue*"
Business Context
"Business*" OR "Organization*" OR "Compan*" OR "Corporation*" OR "Enterprise*" OR "Firm*" OR "Workplace*" OR "SME*" OR "MNE*"
Organizational Context
"Adoption" OR "Strateg*" OR "Implementation" OR "Readiness" OR "Integration" OR "Workforce Transformation*" OR "Execution*" OR "Program*" OR "Initiative*" OR "Learn*" OR "Method*" OR "Transformation*"
Theory
"Theor*" OR "Framework*" OR "Concept*" OR "Approach*"
Method
"Case Stud*" OR "Qualitative" OR "Quantitative" OR "Empiric*"

Table 1: Keywords in Boolean Search Format (own table)

The initial literature search is conducted using the database *Web of Science*, with the following search criteria. In the initial search rounds (Searches 1 and 2), keywords pertaining to *AI* are restricted to appear in the article title to specifically identify core conceptual contributions. In all subsequent searches (Searches 3 to 20), keywords within *AI*, along with additional search terms, are applied to all searchable fields within the databases, acknowledging the widespread and diverse use of AI terminology across publications. To ensure contextual relevance to the broader field of business and management, all search rounds incorporate keywords within *business context*. Recognizing the need for academic relevance and credibility, we solely include journal articles listed in the Chartered Association of Business Schools (2024) Academic Journal Guide (AJG) journal ranking to guarantee that all sources meet recognized quality standards. Given the relative novelty of AI-related skill development as a research area, we consider all AJG levels (1 to 4) to ensure the breadth of findings. We then integrate these journal names into the search queries using Boolean operators within the *Publication Title* field.

Regarding the publication period, we primarily focus on articles published between 2015 and 2025 to capture recent developments in the field. However, in searches 11 to 16, no date restrictions are applied to allow the inclusion of foundational or highly cited earlier works essential for building theoretical context. Additionally, only articles published in English are considered. To further refine the search results and ensure relevance, we limit the subject areas to Management, Business, Economics, International Relations, Computer Science Information Systems and Operations Research Management Science.

Table 2 provides an overview of the Boolean search rounds and the number of articles retrieved in each search round on *Web of Science*, as well as the number of articles that are included for the initial title and abstract screening. This allows for transparency regarding the scope and output of our search process.

Boolean Search Rounds and Articles retrieved on Web of Science	
1. AI (231)	11. AI + Theory (87)
2. AI + Organizational Context (141)	12. AI + Method (50)
3. Skills (708)	13. Skills + Theory (465)
4. Skills + AI (14)	14. Skills + Method (347)
5. Skills + AI + Organizational Context (10)	15. Skill Development + Theory (7)
6. Skill Development (14)	16. Skill Development + Method (5)
7. Skill Development + AI (10)	17. Skills + Specific Skills (0)
8. Skill Development + Organizational Context (10)	18. AI + Specific Skills (17)
9. Skill Development + AI + Organizational Context (5)	19. Workplace Learning (13)
10. Skill Development + Drivers, Aims and Challenges (0)	20. Workplace Learning + AI (5)
Total Number of Articles: 2.139 – 862 (Duplicates) = **1277**	

Table 2: Boolean Search Rounds (own table)

Following the initial search rounds, a follow-up search is conducted using the database *Scopus* to expand our literature base. This additional search applies similar categories, filters and keywords as in the previous rounds, while also focusing on the AJG-listed journals within Scopus. This follow-up search results in the identification of 115 additional articles, which are subsequently added to the pool of articles selected for initial screening. To ensure an organized literature review, all relevant article data, including author(s), article title, source title and abstract retrieved from the keyword search, are downloaded as CVS-files.

To narrow down the initial pool of 1,392 (*Web of Science*: 1,277 + *Scopus*: 115) retrieved articles to a more focused selection relevant to our research objective, a first screening based on titles and, where necessary, abstracts, is conducted. This initial screening aims to identify articles that explicitly address topics related to workplace learning, skill development and the context of AI in organizational settings. Articles are excluded if their title or abstract indicates a focus that was clearly unrelated to our research scope, for example, studies dealing exclusively with technical AI model development, highly specialized industry applications without connection to learning or skills, or AI adoption outside of workplace or employee-related contexts (e.g. AI in education or AI in consumer products). This process results in a substantial reduction of the initial dataset to 89 articles that demonstrate clear thematic relevance and potential contribution to our research focus. Those articles are then put in a structured table containing information such as author(s), article title, source title, journal ranking, abstract, keywords used in the search process and additional comments. This process allows us to effectively analyze, thematically categorize and synthesize insights across articles. Following this initial screening of the literature, we then review and discuss articles based on their relevance to our research question. To further refine our literature base, we utilize snowballing within selected studies, identifying further relevant articles that may not have been captured in our original search.

It is important to acknowledge that the literature search was primarily conducted in February 2025. Consequently, if the search was to be replicated at a later point in time using the same databases, filters and keywords, the number of retrieved results might differ due to ongoing database updates, newly published articles or changes in indexing practices. A detailed outline of our literature review approach is illustrated in Figure 1.

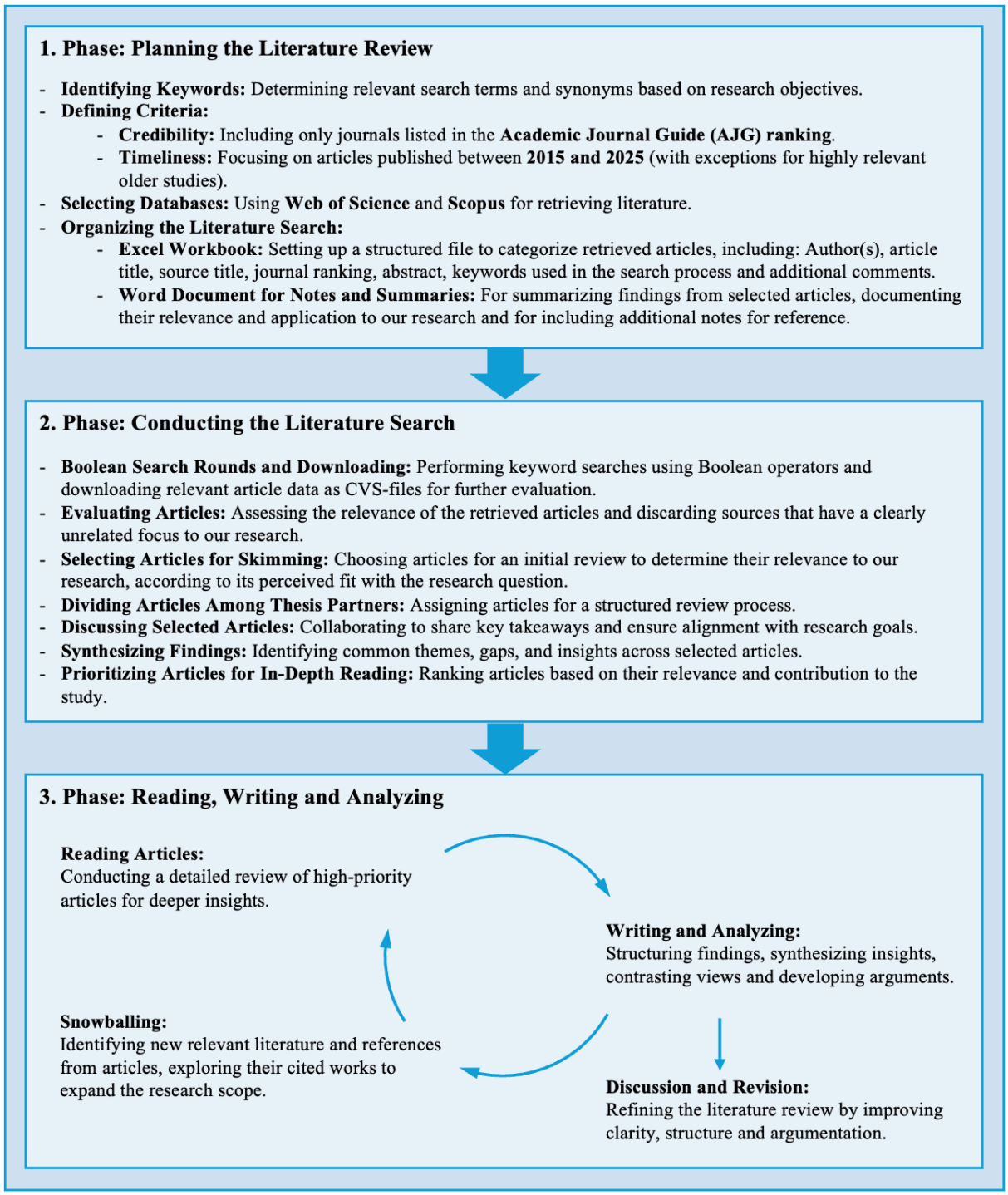


Figure 1: Literature Review Approach (own figure)

The following part describes the structure of our literature review. Overall, we follow a structured funnel approach, moving from the discussions on AI and skills to the more specific topic of workplace learning.

The first section (2.2.) discusses the way AI transforms workplaces, including AI's application and organizational use. The second section (2.3.) focuses on skills in the AI-impacted workplace, providing key definitions, scrutinizing different types of skills relevant to AI, as well as providing relevant terminologies in the realm of skill development. The third section (2.4.) investigates workplace learning, including formal (2.4.1.) and informal learning (2.4.2.). The fourth section (2.5.) views these three research streams through the theoretical lens of the STS theory. Through this structure, we gain insights from multiple perspectives to expand our knowledge of the research phenomenon, concluding with a summary of the literature review (2.6.).

2.2. AI and Workplace Transformation

As defined by the EU Artificial Intelligence Act, an AI system refers to a machine-driven system designed to function with different degrees of autonomy, potentially demonstrating adaptability post-deployment. It processes received inputs to produce outputs, such as forecasts, recommendations, content, or decisions, aimed at achieving specific or implicit objectives, impacting both physical and digital workplaces (European Parliament and Council of the European Union, 2024). Davenport and Ronanki (2018) analyze AI through the lens of business capabilities and therefore categorize it as a supportive tool for different business needs, such as the automation of operational workflows, the extraction of insights through data analytics and the interaction with both customers and employees. While AI's transformative potential is widely acknowledged (Matthews et al., 2025), it also raises concerns about job displacement (Huang & Rust, 2018) and shifting skill requirements (OECD, 2019a). Huang and Rust (2018) argue that job displacement occurs in a structured manner, with AI initially augmenting human work before fully automating tasks. They suggest that lower-skilled roles, referring to jobs that involve repetitive and basic tasks, are more vulnerable to displacement as AI advances from basic technical to analytical and eventually to intuitive tasks. Similarly, the OECD (2019a) highlights that as AI adoption accelerates, the demand for skills connected to this rises, while lower-skilled jobs face a higher risk of redundancy, necessitating proactive skill development efforts. This connects to whether AI automates tasks, augments human work, or operates in a hybrid role that blends both approaches (Raisch & Krakowski, 2021).

Automation refers to AI systems taking over human tasks entirely, often replacing workers in repetitive tasks (Raisch & Krakowski, 2021). Augmentation, on the other hand, means human-AI collaboration, where AI complements human capabilities rather than completely replacing

them (Raisch & Krakowski, 2021). There are contrasting perspectives in academic literature on which approach should be prioritized, with varying implications for employment. Raisch and Krakowski (2021) argue that automation and augmentation are not distinct but interdependent. Their perspective suggests that reliance on either approach can lead to negative consequences. While automation can reduce costs and make processes more efficient, it may result in workforce displacement and the loss of employee skills. Conversely, augmentation demands investments in employee training and organizational adaptation. The authors argue for a balanced approach, where companies integrate automation and augmentation to optimize performance while minimizing disruptions in the organizational culture. Some researchers view AI as a complementary tool that enhances human capabilities rather than replacing them. Anthony et al. (2023) argue that AI and humans can form *super teams*, where AI takes over routine tasks, allowing employees to focus on problem-solving and creative work. Similarly, Raisch and Fomina (2024) introduce the concept of hybrid problem-solving, where AI supports employees in generating solutions. Shao et al. (2024) take on an employee-centric perspective, examining how workers experience augmentation in daily tasks. Their findings highlight that while augmentation-based AI can enhance learning and efficiency, it also introduces cognitive overload, potentially weakening decision-making abilities and productivity. This research suggests that augmentation is not an entirely risk-free solution, it requires careful implementation.

One common challenge for companies is the failure to transition from pilot projects to full-scale implementation (Hopf et al., 2023). Many firms struggle to extract value from AI initiatives, as Hopf et al. (2023) highlight. They connect this to misalignment between managerial expectations and work reality, where managers assume AI projects follow a predictable, structured process, while employees actually engage in highly experimental work. This disconnect can lead to the standstill of projects and inefficient AI adoption. Additionally, organizational challenges arise when AI integration lacks alignment with existing technological structures, leading to inefficiencies and higher maintenance costs (Ångström et al., 2023). Furthermore, Ångström et al. (2023) highlight the challenge of employee resistance. The authors argue that this resistance is particularly present when workers fear losing autonomy or distrust AI's decision-making capabilities. Addressing this, Woo et al. (2024) argue that AI-related skill development should address bias in AI models to create trust and engagement. Choudhary et al. (2025) and Hopf et al. (2023) emphasize that unrealistic expectations, insufficient training and a lack of organizational support often create a barrier to successful AI

adoption. Besides these obstacles, the skills gap is another common challenge. Many firms struggle to integrate AI effectively due to a lack of employees with the necessary expertise. The OECD has found that while the AI workforce has more than tripled since 2012, the demand for AI-related skills far exceeds supply. This discrepancy can hinder adoption and reduce the effectiveness of AI implementation (OECD, 2023).

2.3. Skills in the AI-impacted Workplace

Skills can be defined as the capacity to utilize acquired knowledge and competencies to achieve specific objectives or tasks, representing a capability that is developed and demonstrated through performance rather than being innate (Katz, 1974; Northouse, 2018; OECD, 2019b). While some researchers explicitly analyze skills essential for working with and alongside AI (Chuang, 2024; Jaiswal et al., 2021; Zirar et al., 2023), others explore skills for AI-impacted workplaces more indirectly by scrutinizing broader themes of new work landscapes (Chalutz-Ben Gal, 2023), digitalization (Sousa & Wilks, 2018), or Industry 4.0 (Li, 2024). Within this notion, several differentiations are made to describe skills that are becoming less important and those that remain relevant. For instance, Chuang (2021) identifies frequently mentioned skills within at-risk jobs in the US, such as machine workers or information clerks, which are threatened with being displaced by AI. The author summarizes such competencies as skills involving *"repeated physical motion and performance, information process and analysis, repeated physical control of equipment, or individual effective performance"* (Chuang, 2021, p.629). This investigation closely aligns with other researchers. Jaiswal et al. (2021) find that routine and rule-based tasks such as data entry, coding, basic statistics, or database management become less important to upskill, while Huang and Rust (2018) emphasize that basic, repetitive and manual skills become increasingly obsolete since they are easily performed by AI. While recognizing skills that are becoming obsolete is a widely researched topic within contemporary literature, the following sections scrutinize essential skills in AI-impacted workplaces.

To provide a structured overview of skills requirements, Zirar et al. (2023) suggest utilizing the three-skills approach by Katz (1974) to categorize skills relevant to AI-impacted workplaces. Katz's approach is derived from leadership research and outlines *technical*, *human* and *conceptual skills*.

Technical skills refer to the knowledge of certain activities, especially involving tools or processes (Katz, 1974; Peterson & Van Fleet, 2004). In today's context, these skills can be described as the ability to work with technology and AI-driven tools (Zirar et al., 2023). Jaiswal

et al. (2021) highlight that in the ICT industry, possessing and developing advanced technical and digital skills, such as data analysis, is vital. Moreover, AI skills receive particular attention from contemporary researchers and industry reports alike. The OECD (2023) distinguishes between (1) special knowledge to develop and maintain AI systems and (2) skills to interact with AI applications. Specialized AI knowledge for AI models, tools, or software, such as machine learning or natural language processing, is concentrated in specialized ICT occupations (Alekseeva et al., 2021; OECD, 2023). Alekseeva et al. (2021) further note that demand for AI and big data knowledge in the US has increased tenfold from 2010-2019 in such occupations. However, given the broad implementation of AI in workplaces, the substantial importance of complementary skills to work with AI, such as basic AI knowledge or profound digital skills across occupations, is emphasized (Alekseeva et al., 2021; OECD, 2023; Stephany & Teutloff, 2024). Basic AI knowledge often refers to the term AI literacy and describes the acquisition of knowledge on AI concepts and to learn using AI tools (Li & Kim, 2024). Nevertheless, Sanders and Wood (2023) assert that digital proficiency is becoming a given skill, but it is the unique human skills that drive success in the era of AI.

Human skills refer to the ability to work with people (Katz, 1974; Peterson & Van Fleet, 2004). In the context of AI, scholars frequently emphasize that human skills are indispensable competencies that are difficult to replicate by AI and thus they represent a critical competitive advantage of the human mind (Chuang, 2024; Sanders & Wood, 2023). According to research, examples of human skills involve competencies such as emotional intelligence, communication, conflict resolution and collaboration (Chuang, 2024; Zirar et al., 2023). However, Jaiswal et al. (2021) underscore that interpersonal skills such as communication and leadership competencies are considered fundamental in workplaces regardless of the current technological advancements. Additionally, Sanders and Wood (2023) highlight that domain knowledge, which refers to profound expertise within one's field, is a further crucial human skill that becomes particularly essential if AI makes mistakes or if automation systems become unavailable.

Conceptual skills refer to the ability to comprehend concepts and interrelations (Katz, 1974; Peterson & Van Fleet, 2004). Related to AI-impacted workplaces, this set of competencies describes employees' capability to comprehend interrelations between AI systems, components and mechanisms (Zirar et al., 2023). This involves skills such as critical and analytical thinking, decision-making, problem-solving, or creativity (Jaiswal et al., 2021; Sousa & Wilks, 2018; WEF, 2025). Nevertheless, it is notable that this conceptual skill category is also often viewed

in the light of further unique human or cognitive abilities (Jaiswal et al., 2021; Sousa & Wilks, 2018; WEF, 2025). Moreover, Stephany and Teutloff (2024) note that success in the workplace does not depend on mastering a specific single skill, rather, it is about leveraging various complementary skills and combining them to remain competitive. Hence, these aspects underline the digital prevalence of the current work environment and the essential need for employee skill development for AI-impacted workplaces (OECD, 2023; Tamayo et al., 2023).

As AI continues to reshape workplaces, organizations face increasing pressure to upskill and reskill their workforce. Omrani et al. (2022) identify digital transformation as the main motivator for organizational skill development, where companies should enhance their technological infrastructure and digital literacy to remain competitive. Similarly, Chuang et al. (2024) argue that AI is restructuring job roles, making AI literacy essential for career sustainability and to fill skill gaps. To meet these evolving demands, research suggests that organizations should invest in AI-related skill development to future-proof their workforce (Tamayo et al., 2023).

Upskilling can be defined as acquiring new skills for a current job role (Li, 2024). In the context of upskilling for AI, Jaiswal et al. (2021) describe upskilling more narrowly as developing new skills to improve employees' capabilities to comprehend and apply AI tools. The authors thereby clearly articulate that it is essential for businesses to improve employees' skillset to remain competitive in the market. In contrast to upskilling, reskilling refers to obtaining new skills for an entirely different job responsibility (Li, 2024). Due to today's rapid AI adoption in workplaces, Tamayo et al. (2023) argue that considering reskilling is crucial for businesses to cope with potential job modifications and displacements.

However, despite this terminological distinction, it is important to note that the terms upskilling and reskilling are often used simultaneously in both academic and industry discourses to describe skill development aimed at enhancing employees' competencies and improving the interactions between AI and humans in workplaces (WEF, 2025; Zirar et al., 2023). Hence, in our study, we utilize the term skill development to refer to the broader process of developing and adapting skills in response to changed skill requirements for AI-impacted workplaces. We apply a concrete distinction between upskilling and reskilling if a clear differentiation between improving skills for a current job role or transitioning into a new one is intended.

Researchers note that skill development within digitalization involving AI can be self-initiated by individuals (Ostmeier & Strobel, 2022) or induced by organizations through training initiatives (Tamayo et al., 2024). While self-initiated skill development may occur as an individual response to industry changes (Ostmeier & Strobel, 2022), organizational training initiatives for skill development often result from the rapidly changing circumstances in today's business landscape (Tamayo et al., 2023; Tamayo et al., 2024). Additionally, Li (2024) argues that commitment of both employees and businesses is required for successful skill development. Thereby, the author highlights that up- and reskilling may involve various approaches, including life-long learning, skill development through formal education degrees and workplace training delivered by employers or external providers (Li, 2024).

2.4. Workplace Learning

Workplace learning refers to the process of acquiring skills and knowledge through work-related experiences, interactions and training initiatives (Manuti et al., 2015). The research vein of workplace learning broadly differentiates between two types of learning in workplaces, namely formal learning (FL) and informal learning (IL) (Manuti et al., 2015).

Manuti et al. (2015) refer to FL in organizations as planned learning activities aimed at developing employees' skills and competencies in alignment with business objectives. IL, on the other hand, is referred to as unstructured, experience-based learning that occurs naturally through daily work activities, social interactions and problem-solving processes rather than through planned training programs (Manuti et al., 2015).

Recent research emphasizes that the adoption of advanced technologies such as AI can act as a catalyst for both learning types by triggering processes that either reinforce top-down, exploitative learning or encourage bottom-up, explorative approaches (Engström et al., 2024). These processes are shaped by the way employees perceive and interact with AI systems, whether as abstract concepts requiring instruction or as concrete tools embedded in everyday tasks. In the following sections, we explore considerations within each learning type and their relevance to contemporary workplace settings.

2.4.1. Formal Learning

FL represents a structured approach to workplace learning. For instance, it includes classroom-based training, corporate learning programs, online courses, webinars, workshops and certification programs (Manuti et al., 2015; OECD, 2019a; Sparr et al., 2017). FL usually follows a predefined curriculum, is typically instructor-led and often results in an official qualification or certification (Sparr et al., 2017). It primarily occurs in designated educational settings, whether within corporate training centers or through digital learning platforms (OECD, 2019a). The growth of digital learning platforms has expanded FL beyond traditional settings, incorporating AI tools, virtual reality simulations and e-learning modules (OECD, 2019a). These programs aim to develop employees' skills, ensuring that workforce competencies align with industry standards and organizational objectives (Sparr et al., 2017). The impact of FL is widely recognized, especially in employee development and leadership training (Gallagher et al., 2023; Sparr et al., 2017). Moreover, FL often provides employees with accreditations that enhance their career mobility and employability, making it an essential component of talent development strategies (Watkins & Marsick, 2023). Furthermore, Li and Yeo (2024) highlight that organizational training can help to prepare employees for AI-human integration, especially regarding AI literacy and digital transformation skills.

However, several scholars question the effectiveness of FL when not complemented by practical application and post-training reinforcement strategies, such as feedback-seeking (Sparr et al., 2017). Similarly, Manuti et al. (2015) suggest that FL alone may not be sufficient in dynamic workplaces, particularly when continuous on-the-job training and informal knowledge sharing are important for skill adaptation. Additionally, several challenges can limit the effectiveness of FL. Sparr et al. (2017) emphasize that knowledge transfer from FL to workplace application is often weak, as employees struggle to implement theoretical concepts in on-the-job situations. Watkins and Marsick (2023) argue that organizations should shift towards integrated learning ecosystems that blend FL with IL. Additionally, Gallagher et al. (2023) highlight the issue of knowledge loss, where employees forget learned skills if they are not reinforced through practice and continuous learning on the job. This closely relates to Rinta-Kahila et al.'s (2023) concept of skill erosion. Despite its limitations, FL remains an important part of workforce development (Manuti et al., 2015). It is especially effective when combined with IL methods, ensuring employees can apply acquired knowledge in practical settings (Sparr et al., 2017).

2.4.2. Informal Learning

The importance of IL with its rather unstructured characteristics is widely acknowledged by researchers and considered an essential aspect within workplaces (Cerasoli et al., 2018; Jeong et al., 2018; Manuti et al., 2015; Watkins & Marsick, 2023). Eraut (2000) clearly articulates that IL should not be treated as a by-product of FL, but instead, its versatility and constant presence in workplaces should be acknowledged. Concrete activities of IL as cited by Marsick and Volpe (1999, p.4) involve *"teaming, meetings, customer interactions, supervision, mentoring, shift change, peer-to-peer communication, cross-training, exploration, on-the-job training, documentation, execution of one's job, site visits."* Cerasoli et al. (2018) add a further perspective to these activities, outlining that IL behavior, which refers to the actual behavior within such activities like observing colleagues, discussing, or asking questions, offers a resource-efficient alternative for skill development to FL initiatives, especially within rapidly changing business environments.

Although research identifies and classifies certain activities as IL, scholars emphasize that IL should be viewed in a much more complex and nuanced manner. Eraut (2000) describes that IL can occur on different intentional levels, ranging from completely implicit, mirroring non-intentional learning, to reactive learning, which appears as a response to a specific action and deliberate learning, where a clear learning goal is intentionally set. Jeong et al. (2018) expand on these aspects by emphasizing the multidimensionality of IL involving intentional levels, various actors and diverse cognitive processes. Moreover, Clardy (2018) underscores that learning is inherently embedded within work tasks themselves, such as learning while performing tasks and interacting at workplaces. Given these diverse forms and the continuous presence of IL in workplaces, several factors shape the application and outcome of IL.

Cerasoli et al. (2018) find that personal determinants, such as personality traits or demographics, along with situational factors, such as job attributes or organizational support like rewards, are impacting the outcomes of IL, such as attitudes or skill acquisition. For instance, individuals with a personality trait of openness to experience are more likely to engage in IL (Cerasoli et al., 2018). Additionally, the situational impact factors identified by Cerasoli et al. (2018) also closely align with Clardy's (2018) propositions, outlining that different jobs and tasks demand different types and levels of learning. For example, inexperienced employees might require more task mirroring while highly professional workers might require more structured learning opportunities (Clardy, 2018). Blume et al. (2024) add a further perspective

to these assertions by underscoring the crucial role of managers as facilitators for the actual transfer of acquired knowledge to the application on the job. For instance, managers can offer direct assistance, like concretely showing ways of applying learning, they may provide guidance, providing advice on future skills needed and managers are vital for emotional support, such as building confidence if employees face challenges in learning (Blume et al., 2024). Hence, research depicts that IL is not a standalone process but is impacted by various factors.

Aside from these various factors shaping and impacting IL, the distinction between IL and FL is criticized. Clardy (2018) challenges the assumption among a considerable body of research that IL holds greater importance than FL. Instead, the researcher advocates for a more nuanced perspective on workplace learning, recognizing the value of both FL and IL. Thereby, the scholar emphasizes the importance of creating a culture of learning and structuring such an environment, whether formal or informal, through establishing defined learning goals, providing learning materials and creating opportunities to connect with people (Clardy, 2018). Building on these broad perspectives on AI, skills and workplace learning, the following section presents a summary of our literature review.

2.5. Linking AI, Skills and Workplace Learning

To synthesize the insights from the research streams on AI, skills and workplace learning, this section introduces a theoretical lens that connects these domains and supports our conceptual framing. One frequently applied and recognized theory within literature on technological advances and skills is the sociotechnical systems (STS) theory (Chuang, 2024; Chuang et al., 2024; Engström et al., 2024; Li & Yeo, 2024; Trist, 1981). The theory underscores the importance of aligning technological aspects, such as technical tools or processes, and social aspects, such as employees and their skills, within organizations for mutual optimization of both elements (Trist, 1981). Trist (1981) argues that social and technical components should be balanced, as changes in one automatically impact the other. Additionally, both systems are impacted by environmental factors, such as organizational contexts or workplace adaptations (Chuang, 2024; Trist, 1981). The STS theory remains relevant within contemporary research, illustrated through the application by various authors. Chuang (2024) utilizes this theory to emphasize that firms should invest in developing human skills when implementing AI systems to improve both employee and firm performance. Li and Yeo (2024) employ the STS theory to analyze the impact of AI on work and internal processes. They further contextualize the theory

to derive recommendations for implementing AI tools in organizations. Engström et al. (2024) add that AI today presents more than a technological tool but also acts as agent within organizational systems. This recognition of AI as an agent, rather than a passive tool, advances our theoretical framing and informs the way we conceptualize the interaction between learning and technology.

However, viewed from a critical perspective, while the STS theory offers a valuable lens to examine this interplay between technological and social systems, it might overlook the capacity of organizations to respond symmetrically to technical change. As these technological changes, as well as environmental factors, emerge dynamically, organizational reactions may happen asymmetrically, a factor that the STS theory tends to understate. This asymmetry is particularly relevant in the context of AI adoption, where technical systems may evolve rapidly, while the social system may lag behind (Davenport & Ronanki, 2018). This complexity adds a nuanced perspective to our study by highlighting the dynamics between both systems and in what form consequences emerge when organizations fail to respond adaptively. Moreover, while the STS theory provides a systems-level view of the interaction between social and technical elements, it does not specifically provide insights into the individual employee level, which is the unit of analysis in our research. Nevertheless, similar to the way in which Chuang (2024) applies the theory to emphasize the importance of human skills and their development within organizations, we adopt the STS theory to guide the development of our conceptual framework. By synthesizing our findings on individual employees' learning experiences, the framework contributes to a more nuanced view of the way AI-related skill development unfolds within the broader sociotechnical system.

Furthermore, the STS theory provides a useful lens for advancing knowledge on how workplace learning influences employees' AI-related skill development, as both the technological system and the social system are core aspects of our research and therefore help to conceptualize the influence workplace learning has on the dynamics between AI adoption and skill development in an organizational setting. This theoretical lens provides a foundation for our conceptual framework, through which we explore the way workplace learning, particularly in response to AI, shapes the evolving dynamics between the social and technical systems within organizations.

2.6. Summary of Literature Review

Within the literature review, we outline AI's impact on workplaces, highlighting the transformation of work structures and job roles, with some tasks or roles being automated, while others require augmentation. While automation enhances efficiency, it also contributes to job displacement, particularly in routine-based jobs (Huang & Rust, 2018). Augmentation, in contrast, facilitates collaboration between AI and human workers but demands new skills, creating the need for AI-related skill development (Raisch & Krakowski, 2021). AI's integration into the workplace reshapes skill requirements, necessitating a mix of technical, human and conceptual skills (Zirar et al., 2023). Technical skills include AI literacy, data proficiency and the ability to interact with AI-driven tools (Jaiswal et al., 2021). Human skills, such as communication, collaboration and emotional intelligence, remain important, as they differentiate humans from AI (Sanders & Wood, 2023). Conceptual skills, including critical thinking, problem-solving and decision-making, allow employees to use AI systems meaningfully. To meet these changing skill demands, organizations recognize skill development through up- and reskilling as especially important. Workplace learning is categorized into FL and IL (Marsick & Volpe, 1999). FL may include structured training initiatives, certifications and courses, while IL can occur through on-the-job experiences, interactions between colleagues and self-initiated exploration (Manuti et al., 2015). Research highlights the necessity of integrating both learning approaches for skill development. We utilize the STS theory to conceptually link the literature streams of AI, skills and workplace learning. The STS theory emphasizes the alignment of technological and social systems within organizations and is applied in contemporary literature to explore aspects of human skill development alongside AI adoption.

In light of our literature review, we see increasing attention on the way AI reshapes workplaces, skills and learning in organizations, with the STS theory offering one conceptual lens through which these shifts can be framed. These contributions expand our knowledge on AI's impact, the skills required in response and workplace learning within organizations. However, we still see that empirical insights remain lacking when it comes to the individual-level learning experiences of employees adapting to AI in their work. There is limited research on how workplace learning influences employees' AI-related skill development, particularly in relation to the dynamics connected to AI adoption. This highlights the need to advance knowledge in this field, an area our study aims to address. Building on these insights, the following chapter outlines the methodology employed within our study.

3. Methodology

This chapter presents the methodology utilized within our thesis. First, we outline our philosophical foundations of relativism and social constructionism. Second, we highlight our research design of an inductively investigated qualitative study. Third, we show our research strategy of a single case study research. Fourth, we present our methods utilized, involving interviews, observations and secondary data. Finally, we outline our data analysis and quality.

3.1. Research Philosophy

Research philosophy describes the underlying beliefs and assumptions of us, as researchers (Easterby-Smith et al., 2021; Saunders et al., 2016). It is essential to reflect on our philosophical foundation, since it guides the research design, strategy and methods applied in our thesis. According to Easterby-Smith et al. (2021), research philosophy involves ontology and epistemology.

The ontology, the core of the research, represents the researchers' belief about reality. According to Easterby-Smith et al. (2021), it demonstrates what we, as researchers, consider as truth and how we view the world. Within the notion of ontology, we identify as relativists, recognizing that multiple truths exist and that facts depend on the observers' viewpoints (Easterby-Smith et al, 2021). According to Easterby-Smith et al. (2021), relativism is situated along a continuum between the extremes of realism, which asserts that only one truth exists and nominalism, stating that no truth exists and all facts are created by humans. Our relativist ontological assumptions surface primarily in two ways. First, we acknowledge various human viewpoints, recognizing that workplace learning and its influence on AI-related skill development may be interpreted differently by each employee. Therefore, we examine the perspectives of multiple employees to investigate the influence of workplace learning on AI-related skill development. Second, we acknowledge that several forms of workplace learning and skills exist. Hence, employees may have differing perspectives on IL and FL, as well as technical, human and conceptual skills, including their impact and relationship to each other.

The epistemology, which builds upon ontology and constitutes the researchers' beliefs about knowledge, depicts how we believe knowledge about truth is acquired (Easterby-Smith et al., 2021; Saunders et al., 2016). Concerning epistemology, we position ourselves as social

constructionists. Social constructionism connects to the ontological viewpoint of relativism and asserts that reality is created by people. Thereby, it emphasizes the relevance of acknowledging subjective viewpoints to foster knowledge of reality (Easterby-Smith et al., 2021). Considering these aspects, social constructionism stands in contrast to the epistemological perspective of positivism, which stresses that reality is external and objective, linking to the ontological viewpoint of realism (Easterby-Smith et al., 2021).

Beyond aligning with our relativist ontological belief, further characteristics of social constructionism coincide with our research. Easterby-Smith et al. (2021) state that from a social constructionist perspective, researchers actively take part in the research process. This corresponds with our research, since we conduct interviews and observations. Furthermore, social constructionists seek to enhance general comprehension of situations. This aligns with our research, as we investigate initiatives within workplace learning to comprehend their influence on employees' AI-related skill development (Easterby-Smith et al., 2021). Moreover, social constructionists collect in-depth data to generate insights, often from a small number of cases. This coincides with our choice of case study research for detailed investigation within a specific context (Saunders et al., 2016). Additionally, social constructionism acknowledges multiple perspectives and the complexities of situations. As stated, we consider insights from various employees and recognize varying forms of workplace learning and skills. Nevertheless, social constructionism also presents weaknesses, such as difficulties in accessing data or synthesizing the diverse information collected. We address these challenges by fostering close collaboration with our case, collecting and analyzing data in a structured way, as well as continuously discussing findings and interpretations (Easterby-Smith et al., 2021). Taken together, we adopt the ontological belief of relativism with the epistemological view of social constructionism.

3.2. Research Design

The research design of a study outlines a general plan for the way a research question will be answered (Saunders et al., 2016). In the context of our research, we conduct a qualitative study. Qualitative studies primarily draw on non-numerical data, such as spoken words, written text, or visuals and thereby contrast with quantitative studies, which focus on gathering numerical data (Collis & Hussey, 2021). This characteristic aligns with our investigation of collecting non-numerical data through semi-structured interviews, observations and secondary data analysis. Moreover, qualitative data typically presents rich and complex insights that may

involve multiple meanings based on individual perspectives (Bell et al., 2022; Saunders et al., 2016), which further connects to our research. Congruent with these aspects and our social constructionist philosophical stance, we explore AI-related skill development utilizing multiple data sources and incorporating various employee viewpoints. Additionally, qualitative research allows us to remain flexible, formulate open-ended questions and adjust our investigation based on the participants' responses during interviews and observations (Bell et al., 2022; Saunders et al., 2016).

Moreover, our research design follows an exploratory purpose. This is evident for several reasons. First, exploratory research questions often start with *how or what* (Saunders et al., 2016). This aspect aligns with our research question of how workplace learning influences employees' AI-related skill development. Second, exploratory research aims to obtain new insights into a topic where the phenomenon is insufficiently explored (Saunders et al., 2016). In the context of our research, this can be related to the limited academic discourses centering around AI-related skill development, highlighting the need for further investigations and data on training methods (OECD, 2023; Zirar et al., 2023). Third, exploratory research often involves in-depth interviews to capture the distinct experiences of participants (Saunders et al., 2016). Therein, our study employs semi-structured interviews, allowing the inclusion of additional questions alongside the interview guideline based on the participants' responses. Nevertheless, the exploration of qualitative data can also be difficult due to the level of flexibility and planning required throughout the research process (Easterby-Smith et al., 2021). We address this challenge by setting clear criteria for each research step as well as allocating sufficient time for planning and incorporating our interpretations within the research process.

Furthermore, it is important to consider in which way theory is utilized and developed within research (Saunders et al., 2016). Theory development refers to the way data is organized and interpreted to derive conclusions from it, a process that involves different forms of reasoning (Easterby-Smith et al., 2021). In our research, we reason inductively. Inductive reasoning describes that researchers start by collecting data through which theory is built after data analysis (Saunders et al., 2016). However, within this notion, Saunders et al. (2016) highlight that inductive reasoning does not disregard existing theories and that researchers can still familiarize themselves with existing frameworks to constitute the research question and research process. The authors argue that most researchers start with some form of theory within their research investigation (Saunders et al., 2016). Additionally, inductive reasoning is frequently used for research topics that are new with little existing research (Easterby-Smith et

al., 2021; Saunders et al., 2016). Within our thesis, we utilize existing theoretical knowledge to support our research investigation, while allowing ourselves to inductively investigate the limited research area of how workplace learning influences employees' AI-related skill development. This allows us to explore what the empirical data reveals, aiming to generate new theoretical contributions within this specific research phenomenon. Nevertheless, as Saunders et al. (2016) point out, inductive reasoning often involves a longer and more uncertain process of data collection and analysis. To address the limited timeframe of our thesis, we establish a clear data analysis structure early on and prioritize timely coding and synthesis after each interview.

3.3. Research Strategy

A research strategy can be described as the methodological link between research philosophy and the choice of methods for data collection and analysis (Denzin & Lincoln, 2017; Saunders et al., 2016). Within our thesis, a case study strategy is applied. Case studies refer to the in-depth investigation of a phenomenon within its specific context, whereby the case as such may be a person, group, business, process, event, or other subjects (Saunders et al., 2016; Yin, 2014). Within case study research, we adopt a single case study. Single case studies focus on an in-depth inquiry of one specific case, which contrasts with multiple case studies, focusing on comparability across cases (Saunders et al., 2016).

3.3.1. Single Case Study Rationale

We chose to conduct a single case study to gain in-depth, rich and contextual insights into the underexplored research phenomenon of how workplace learning influences employees' AI-related skill development. Given that single case study research allows for in-depth exploration of one specific setting (Saunders et al., 2016; Stake, 1995), this research strategy is particularly valuable for our study, as the phenomenon of AI-related skill development in organizations remains underexplored and insufficiently studied. Existing research offers limited insights into skill development and the way those skills are shaped through workplace learning, making an in-depth, contextualized exploration essential. This aspect is further underlined by Yin (2014), highlighting that single case studies are especially appropriate when the research seeks to gain detailed, contextual insights into a social phenomenon within its specific context. Thereby, rather than aiming for breadth and comparing across cases (Saunders et al., 2016), we aim for depth and richness to capture the complexity and nuances of AI-related skill development within one specific case (Stake, 1995).

Furthermore, conducting a single case study also reflects our exploratory research design, where a single case study allows us to uncover insights where theory is still emerging (Saunders et al., 2016). Similarly, conducting a single case study also corresponds with our epistemological stance of social constructionism, as this research strategy allows us to investigate multiple perspectives and socially constructed viewpoints in-depth. Easterby-Smith et al. (2021) state that social constructionist case studies involve direct contact, observation and data collection from multiple sources within a single case. These aspects are in line with our research investigation and allow us to explore the rather unknown phenomenon within a single case study. Direct contact is achieved by conducting interviews, rapport building at the beginning of each interview and weekly meetings with our case's contact person. Furthermore, we conduct observations, which offer an additional lens to advance our knowledge of workplace learning. These observations complement the interview data by allowing us to capture behaviors, interactions and contextual factors that might remain implicit or unspoken during interviews. Interview and observational data are gathered from multiple employees across departments and job roles. In total, we retrieve information from three bases, namely interviews, observations and secondary data on company training and learning material. This allows us to obtain insights from current perceptions while also acknowledging retrospective information (Easterby-Smith et al., 2021). Thus, given these considerations, we deem a single case study as a particularly well-suited research strategy for answering our research question.

Nevertheless, beyond our rationale for conducting a single case study, it is also important to reflect on the weaknesses associated with this research strategy (Saunders et al., 2016; Yin, 2014). A common challenge presents the criticism around a single case study's validity (Saunders et al., 2016). However, in line with the social constructionist perspective of Stake (1995), we enhance validity by employing data triangulation through enriching interview data with observational and secondary data, while also incorporating data interpretation perspectives from both of us as researchers. Another challenge of single case study research links to the difficulties of comprehending in-depth data and gaining access to the case study setting (Saunders et al., 2016). We address this challenge by implementing a structured plan for data collection and clearly defining our case context, research question and unit of analysis (Yin, 2014).

3.3.2. Single Case Study Selection

To identify a suitable case study, we followed three steps. First, several authors repeatedly exemplify companies implementing AI-related skill development initiatives, which initiated our first research on potential companies (Brown et al., 2024; Goel et al., 2022; Tamayo et al., 2023). Second, we reach out to Sweden's National Center of AI, as well as a large nearby innovation hub and our university's industry collaboration network, to identify further case study options. This results in the third step of iteratively researching, identifying and contacting organizations via email and LinkedIn.

Our selection criteria for approaching companies were guided by several considerations to ensure the suitability of our case for in-depth investigation. Primarily, we focus on organizations demonstrating active involvement in AI-related skill development through workplace learning initiatives to develop AI-related skills among employees, either in the past or currently ongoing. Beyond this core criterion, we seek companies that offer access to a diverse range of employees across departments, roles and levels of seniority, allowing us to capture multiple perspectives on AI-related skill development. Moreover, the companies need to be willing to actively participate in our research, including engagement in interviews, opportunities for observation and the provision of relevant materials or data. In addition, we consider the longevity of the companies' AI initiatives, aiming to capture settings where skill development is an ongoing and relevant topic rather than a completed or conceptual project. Taken together, these criteria allow us to identify suitable cases where AI-related skill development is both practically embedded in work practices and accessible for empirical research. In total, we contact three companies that align with these selection criteria. While the response rate is low, our selected case shows strong interest and meets our criterion. Therefore, we continue collaboration with this case.

3.3.3. Single Case Study Context

The case selected for our study is a specialized business unit, presenting an integral part of a larger corporate group. To ensure complete anonymization, we utilize the term *Company X* within our thesis, referring to this specific business unit. Company X operates within the ICT industry, developing a range of different digital services across products within the corporate group.

Company X has several internal learning platforms in place, specific AI-related skill development initiatives have already been introduced and upcoming learning initiatives are planned. Past internal initiatives include hackathons, webinars and meetings centered around AI-related skill development. External providers are additionally utilized by Company X in the form of learning platforms, seminars, or certification programs. Currently, the usage of different AI technologies varies across departments and roles, which creates a rich ground for investigation, capturing various perspectives centered around AI-related skill development. Company X employs approximately 1000 employees, with its headquarters located in Northern Europe. In addition to its main office, Company X maintains three further international sites, enabling cross-border collaboration and reflecting its global scope of operations. Its workforce is characterized by a high degree of professional diversity, ranging from software developers to roles in human resources and communications. As Company X employs a considerably high number of employees and operates globally, this allows us to collect data from employees in various departments, job roles and areas of expertise.

Operating within the ICT industry situates Company X in a highly dynamic sector, where technological advancements and digital innovation play an important role in creating competitive advantage. The ICT industry is characterized by fast-paced development cycles, increasing reliance on data and connectivity and the growing need for specialized digital skills among employees (OECD, 2019a). Organizations within this industry face constant pressure to innovate, adapt to emerging technologies such as AI and create continuous learning cultures to remain competitive (WEF, 2025). Therefore, conducting research within the ICT industry represents a *critical case* for AI-related skill development (Yin, 2014). As one of the rather AI-mature sectors, ICT allows us to explore the way organizations already navigating AI adoption utilize workplace learning. While we acknowledge that ICT firms may be more AI-aware than other industries that do not specifically focus on technology, this positioning offers rich ground for research. It allows the identification of mechanisms that may become relevant in other industries as AI adoption expands. Thus, our findings are not intended to be statistically generalizable but rather analytically generalizable (Yin, 2014), offering insights from this particular case, which can inform both theory and practice in similar organizational settings. Overall, the ICT industry provides a particularly relevant setting for investigating AI-related skill development, as the demand for those skills is not limited to technical experts but increasingly extends across diverse organizational roles (WEF, 2025). Therefore, given these considerations, we deem Company X a well-suited case for conducting our research.

3.4. Methods

Easterby-Smith et al. (2021) and Saunders et al. (2016) provide extensive insights for research methods in management and business studies. They emphasize the importance of aligning research methods with epistemological and ontological positions to ensure methodological coherence. Easterby-Smith et al. (2021) argue for structured qualitative research that emphasizes methodological accuracy, highlighting the importance of techniques such as case studies, interviews and observations to generate in-depth insights into complex business phenomena. Easterby-Smith et al. (2021) further emphasize the value of reflexivity in the research process, ensuring coherence between epistemological positions and data collection methods while enhancing the credibility and trustworthiness of qualitative research. Similarly, Saunders et al. (2016) highlight adaptability in research design, ensuring flexibility in selecting methods that align with the research objectives. Easterby-Smith et al. (2021), as well as Saunders et al. (2016), highlight the importance of methodological coherence in business research, supporting structured data collection and analysis techniques that generate credible findings.

3.4.1. Data Collection

In line with Easterby-Smith et al. (2021) and Saunders et al. (2016), we utilize multiple sources of data to enhance the credibility and depth of our findings. Primary data is gathered through interviews, which are then enriched by observations, allowing for an exploration of participants' experiences and contextual factors. Additionally, secondary data, including archival documents such as training material and company reports, provides further insights that contribute to the exploration of the phenomenon. While interviews serve as the main source of data and form the core of the analysis, observations and secondary documents are used to enrich and contextualize our findings. This aligns with our research question and the aim to advance academic and practical insight into the phenomenon of AI-related skill development. This form of data collection allows us to gain insights into Company X by utilizing multiple sources of data. Given the characteristics of qualitative research, data collection remains adaptive to practical conditions (Yin, 2018). Flexibility in the data collection process allows for the incorporation of emerging insights while maintaining methodological accuracy. The following sections will further detail the procedures and considerations specific to primary and secondary data collection.

3.4.1.1. Primary Data

Interviews

Interviews are one of the most common qualitative research techniques, especially in case studies, as they allow for an in-depth exploration of participants' perspectives, interpretations and experiences (Easterby-Smith et al., 2021; Yin, 2018). Interviews provide a direct source of information and are beneficial for comprehending individuals' viewpoints on specific topics, including their attitudes, behaviors and decision-making processes (Saunders et al., 2016). As an essential tool for qualitative research, interviews allow researchers to gather insights into complex social and organizational dynamics that would be difficult to capture through other methods (Thomas, 2017).

For our study, semi-structured interviews are chosen as the primary data collection technique. According to Easterby-Smith et al. (2021), semi-structured interviews are particularly effective when the objective is to explore participants' perspectives in detail while maintaining some level of structure. This interview format allows researchers to prepare a set of pre-determined questions while also providing flexibility to ask follow-up questions when necessary. This balance ensures that key themes are covered while allowing participants to elaborate on their thoughts and experiences (Thomas, 2017). The semi-structured format is especially useful when addressing *how* and *why* questions, as it allows the interviewer to go more in-depth regarding specific responses and to explore underlying meanings (Yin, 2018). A purposive sampling strategy is applied to ensure that participants are selected based on their relevance to the research question (Easterby-Smith et al., 2021). A total of 15 interviews are conducted with employees who are currently employed at Company X and have been with the company for at least six months, ensuring that all participants have sufficient familiarity with the organization's culture, structure and processes. This minimum employment duration is chosen to ensure that interviewees have meaningful experiences to share regarding the research topic. Participants are chosen from different departments, positions and genders to ensure a diverse range of perspectives and insights. This helps us to capture experiences, perspectives and potential challenges faced by employees at different organizational levels (Saunders et al., 2016). A diverse sample is important for avoiding a one-dimensional perspective and enhancing the validity of findings by incorporating multiple viewpoints (Easterby-Smith et al., 2021). To facilitate recruitment, a key contact within the company assists in identifying employees who meet the inclusion criteria. Once potential participants are identified, they are invited to take

part in our study via email. Table 3 showcases an overview of the participants, their characteristics, as well as the duration of each interview. Participants' names are removed and each respondent is assigned a unique identifier (P1, P2, etc.). These same identifiers are used in our findings section to ensure both clarity and confidentiality.

Interview Overview						
No.	Age	Nationality	Gender	Position	Employment Tenure	Interview Duration
P1	41	U.S. American	male	Software Engineer	2 years	44 minutes
P2	30	Indian	female	Software Engineer	9 years	43 minutes
P3	40	Indian	female	Software Engineer	4 years	39 minutes
P4	36	Indian	female	Software Engineer	4 years	45 minutes
P5	32	Indian	male	Product Owner	1.5 years	53 minutes
P6	43	U.S. American	female	Software Engineer	8 months	46 minutes
P7	38	Indian	female	Software Engineer	3 years	42 minutes
P8	29	Swedish	male	Business Analyst	2.5 years	40 minutes
P9	44	Swedish	male	Business Analyst	1.5 years	56 minutes
P10	45	Swedish	male	Communication Manager	1.5 years	42 minutes
P11	31	Swedish	male	Software Engineer	2 years	58 minutes
P12	39	Swedish	female	Talent Outreach Communicator	4 years	45 minutes
P13	52	Swedish	male	Business Analyst	3 years	49 minutes
P14	29	Iranian	male	Software Engineer	2 years	42 minutes
P15	36	Swedish	male	Senior Solutions Architect	5.5 years	53 minutes

Table 3: Interview Overview (own table)

Informed consent is obtained from all participants before the interviews commence, ensuring voluntary participation and confidentiality following research ethics guidelines (see Appendix 1) (Saunders et al., 2016). All interviews are conducted online via the video conferencing platform *Microsoft Teams*, which allows for greater accessibility of international employees and flexibility while ensuring the richness of discussion is maintained (Saunders et al., 2016). To create a comfortable and open discussion environment, interviews begin with rapport building, a process where the interviewer engages in small talk to help the participant feel at ease (Thomas, 2017). Informal conversational topics, such as recent holidays or how the participants' day has been so far, are introduced as a form of rapport building before

transitioning into the core interview questions. Establishing trust and rapport is essential in qualitative research, as it encourages participants to share more openly and provide detailed responses (Easterby-Smith et al., 2021). Before beginning the formal questioning, each interview starts with a brief presentation, where participants are informed about the purpose of our study, the confidentiality of their responses, their rights as participants, and in which way the data is used (see Appendix 2). This introduction ensures transparency and helps establish trust between the interviewers and interviewees.

The interview guideline is outlined to ensure a balance between structured and exploratory questioning. The interview questions are based on insights from the literature review, formulated to align with our study's research objectives and designed to allow for flexibility in exploring participants' experiences (see Appendix 3). The interview guideline includes open-ended questions that allow participants to elaborate on their experiences, along with questions to clarify or expand on certain topics (Saunders et al., 2016). This ensures that the interviews remain focused while allowing flexibility for participants to express their thoughts in their own words. To minimize interviewer bias and ensure consistency across interviews, a standardized protocol is followed. Both researchers are present in each interview, actively asking questions and subsequently taking observational notes to ensure reflexivity, minimize bias and enhance the reliability of the collected data. Each interview lasts between 39 and 58 minutes, a duration considered optimal for maintaining participant engagement while giving enough time to explore main themes in depth (Easterby-Smith et al., 2021). In total, the interviews resulted in 11 hours and 37 minutes of recorded material. While we do not claim full data saturation, common insights across the final interviews consistently become visible, with fewer new findings emerging. This suggests that we may have reached a sufficient depth of perspectives for our research purpose, while still capturing variation across roles.

All interviews are audio- and video-recorded with participant consent to ensure that responses are accurately captured (Yin, 2018). After each interview, the recordings are transcribed using the tool *MaxQDA* to facilitate detailed analysis. According to Thomas (2017), transcribing interviews allows for a more structured review of responses, making it easier to identify patterns, themes and variations across participants. In addition to transcripts, field notes taken during interviews are used to capture non-verbal signals, emotions and contextual factors that could provide additional layers of meaning (Saunders et al., 2016). This is specifically important in cases where body language, pauses, or tonal variations suggest nuances that might not be explicitly stated in the transcript. To ensure confidentiality, all interview data are

anonymized before analysis. The raw data, including recordings and transcripts, are securely stored and only accessible to us. Additionally, data storage and handling adhere to General Data Protection Regulation (GDPR) standards to ensure compliance with ethical and legal requirements (Saunders et al., 2016). To strengthen the validity and reliability of the research findings, member-checking is conducted during and after interviews. This technique involves summarizing key points with participants at the end of each interview to ensure that their responses are accurately understood and interpreted (Saunders et al., 2016). By allowing participants to verify or clarify their statements, member-checking contributes to the trustworthiness of the data and minimizes misrepresentation of their perspectives. Nonetheless, interviews are limited by participants' ability and willingness to articulate their experiences. We address this by combining interviews with observational and secondary data to strengthen credibility. The following section will discuss primary data collection through observations, which will complement the insights gathered from interviews by providing contextual and behavioral data.

Observations

Observation is a widely used qualitative research method that allows researchers to capture behaviors, interactions, and contextual factors in their specific settings (Easterby-Smith et al., 2021). Unlike interviews, which rely on participants' self-reported experiences, observations provide direct insights into the way individuals behave within a specific environment. This method is particularly useful for observing organizational processes and group dynamics, as it allows researchers to examine patterns of interaction as they unfold (Saunders et al., 2016). Observations play an essential role in case study research, as they provide contextual insights that participants might not explicitly articulate (Yin, 2018). Stake (1995) emphasizes that observations help researchers to capture nuances that may be difficult to express verbally. However, he also cautions that interpretations of observed behavior can vary among researchers, making it essential to document observations systematically to enhance reliability and consistency (Easterby-Smith et al., 2021). For our study, the observer-as-participant method is chosen, as it allows researchers to observe interactions in the workplace while minimizing disruptions to natural behavior (Easterby-Smith et al., 2021). This allows us to examine communication patterns, team dynamics and learning processes while ensuring that participants are aware of the observation but not considerably impacted by it. The method is particularly suited for capturing authentic workplace interactions without excessive interference from the researchers.

In the context of our research, three observations are conducted. Two observations are conducted with a specific focus on individual learning behavior. These observations, referred to as Observation 1 (O1) and Observation 2 (O2), capture the way employees engage with digital learning platforms during their workday. O1 lasts 46 minutes and O2 lasts 43 minutes. In both cases, a single participant shares their screen while navigating learning materials on internal and external workplace learning platforms. During O1, the participant completes a self-assessment, reviews their personalized learning path, plans learning modules in preparation for an upcoming certification and explores newly available learning content. O2 focuses on the participant's engagement with a specific learning module aimed at developing AI-related skills. The participant navigates through a structured module on an internal learning platform. Throughout the session, the participant shares their screen, allowing for an observation of their interaction with the content. In addition to completing the assigned module, the participant proactively seeks out supplementary resources by exploring a second learning platform and searching for related explanatory videos on YouTube.

Additionally, another observation is conducted to capture team-level dynamics during a meeting focused on AI tooling and its impact on internal metrics. Observation 3 (O3), lasting 60 minutes, brings together a cross-functional group of employees, with a noticeable presence from data-oriented roles. The meeting is led by a key responsible for AI adoption, who presents current developments and engages participants in discussions around AI tools. While the primary objective of the meeting is to evaluate the use and effectiveness of these tools through usage metrics, the conversation also touches on issues indirectly related to AI literacy, developer practices and the challenges of assessing technical engagement. Although not explicitly framed as a learning session, the observation provides valuable insights into employee discussions, interpretations and criticism surrounding AI initiatives, offering contextual information that supports the interview findings and the prior observations of individual learning behavior. However, access to observations is limited to those three specific sessions, and as such, might overlook further workplace learning behavior. During all observations, which last in total 2 hours and 49 minutes, we mitigate this by taking detailed field notes to document interactions, environmental factors and relevant contextual details. Field notes play a substantial role in structuring observational data and ensuring that insights are accurately captured (Easterby-Smith et al., 2021). Table 4 showcases an overview of the observations and their specific characteristics.

Observation Overview		
No.	Type of Observation	Observation Duration
O1	Observation of Individual Learning Behavior	46 minutes
O2	Observation of Individual Learning Behavior	43 minutes
O3	Observation of AI Tool Impact Metrics Meeting	60 minutes

Table 4: Observation Overview (own table)

Stake (1995) suggests that observational data collection should follow a structured process, including initial notes made during the session, expanded field notes written shortly after and theoretical reflections where researchers analyze the observed patterns. To ensure the reliability of the data, we independently take notes during observations before discussing them. This method helps minimize potential biases and allows for multiple perspectives on the same events (Stake, 1995). Once the individual observations are documented, they are synthesized to identify common themes and any discrepancies, reinforcing the credibility of our findings (Easterby-Smith et al., 2021). The collection of primary data results in a total of 14 hours and 6 minutes of material. The next section discusses secondary data collection, which complements the primary data by providing additional context and supporting evidence.

3.4.1.2. Secondary Data

Secondary data refers to information that has been previously collected by external sources outside of our study and is used to complement primary research (Easterby-Smith et al., 2021; Saunders et al., 2016). It provides valuable contextual background, helping researchers validate findings from interviews and observations while offering additional insights into the research topic. Secondary data can take various forms, including company reports, official documents, websites and available publications (Saunders et al., 2016). For our study, secondary data is collected from multiple sources, including company reports, internal documents, as well as external learning material utilized by Company X (see Table 5). Company X's public website provides valuable insights into its mission, values and operational structure, while internal reports and learning materials offer a more detailed perspective on workplace learning and initiatives. However, careful evaluation of secondary sources is necessary to ensure the reliability and accuracy of the information used (Saunders et al., 2016). Consideration is given to the authenticity, relevance and recency of the data to avoid potential biases or outdated information (Easterby-Smith et al., 2021). By integrating secondary data with interviews and observations, our study offers further perspectives on the research topic.

Secondary Data Overview			
No.	Content	Data Type	Availability
S1	AWS Immersion Days	Website	Publicly available
S2	AWS Skill Builder	Website	Publicly available
S3	European Cyber Security Month	Website	Publicly available
S4	AI Champions Network	3 PowerPoint Presentations	Internal Documents
S5	AI Hackathons	5 PowerPoint Presentations	Internal Documents
S6	AWS Trainings and Certifications	12 PDF Documents	Internal Documents
S7	Developer Experience Center	12 PDF Documents	Internal Documents
S8	Cyber Security Month	18 PDF Documents	Internal Documents
S9	AWS Summit	1 PowerPoint Presentation	Internal Document
S10	Risk Assessment Training	1 PowerPoint Presentation	Internal Document

Table 5: Secondary Data Overview (own table)

3.4.1.3. Triangulation

To strengthen the validity of our study and reduce potential bias, data triangulation is applied (Saunders et al., 2016). Triangulation involves using multiple sources of data to cross-verify findings, ensuring that conclusions are not based on a single perspective but rather on a combination of complementary insights (Easterby-Smith et al., 2021). This enhances the credibility and reliability of qualitative research by identifying consistencies and discrepancies across different data sources (Yin, 2018). Since employees' perceptions and workplace experiences are shaped by various organizational influences, such as company policies and team dynamics, it is essential to incorporate multiple perspectives (Stake, 1995). Our study applies triangulation by combining interviews, observations and secondary data. While interviews represent the primary source of data and form the core of the analysis, observations and secondary data are used to enrich, contextualize and cross-check the interview findings. Observations provide insights into employees' learning behavior in practice, while secondary data, such as company documents and learning materials, offer contextual background and help validate participants' descriptions (Easterby-Smith et al., 2021). Thus, triangulation in our study does not imply equal weighting of all data sources but rather reflects a complementary use of data sources, where different types of data contribute to a broader perspective on the research phenomenon (Stake, 1995; Yin, 2018). This enhances the credibility of our findings by enabling the consideration of multiple perspectives within the single case context.

3.4.2. Data Analysis

Analyzing qualitative data in a structured manner ensures findings are credible, well-organized, and aligned with the research objectives (Easterby-Smith et al., 2021; Saunders et al., 2016). In our thesis, we apply grounded analysis as outlined by Easterby-Smith et. al (2021). This form of data analysis ensures that our findings emerge directly from the data rather than being shaped by predefined categories or theoretical assumptions (Easterby-Smith et al., 2021). Grounded analysis is well-suited for our exploratory research design, as it grants flexibility and openness to new insights while maintaining a structured way of making sense of qualitative data (Easterby-Smith et al., 2021).

It is important to note that grounded analysis is not equivalent to grounded theory, despite their similar terminology and relations (Easterby-Smith et al., 2021). Grounded theory, originally developed by Glaser and Strauss (1967), presents a rigorous and comprehensive research strategy that emerged as a response to the prevalence of scientific positivist methodologies in social research (Denzin & Lincoln, 2017; Suddaby, 2006). In contrast, grounded analysis, as described by Easterby-Smith et al. (2021), demonstrates a data analysis method to inductively move from data to theory.

While we acknowledge the connection to grounded theory, we point out that we do not intend to develop grounded theory as such (Easterby-Smith et al., 2021). As Suddaby (2006) notes, grounded theory is a comprehensive and demanding research methodology, involving core attributes and specific techniques. Instead, we use the term grounded analysis to describe our effort to ground the theory development in our collected empirical data (Saunders et al., 2016). In doing so, we allow our empirical data to speak for itself without constraining ourselves to pre-existing codes and theoretical assumptions. This process, in turn, aligns with our constructionist epistemology and exploratory, inductively reasoned qualitative single case study.

Easterby-Smith et al. (2021) propose the below mentioned seven steps for grounded analysis, which allows us to transition from unstructured qualitative data to a list of initial codes and more abstract analytical categories to ultimately derive aggregated conceptual dimensions (Easterby-Smith et al., 2021; Saldaña, 2015). Therefore, we follow the seven steps employed by Easterby-Smith et al. (2021).

1. Our data analysis begins with *familiarization*, where we carefully review all interview transcripts. This step allows us to gain an initial perception of the data and recognize emerging themes without applying external structures. To enhance engagement with the material, we take additional notes on reflections that arise during this phase.

2. Next, we engage in *reflection*, a phase in which we critically examine the initial impressions formed during familiarization. This step helps us remain open to the complexity of the data while ensuring that our interpretations are guided by what the participants express rather than by our own assumptions.

3. We then proceed with *open coding*, where we break down the data into smaller segments and assign descriptive labels to capture their meaning. While we do not apply predefined codes, the coding process is guided by theoretical sensitivity, allowing us to remain open to emerging insights from the data while also being informed by concepts and themes identified in the literature. In our analysis, this results in first cycle codes.

4. Once the initial codes are established, we move to *conceptualization*, where we analyze the relationships between codes to form broader categories. This involves comparing and grouping codes that share common characteristics, identifying themes across different data sources and refining categories based on their importance. In our analysis, this results in second cycle categories.

5. After establishing key categories, we conduct *focused re-coding* to refine our initial coding structure. This step involves re-examining our data with a more defined set of codes, ensuring that emerging patterns are consistently identified across all conducted interviews.

6. We then focus on *linking*, where we explore the relation of the main themes to one another and what broader patterns emerge. By comparing different categories, we look for connections, contradictions and overarching trends. In our analysis, this results in aggregated dimensions.

7. Finally, we engage in *re-evaluation*, ensuring that our interpretations are grounded in the data. We revisit our categories and codes, assessing whether they accurately reflect the collected data. If necessary, we refine our coding structure further.

Throughout this process, we also engage in triangulation, synthesizing findings from interviews, observations and secondary sources to ensure consistency and credibility (Yin, 2018). Figure 3 showcases the overall coding structure.

First Cycle Codes	Second Cycle Categories	Aggregated Dimensions
Gradual Adaptation to AI Productivity Gains through AI AI as Collaborative Assistant	Integrating AI into Work	Adoption of AI in the Workplace
Cautious Engagement with AI Hesitation and Resistance Related to AI Adoption Environmental Concerns Regarding AI	Critical Reflections on the Use of AI	
Differing AI Knowledge Levels Understanding the Concept AI	Building Foundational AI Knowledge	Transformation of Knowledge and Skills through AI
Relevance of Prompting Skills Importance of Domain Knowledge Need of Human Touch when Working with AI	Evolving Skill Requirements due to AI	
Learning through Internal Opportunities Learning through External Providers Highlighting the Need for Advancing Formal Initiatives	Opportunities within Formal Learning	Dynamics within Workplace Learning
Learning through Experimentation and Usage Knowledge Sharing and Collaborative Learning Self-directed Learning through External Platforms	Opportunities within Informal Learning	

Figure 2: Coding Structure Overview (own figure)

3.4.3. Data Quality

Ensuring data quality is a fundamental aspect of qualitative research, as it directly affects the credibility and trustworthiness of a study (Easterby-Smith et al., 2021). The quality of qualitative research depends on the way we design, conduct and document our work, from the initial research proposal to the final presentation of findings. Transparency and accuracy in these processes help establish confidence in a study and reduce concerns regarding potential biases or misinterpretations (Easterby-Smith et al., 2021). However, qualitative research also presents challenges, as findings are derived from interactions with specific individuals at moments in time, making direct replication difficult.

To address these challenges, Guba (1981) identifies four key criteria for ensuring trustworthiness: credibility, transferability, dependability and confirmability. These factors provide a structured framework for evaluating the quality of qualitative studies and ensuring that findings are reliable and reflective of participants' experiences (Easterby-Smith et al., 2021). The following sections outline each criterion.

3.4.3.1. Credibility

Credibility refers to the extent to which research findings accurately represent the perspectives and experiences of participants while ensuring that the interpretations made by researchers remain trustworthy and reasonable (Easterby-Smith et al., 2021; Guba, 1981). To establish credibility, it is essential that the research process is transparent, structured and reflective of the data collected. This involves aligning the research design, data collection and analysis with established qualitative research principles while maintaining a strong connection between participant responses and the final interpretations. We enhance credibility through triangulation, integrating interviews, observations and secondary data to cross-verify findings and minimize bias. Iterative questioning is utilized during interviews to clarify responses and explore topics in-depth (Saunders et al., 2016). Both researchers are involved in data collection and analysis, ensuring consistency and reducing subjective interpretation. Additionally, we maintain transparent documentation of coding and data structure development, continuously comparing findings with the original data and relevant literature. These measures strengthen the reliability of our findings and ensure that our study accurately represents participant experiences.

3.4.3.2. Transferability

Transferability refers to the extent to which research findings can apply to other contexts (Guba, 1981). While qualitative research does not aim for statistical generalizability, providing detailed contextual information allows others to assess its relevance to their studies (Easterby-Smith et al., 2021). Since researchers cannot determine transferability beyond their study, transparency allows readers to make informed judgments (Saunders et al., 2016). To enhance transferability, we provide details about Company X, participant characteristics and research setting. Additionally, we offer detailed information about data collection and analysis, allowing others to replicate or adapt our methodology. By outlining influencing factors, we enable future research to explore similar contexts and build upon our results (Easterby-Smith et al., 2021).

3.4.3.3. Dependability

Dependability refers to the consistency and stability of research findings over time, ensuring that a study's process is structured and well-documented (Guba, 1981). While qualitative research does not require findings to be identical if repeated, it is vital that the research process remains transparent and traceable (Guba, 1981). To enhance dependability, we provide a detailed outline of our research design, data collection and analysis procedures, allowing future

researchers to follow the same steps and assess the reliability of our research (Easterby-Smith et al., 2021). One way to strengthen dependability is by using overlapping methods, where different data collection techniques complement each other (Guba, 1981). By integrating semi-structured interviews, observations and secondary data, we ensure that findings are supported by multiple sources, reducing the risk of inconsistencies. Additionally, we maintain a clear and structured documentation process, recording each stage of our study to ensure that data collection and analysis align with the research design (Saunders et al., 2016). These measures improve the transparency and replicability of our study, reinforcing the trustworthiness of our findings.

3.4.3.4. Confirmability

Confirmability ensures that research findings are derived from the data rather than impacted by researchers' biases or subjective interpretations (Guba, 1981). It ensures that conclusions accurately reflect participants' perspectives and experiences. To strengthen confirmability, both researchers are actively involved in data collection and analysis. All interviews are conducted by two researchers, recorded and transcribed to ensure accuracy and prevent misinterpretation. Member-checking is also conducted at the end of each interview to validate participants' responses. During analysis, coding is performed separately before comparing results, reducing the risk of individual bias in code identification. Additionally, detailed documentation of all methodological decisions is maintained, ensuring transparency in data analysis and drawing conclusions (Saunders et al., 2016).

3.4.4. Ethical Considerations

Ethical considerations are fundamental in ensuring the integrity of research and the protection of participants throughout the study process (Easterby-Smith et al., 2021). Researchers should conduct studies responsibly, balancing data collection with ethical responsibilities to participants, institutions and the wider research community. A core ethical principle in research is to do no harm, which requires researchers to obtain informed consent, maintain confidentiality, ensure anonymity and safely handle collected data (Easterby-Smith et al., 2021). Additionally, ethical reflexivity is necessary, as researchers should constantly assess their potential impact on a study and mitigate biases that could shape findings (Saunders et al., 2016).

To uphold ethical standards, all participants provide informed consent before data collection. We use an opt-in approach, ensuring that individuals voluntarily agree to participate after receiving detailed information about our study's purpose, their rights and the way their data will be handled. Participants are explicitly informed of their right to withdraw at any time, in which case all associated data will be deleted (Thomas, 2017). Anonymity is ensured by assigning code names to all participants. Confidentiality is maintained through secure data storage. All interview recordings, transcripts and notes are digitally stored, so that they are only accessible to the researchers. This measure aligns with best practices in data protection and ensures compliance with ethical research guidelines (Easterby-Smith et al., 2021). Another key ethical challenge in qualitative research is maintaining neutrality in reporting findings. Researchers should remain transparent in their interpretations and avoid misrepresenting participant responses. To reduce this risk, interviews are conducted by two researchers and any potential ambiguities in participant responses are clarified during the interview process through follow-up questions, ensuring that the data accurately captures their perspectives (Saunders et al., 2016). By adhering to these ethical principles, we ensure that our research upholds the standards of integrity, protecting participant rights while maintaining transparency and accuracy in the research process.

4. Empirical Findings

This chapter presents the empirical findings derived from interviews, observations and secondary data. We structure this chapter following the aggregated dimensions developed through grounded analysis, capturing key topics relevant to the research questions. Empirical insights are supported by participant quotes and where relevant, observational and secondary data are used to enrich and validate the interview-based findings.

4.1. Adoption of AI in the Workplace

The aggregated dimension *Adoption of AI in the Workplace* represents the first building block in our empirical analysis and sets the foundation for answering our research question on how workplace learning influences employees' AI-related skill development. As employees begin adopting AI in their daily work, existing ways of working and collaborating are gradually reshaped. The two second cycle categories, *Integrating AI into Work* and *Critical Reflections on the Use of AI*, capture both the perceived benefits and tensions emerging in this phase of adoption. Each second cycle category consists of underlying first cycle codes that illustrate employees' experiences, ranging from gradual adaptation to environmental concerns. In the sections that follow, we present this first dimension as the entry point in a broader transformation process, before turning to the knowledge and skill transformation accompanying it (4.2.) and the dynamics within workplace learning that influence them (4.3.).

4.1.1. Integrating AI into Work

Gradual Adaptation to AI

Participants across interviews highlight that the integration of AI into their work is not marked by a sudden transformation, but rather by a gradual, ongoing process of adaptation. This progressive adjustment emerges consistently, reflecting a learning curve that varies across individuals and organizational settings. As P7 explains: *"I would say as the world is moving fast with AI, we need to mold ourselves to get used to it. Start leveraging what is available in the market because we don't want to fall behind"*. This statement reflects an underlying sense of urgency and self-directed responsibility among employees. Rather than viewing AI adoption as a sudden shift, P7 frames it as an ongoing process that requires individuals to continuously adapt. The use of *"mold ourselves"* suggests a proactive but also potentially pressured form of

adaptation, where employees feel the need to align with rapidly evolving technologies to remain relevant (P7). This highlights that AI integration is not only technological but also demands continuous human engagement rather than a one-time adjustment. P2 captures this clearly: *"Once you start using an AI tool, it's not that, within one or two days, you can completely adapt to the tool – it takes time"*. The participant recognizes that AI, despite its user-friendly interface, often requires repeated engagement before users become confident and proficient (P2). This suggests that the adoption of AI tools is a dynamic and highly individual yet increasingly necessary process that requires an adaptive mindset. This gradual adaptation also reflects the broader organizational shift from fragmented AI utilization to everyday use. Participants describe this process not as a sudden change but as a layering of new habits and adjustments over time. This highlights that successful adaptation depends less on technical proficiency alone and more on openness, persistence and a workplace environment that encourages exploration without fear of failure. As employees gradually adapt to AI tools and integrate them into their routines, many begin to recognize benefits, most notably, improvements in efficiency and productivity.

Productivity Gains through AI

Participants consistently emphasize that AI reduces routine workload, enhances efficiency and supports employees across a range of diverse tasks. Several participants describe the way AI supports technical optimization, particularly in software development. As P3 explains, *"it is helping us to improve our coding standards and even our application performance",* adding that the integration of AI allows them to shift the focus toward more complex tasks. Beyond software contexts, the perceived productivity gain is widely spread. P13 describes AI as a tool that *"enhances work and adds really good value",* even referring to it as a *"relief of headache"* in day-to-day tasks. Similarly, P12 notes, *"it saves me time"* and estimates a 30% improvement in their overall performance, highlighting the way AI's impact is perceived in individual workflow improvements. This mindset is underscored by participants using terms like *"genius"* (P7), *"empowering"* (P14) and *"efficiency"* (P10) when asked to describe their professional relationship with AI in one word. These characterizations, though brief, underline a strong emotional alignment with AI's usability. P8 even suggests that AI could *"increase productivity by an exponential amount"* and allow individuals to *"achieve a lot more things with [their] job"*. Participants consistently described AI as productivity enhancer, both in measurable outputs and in personal experiences. Overall, participants describe feeling more capable, creative and empowered when repetitive tasks are delegated to AI. This reallocation of

cognitive resources allows individuals to concentrate on problem-solving, innovation and strategic thinking. The growing usage of AI boosts individual productivity but also redefines the way employees perceive their relationship with technology. Rather than viewing AI as a tool in the background, many begin to interact with it more directly and intuitively, shifting from usage to collaboration.

AI as Collaborative Assistant

A recurring topic among participants is the conceptualization of AI not as a replacement for human work, but as a collaborative assistant, a supportive tool that augments human capabilities and enables more efficient and creative work. This reflects a relational dynamic in which AI is viewed as partner or teammate, rather than a competitor. Several participants emphasize the interactive and dialog-oriented relationship with AI. P14 describes human-AI interactions as becoming increasingly *"bidirectional"*, envisioning a future where communication with AI feels less like command-giving and more like an exchange. P13 underlines this by emphasizing: *"Collaboration, between the human and machine […]is really the core of it, because we can do absolutely amazing things as humans. But together, in the combination with AI, I think we can be much better and faster in the end. But we need each other in some way".* P13's statement positions AI not simply as a tool, but as a collaborative partner, one that acts as problem-solving tool in everyday workflows, enhances performance and enables individuals to *"be much better and faster"* (P13). The emphasis on *"we need each other"* suggests an emerging mindset where AI is not seen as a threat, but as an essential component of contemporary workplaces (P13).

Participants often personify AI in ways that underscore its supportive role. Descriptions such as *"my assistant"* (P12), *"collaborative"* (P13) and *"assistant intelligence"* (P11) are used to express a sense of companionship and utility. As P11 notes, *"essentially, it's just assisting me to do something that would maybe take me two days in like one or two seconds"*, a perspective that positions AI as a powerful partner. This belief is reinforced by participants who stress the irreplaceability of human roles. For example, P4 expresses confidence in job security by stating *"99% I'm not worried about my job"*. This suggests that while AI can assist, it cannot replace the contextual judgment that certain roles demand. Moreover, this aligns with a broader trend where AI is seen not just as an executor of tasks, but as a partner for supporting workflows. As employees begin to engage with AI more interactively, also concerns regarding AI usage emerge.

4.1.2. Critical Reflections on the Use of AI

Cautious Engagement with AI

A central topic that emerges during interviews is the cautious engagement with AI. Especially, data security and privacy are often highlighted by participants. P9, for example, articulates this concern clearly, stating that *"we need to be cautious with the type of data […] you should never put any personal or private data into the actual AI tool"*. This is reinforced by P5, who explains the way formal AI training and informal team discussions have shaped their approach: *"It is very important that I perfectly anonymize all the data and […] not reveal anything that we are doing"*. The participant further elaborates on a workplace culture of IL around data management, bias and transparency, underscoring the way critical thinking around AI usage is being developed through both structured and unstructured learning (P5). This mindset reflects more than technical compliance, it suggests an internalized sense of responsibility around data handling, indicating that learning is not limited to acquiring skills but also involves creating shared norms and values.

Participants describe an environment where ethical integrity and risk avoidance are seen as non-negotiable foundations for any AI adoption. As P5 shares: *"We know that [Company X] is very, very ethical. They are extremely cautious about safety"*. The analysis of secondary materials reinforces this emphasis, showing that structured initiatives, such as the European Cyber Security Month (S3), internal awareness campaigns (S8), and mandatory risk assessment training (S10), are regularly used to reinforce security culture and educate employees on safe AI practices. The importance of cautious engagement is also underscored by P1: *"I always take what the AI tells me with a grain of salt. […] I would say it always gets close, but it rarely gets it 100%"*. This underlines that cautious engagement shapes the way employees interact with AI tools and points to an underlying concern. Overreliance on AI could lead to mistakes if users disengage their own judgment. As such, cautious interaction ensures that control remains with the employee even as AI is integrated into their work. Taken together, the participants point toward a culture of increasing AI usage, where cautious engagement is not only encouraged but often learned through practice, knowledge exchange and formal initiatives. This cautious engagement reflects more than just individual precaution, it signals a broader mindset in which trust in AI is not earned easily. While some employees embrace AI with curiosity and care, others experience hesitation or even resistance, which reveals tensions around AI adoption in the workplace.

Hesitation and Resistance Related to AI Adoption

Across interviews, the topic of hesitation and resistance emerges, often anchored in uncertainty about AI's actual usefulness. Hesitation and resistance are repeatedly experienced as reluctance to change, especially among employees working in more traditional work settings. P7 explains: *"People are maybe hesitant to start using AI because they are so used to working in a traditional way"*. The participant acknowledges that while some colleagues use new tools, others resist giving up familiar processes, even if AI helps gain efficiency. This resistance, P7 notes, could only be overcome through hands-on experience and exposure. These reflections highlight that resistance may not result from a rejection of AI itself, but rather from unfamiliarity. This, in turn, indicates the potential of hands-on workplace learning to build acceptance over time.

Furthermore, several participants link hesitation and resistance to generational differences. P10 observes, *"the older you are, the more reluctant you are"*, suggesting that age and experience impact the willingness to try out emerging technologies. Moreover, organizational contexts play a role. P5 describes internal friction where *"seniors in the team […] are not clear if [Company X] wants to go this way"*, while juniors *"don't feel empowered enough in that vision"*. For others, hesitation and resistance come from skepticism. P8 shares that *"a lot of my colleagues are against using AI",* criticizing it for making people *"lazy"*. P14 shares this opinion: *"There are some people who just think this is just a hype"*. These reflections reveal that hesitation and resistance to AI are shaped by a combination of contextual factors, underlining the diverse perceptions of employees.

Notably, not all participants encountered hesitation or resistance. P13 reports, *"I cannot say there's some resistance […] moreover, curiosity"*, linking this openness to their team's strong tech-savviness. P6 similarly states, *"I haven't seen any resistance"*, suggesting that in some contexts, AI adoption happens rather smoothly. In summary, hesitation and resistance to AI adoption come from several sources, underscoring the need for creating trust and readiness for AI adoption. While these experiences of hesitation and resistance vary across teams and roles, they reveal underlying concerns about change, relevance and the perceived usefulness of AI at work. This skepticism forms the broader reflection on the way employees engage with AI. Beyond hesitation and resistance, some participants also raise critical concerns about AI's broader consequences, particularly its environmental impact, which may hinder the adoption process.

Environmental Concerns Regarding AI

In contrast to data privacy or legal compliance, environmental concerns are raised more personally by participants. While not universal, for some employees these concerns act as barrier to greater AI adoption, reflecting a broader ethical consciousness in engagement. For P13, the environmental cost of AI is a central reason for limiting their AI usage: *"The environmental impact and all the queries […] raise a lot of energy consumption and that worries me a lot. And kind of mentally is maybe the only one hinder for me to use it more"*. This indicates that even in technically enthusiastic environments, ecological considerations can reduce the motivation to explore AI tools, especially when users are aware of the cost behind seemingly simple prompts. P15 described AI as an *"environmental disaster"*, underscoring the high energy consumption: *"I don't think I've seen technology burn so much energy so fast like this one. It's crazy"*. The comparison to more familiar tools helps to contextualize these concerns. As P13 pointed out, using AI feels like performing a Google search, yet *"a lot more environmental impact than a Google search"* is involved. This comparison, the participant notes, makes it easy to forget the actual energy costs behind AI, encouraging unsustainable usage patterns. While these concerns are visible at the individual level, participants also reflect on organizational responsibility.

Both P13 and P15 stress that companies should take an active role in minimizing AI's environmental footprint by critically evaluating partnerships. P13 suggests that *"a company should always evaluate what options there are",* especially regarding which AI providers they collaborate with, depending on their efforts to reduce carbon impact. Similarly, P15 advises for choosing those providers specifically because of their sustainability commitments, emphasizing: *"We need to pick our partners carefully, very, very carefully […] from a sustainability aspect"*. In total, while not every participant explicitly addresses AI's environmental consequences, those who do raise urgent concerns. These concerns affect their personal willingness to engage with AI and reveal a strong wish for organizations to act more proactively and transparently in minimizing AI's ecological footprint. This growing awareness also affects the adoption of AI, making the balance between technical efficiency and environmental accountability substantial.

While this aggregated dimension illustrates the adoption of AI in the workplace, the following dimension focuses on the transformation of knowledge and skills, which emerges through the adoption of AI.

4.2. Transformation of Knowledge and Skills through AI

The aggregated dimension *Transformation of Knowledge and Skills through AI* builds on the previous dimension and represents our second building block in the realm of AI-related skill development. As AI becomes increasingly adopted in the workplace, new capabilities and skill requirements emerge. This dimension captures the way employees navigate the evolving need of developing skills to work with and alongside AI. The two second cycle categories, *Building Foundational AI Knowledge* and *Evolving Skill Requirements due to AI*, reflect both the initial efforts to grasp the concept of AI and the transformation of skill requirements. These categories include first cycle codes that range from differing AI knowledge levels to the need of human touch when working with AI. Taken together, this aggregated dimension highlights the way in which the increasing adoption of AI initiates a shift in skill requirements and skill development, linking the adoption of AI in the workplace (4.1.) to the evolving skills it demands. In doing so, this dimension connects to the third aggregated dimension (4.3.), which explores dynamics within workplace learning.

4.2.1. Building Foundational AI Knowledge

Differing AI Knowledge Levels

While participants reflect on the growing presence and impact of AI in their daily work, they also notably reflect on the occurrence of various AI knowledge levels within Company X. Across interviews, participants highlight that some employees are just beginning to explore AI's potential, while others apply it highly competently. For instance, P4 emphasizes: *"Some people are super fast at AI, some people are like, not there".* Similarly, P12 observes: *"I think we are in different stages, actually, of how we use AI",* while P10 notes: *"I am among experts and innovators and people really exploring AI in depth, so I'm pretty much just a follower".* These assertions suggest that even though AI is broadly introduced and utilized in the workplace, AI knowledge among employees differs considerably and closely connects to experience and confidence levels.

From a further perspective, one interviewee underlines that several training formats do not suit everyone's AI skill level. P14 explains: *"They are basic courses that I already know. So if I want to deep dive into one of these aspects, I would say I probably need to do self-research".* This reflection similarly occurs in O2, where the participant expresses dissatisfaction with the limited depth of a recently completed FL course. These examples illustrate the way a lack of

personalized training may hinder continuous engagement with FL initiatives. This, in turn, signals that differing AI knowledge levels translate into learning behavior, perceptions of FL courses and IL engagement. Hence, this section reveals that participants view knowledge about AI as something dynamic with varying levels. Learning opportunities should reflect these differences to be beneficial for employees. As participants acknowledge these varying levels of AI knowledge, they increasingly stress the need to foster a shared understanding of what AI is and how it works.

Understanding the Concept AI

Across interviews, participants strongly emphasize the essence of developing a base knowledge on the concept of AI as integral part of AI-related skill development. P12 notes: *"You need to get a baseline of what is AI and […] how you can use it in the most effective way".* P5 further underscores this: *"Artificial intelligence is about intelligence. It will know. It will solve things for you. What you must do is tell it what to solve, feed it what to solve, feed it all the resources that are required for this. Without that understanding, no matter how much you try to upskill somebody for learning about AI, I have very often seen that they won't be able to get the best outputs using any of those tools".* The participant further stresses: *"It is not necessary for anybody to know the mathematics and statistics behind it. That is frankly beyond scope. But knowing what machine learning is and what AI is and what is it going to do for you that is very important to know".* These insights indicate that while AI is capable of solving complex tasks, employees, regardless of their job position, need to understand the way AI operates in order to use it beneficially. This suggests that AI-related skill development should begin with building foundational AI knowledge across roles. Without this, efforts to *"upskill"*, as P5 notes, risk remaining superficial. Building on this, P5 highlights the importance of making everyone *"AI literate"*, including knowledge about legal requirements, what supports or harms the organization and ethical awareness. Such understanding forms a base from which then different paths, depending on the AI knowledge level, can be explored (P5). This, in turn, indicates that fostering AI literacy extends beyond practical utilization and presents a mechanism that can enhance legal and ethical clarity, which then can support more responsible use of AI in the workplace.

Moreover, the relevance of understanding the concept of AI further surfaces by looking at participants' perspectives on future skill demands. P15 describes: *"You're not going to get replaced by an AI. You're going to be replaced by someone who really understands how to use*

AI", while P8 adds to this perspective: *"If you don't understand how to use it to your advantage, then you will just naturally fall off".* These perspectives showcase that building basic AI knowledge is not only beneficial for utilizing AI, but it also becomes necessary to remain competitive in AI-impacted workplaces. Thus, this section illuminates that foundational knowledge of AI is essential to use AI appropriately, make full use of learning opportunities and stay relevant in contemporary workplaces. Building on this, participants also strongly highlight the evolving skill requirements due to the increasing integration of AI into the workplace.

4.2.2. Evolving Skill Requirements due to AI

Relevance of Prompting Skills

Within the perceived skill shifts brought by AI, participants repeatedly emphasize the importance of developing strong prompting skills. Prompting entails phrasing proper questions when utilizing AI tools, which participants describe as essential to shape the quality and reliability of AI's output (P10 and P15). Participants reflect on this relevance by stating, *"you will never be able to get a better answer than you actually prompt that you insert"* (P9) and *"the better you are at prompting and giving instructions to the AI what you need, the better output you will get"* (P10). These assertions suggest that prompting is not only a skill that enables the utilization of AI tools, but it also presents a competence that requires active cognitive engagement, which can be developed through continuous learning. Its growing relevance underscores that prompting is not solely technical but a reflective learning process, requiring users to grasp the context of AI's responses and adapt their prompts accordingly.

Aside from recognizing the relevance of prompting skills, participants also point out potential challenges. For instance, P14 warns that asking AI tools generic questions results in receiving generic answers, while P15 specifically highlights that *"it might seem straightforward"* but prompting is not just like *"asking a friend"* some questions. Rather, participants emphasize that effective prompting requires providing the right context (P8), often reframing sentences (P7) and providing input in a structured format (P5). These reflections further reinforce that prompting goes beyond a simple technical interaction. Instead, these findings suggest that prompting is seen as a vital evolving AI-related skill that requires both active human reasoning and conscious learning to be utilized in a beneficial manner. These contextual considerations needed for formulating proper prompts connect to the next section, where participants highlight the essence of domain knowledge when working with AI.

Importance of Domain Knowledge

Across interviews, participants notably highlight the importance of retaining and fostering fundamental knowledge of one's professional field when working with AI. P9 describes this aspect concretely: *"You need to have a lot of domain knowledge from the beginning",* emphasizing that without this, others will notice where AI is used if the output does not make sense within the given context (P9). This aspect suggests that AI cannot replace domain knowledge but can only support it. P15 reinforces this idea: *"Get good at your field, […] be the expert in the fundamentals of your field"* and illustrates this with a concrete example from coding, where it is essential to understand the fundamentals of algorithms, to evaluate AI output suggestions and whether those are relevant for usage (P15). This underscores that AI amplifies, rather than replaces, the need for domain knowledge, as employees must critically assess and contextualize AI-generated outputs within their field.

Building upon this, participants point out that a lack of knowledge of handling AI output can lead to considerable setbacks. Concretely: *"If I don't have my fundamentals down now, I don't understand what I am creating"* (P15). However, P11 also notes that the level of required expertise depends on the task and profession. For instance, summarizing text might demand less background knowledge than tasks like coding (P11). This indicates that the depth of expertise, as P11 notes, needed to use AI effectively varies by task, but a basic understanding remains important to ensure appropriate use. In addition to individual knowledge, some participants also extend this idea to organizational contexts. For example, P9 stresses the importance of knowing the *"bread and butter of your organization […] what are actually the key parts that the customers care about".* In this vein, domain knowledge can also be viewed as being aware of the organization's core domain to identify problems that matter to the organization (P9). This highlights that domain knowledge is not only task- and role-specific but also tied to organizational priorities and customer needs. Taken together, these participants' perspectives highlight that while AI offers valuable support, it is human domain knowledge that is required to contextualize and apply AI outputs appropriately. Hence, without retaining and fostering domain knowledge, employees may misapply AI output and miss opportunities to use it in a beneficial way, both for individual and organizational purposes. As participants place notable emphasis on domain knowledge, the interviews further reveal the importance of consistent human involvement in the utilization of AI.

Need of Human Touch when Working with AI

Another key topic within evolving skill requirements across interviews refers to the need for human touch when working with AI. This suggests that technical competences alone are not enough, instead, critical human involvement remains essential in using AI responsibly. Within this notion, P1 emphasizes: *"It does need a human touch to actually make sure it's telling us the right thing",* while P12 highlights: *"I see AI as a base, and then you put your personal layer on everything you do".* Such human inputs appear particularly relevant because AI operates on probability and may frequently provide incorrect results. As P14 explains: *"The answer is accurate, but there's a chance that AI just hallucinated. So, you need to always go back and do the old way of working to check the answers and do your own research".* These examples showcase the awareness of participants to consciously apply human cognition when utilizing AI. This also links to O3 and S4. During O3, one participant emphasizes: *"Humans need to understand the code"* (O3), highlighting the importance of professional knowledge for effective integration of AI within developers' professions. Similarly, survey results highlighted in S4 illustrate that the majority of surveyed employees encounter false output from AI tools. Both aspects further reinforce the interviewees' reflections on the inherent need for continuous *"human oversight"* (S4).

Ultimately, interviews reveal that AI usage is not about passive acceptance but that it requires critical human thinking. P12 points out: *"You need to have a critical eye on everything […] because it never is 100% right"* and adds: *"To be able to analyze the outcome of, you know what is wrong, what is right".* A clear reflection that is also echoed by P2, stating that AI tools offer considerable support, but it still needs an *"extra evaluation check from the user"* in order to use AI properly. These statements suggest that AI utilization does not eliminate human judgment, but instead, it increases the need for human involvement. Hence, rather than relying on AI outputs as final answers, participants emphasize the importance of consistently evaluating and interpreting AI outputs critically as an integral part of AI usage.

While this aggregated dimension illuminates the way AI transforms knowledge and skills, the following dimension brings into focus dynamics of workplace learning, which presents the key connecting element between AI adoption and evolving skill requirements for AI-related skill development.

4.3. Dynamics within Workplace Learning

The aggregated dimension *Dynamics within Workplace Learning* builds upon the previous dimensions and represents our third building block in the area of AI-related skill development. As AI adoption becomes embedded in daily work and reshapes skill demands, employees are not only adjusting the way they work but also responding to these changes through workplace learning. The two second cycle categories, *Opportunities within Formal Learning* and *Opportunities within Informal Learning*, reflect the range of learning experiences that shape skill development. These categories include first cycle codes that span from FL through internal opportunities to self-directed IL through external platforms. Taken together, this dimension highlights the central role of workplace learning as the dynamic mechanism through which employees navigate the transformations brought by AI. It builds upon the adoption of AI (4.1.) and the transformation of knowledge and skills (4.2.), contributing to answering our research question on how workplace learning influences employees' AI-related skill development.

4.3.1. Opportunities within Formal Learning

Learning through Internal Opportunities

FL opportunities within Company X play an important role in introducing employees to AI tools. Participants highlight a variety of internal resources and initiatives, including learning platforms, webinars, internal articles and practical events such as hackathons. One of the most frequently mentioned formats is an internal learning platform, where employees can explore training modules on AI tools, data handling and other related topics. For instance, P2 explains that they *"have access to training about how to use AI based on our security risks and based on our data, how to question AI, what tools we can use",* reflecting a blend of technical and ethical learning (P2). This is often supported with written articles from internal experts, which P1 says is *"not exactly training, but information on how to use AI at work and what to watch out for"*. This is also reflected in O1 and O2, where employees navigate these internal platforms with varying levels of engagement, following personalized learning paths and highlighting the importance of practical application.

Beyond passive content, Company X utilizes active and collaborative learning through events such as hackathons. These events are typically cross-functional, allowing employees to work with colleagues from other teams on AI use cases. P13 recalls an early initiative as a *"way to dip our toes into AI […] through a kind of hackathon that brought people together from different*

areas to experiment and come up with ideas". P3 similarly describes the experience as *"a week-long program where we could present what we learned and show what could be achieved with AI"*, suggesting that this format provides both motivational and educational value and helps employees to develop AI-related skills in a practical way. The analyzed secondary data centered around AI hackathons (S5) also reinforces this perspective, highlighting the way such initiatives are opportunities for hands-on learning, collaboration and creating tangible outcomes that contribute to broader organizational innovation efforts. P5 further highlights: *"Mandatory trainings shouldn't be just centered around how to avoid leaking information, but also around how to triple your productivity directly using the right tools at work, encouraging people to use AI tools, giving them the proper IT systems so that they can use it and apply it while again, knowing how to do it effectively, efficiently and ethically".* This highlights a broader expectation for FL. Employees should not just be informed about risks but actively enabled to use AI in ways that improve their performance. It reflects a view that training should be practical, forward-looking and inclusive, supporting both efficiency and ethical awareness as core elements of AI use at work.

Despite Company X's FL efforts, a recurring topic pertains to participants' perceived challenges that can hinder engagement with FL initiatives. One such barrier is time. P2 explains that they did not attend many trainings due to general time constraints, while P4 shares that meetings may take up much of a workday, which reduces the available time for fully discovering internal learning platforms. Besides time constraints, participants also note that several trainings appear very specific for certain roles or that they do not meet their personal learning needs. P9 notes: *"Many of the trainings, they are more focused and aimed towards the developers"*. Adding to this, P5 reflects on their own learning path, highlighting that the training offered by Company X did not meet the personal learning level and as a response, the participant decides to focus on IL to foster AI-related skills: *"From [Company X] there are optional courses available on our internal platform. But I didn't go through that process because I felt that it wasn't up to the level that I required. I work hands-on, so I wanted to go with the informal way of learning outside of the workplace and try to upskill a lot faster" (P5).* This aspect also closely relates to insights gained within O2, where the participant, after watching a course on an AI system, states that the course was rather basic, expressing the wish for more depth to advance personal learning more properly. These perceived limitations within internal FL opportunities, whether due to time, content depth, or relevance, lead some employees to seek out alternatives beyond the organization.

Learning through External Providers

In addition to internal initiatives, external providers play an important role in workplace learning for AI. Participants frequently refer to offerings from industry leaders such as Amazon Web Services (AWS), as well as digital learning platforms like Pluralsight, Udemy, or Coursera, which are recommended by Company X and therefore considered part of FL in our study. Several participants highlight FL events and workshops hosted by AWS as highly valuable opportunities for both foundational AI knowledge and hands-on practice. P3, for example, describes participating in a workshop where they learned about AI technologies and the way they could be applied in internal processes. This is further supported by the analysis of secondary data, including documentation from AWS Immersion Days (S1), the AWS Skill Builder platform (S2) and internal records of AWS Trainings and Certifications (S6). These resources confirm a systematic collaboration with external providers and a strategy to offer learning pathways that are often recognized with certificates, as mentioned by P3. Additionally, materials from the AWS Summit (S9) and the Developer Experience Center (S7) reinforce the way external learning formats are used to develop AI-related skills. This demonstrates that learning through external providers is not treated as supplementary but is actively embedded into Company X's FL offerings.

Parallel to this, many employees take initiative to engage with self-paced learning platforms. P11 explains that they *"started to use Pluralsight",* which provides a curated set of courses and assessment tools, including skill tests and channel-based learning. However, some participants noted a lack of interactivity in these platforms. As P11 remarks, *"I wish it could be more hands-on",* suggesting that while digital courses are accessible, they sometimes lack the engagement and practice-oriented features needed to develop skills. Observational data supports this criticism. During O1 and O2, participants navigate platforms like Pluralsight, often selecting content based on personal interest or job relevance. This illustrates that FL can take on a flexible, self-directed form when structured platforms are made accessible by the organization. In summary, FL through external providers plays a critical complementary role in AI-related skill development. Those offerings enable employees to access specialized content, gain certifications and explore tools not yet available internally. When structured to encourage active engagement and aligned with work demands, they provide a valuable source for advancing knowledge and enabling self-directed learning. However, participants also point to areas where existing FL structures fall short, highlighting the need for advancing FL initiatives.

Highlighting the Need for Advancing Formal Initiatives

While FL initiatives around AI exist within Company X, many participants emphasize the need to expand and personalize these efforts. A central topic is the wish for more practical and structured training pathways that go beyond theoretical sessions or general overviews. Therein, participants express a preference for hands-on, instructor-led formats over passive content such as internal articles. P3 states, *"it would be good to have sessions instead of articles. That will provide more, better information"*, underscoring a demand for experiential learning. This call for more hands-on learning is further echoed by participants' reflections on the limits of purely theoretical content. P15 notes clearly: *"You can do all the reading in the universe […] if you don't build anything, you don't really understand how it works. The practice is the only thing"*. This is underlined by O1 and O2, where employees engage most effectively when learning content includes practical demonstrations or direct application.

Another notable topic is the importance of organization-wide inclusivity in FL efforts. P5 argues for *"an organization-wide approach to make everyone AI-literate"*, while P7 emphasizes the need for each team to develop a clear FL plan aligned with targeted outcomes from AI usage. In this vein, participants also highlight structural limitations of current learning formats. P9 criticizes the fragmentation of initiatives, describing them as *"one-time activities"* that fail to provide continuity: *"It's more like, okay, now we have these AI days, and then we move on to something else […] it would be better to have a path you could follow to gradually learn more"*. The participant, like others, advocates for a more coherent learning journey, one that builds over time, supports reflection and enables skill development. These insights are underscored by observations. For example, during O1 and O2, participants often feel uncertain about the way FL modules fit into their development plans or organizational priorities. While some used internal platforms to define goals and select courses, others appeared to rely on personal motivation. Taken together, these findings suggest that while FL infrastructure exists, its usefulness is constrained by limited customization and underdeveloped strategic integration. There is a clear wish for more accessible, relevant and motivating learning formats that not only inform but empower employees across the organization to develop AI-related skills in ways that align with their roles and the company's broader goals. These calls for more practical, inclusive and sustained FL efforts highlight a growing awareness surrounding gaps in FL. As these gaps in depth, continuity and customization persist, many employees begin to shape their own learning journeys, turning to IL pathways to build the skills they need.

4.3.2. Opportunities within Informal Learning

Learning through Experimentation and Usage

Across interviews, IL emerges as a vital component within employees' learning journeys. Therein, a recurring notion is learning through experimentation and usage, which participants perceive as an essential part in developing AI-related skills. Similar to the wish for more hands-on learning within FL initiatives, participants across interviews stress the importance of direct engagement and hands-on learning experiences within IL. P14 captures this aspect directly: *"Just getting my hands on it and trying to implement something myself, that's the best way to learn for me".* Moreover, P10 stresses their perceived importance of application and repetition when learning: *"It's learning by doing. You need to do it over and over and over again. […] to be able to make it really useful, you need to apply it over and over".* These reflections highlight that if FL lacks opportunities for experimentation, employees often leverage the flexibility and self-determination of IL, which in turn illustrates the underlying dynamics within workplace learning. P4 extends on this emphasis of direct application. They describe using two screens to follow video training material on one monitor while simultaneously trying to implement the content on the other (P4). Relatedly, P12 notes that if training videos are designed for direct following, they are perceived as particularly valuable for their learning experience, reinforcing the importance of immediate interaction with the material. This underlines that the perceived usefulness of IL is often dependent on its actual integration into workflows, allowing employees to test and directly apply knowledge rather than passively consuming information.

Beyond these individual experiences, interviewees also touch upon broader instances of hands-on learning. For instance, P5 points out that working on a *"real life AI project"* is an opportunity that truly allows oneself to apply thinking and directly utilize the gained knowledge in one's work role. This suggests that engaging in a dedicated project directly related to AI can enable employees to internalize new AI-related skills through direct, contextualized use. Taken together, participants highlight active trial, deliberate repetition and direct application as vitally important for developing AI-related skills. This reflects that IL is particularly beneficial when embedded in action and immediate application, where skills build gradually through doing rather than through instruction alone. Nevertheless, aside from these active approaches, the interviews further reveal that IL often does not occur in isolation. Instead, IL opportunities are also closely connected to social interactions, continuously appearing through knowledge exchange and collaborative learning in the workplace.

Knowledge Sharing and Collaborative Learning

Participants repeatedly highlight the importance of knowledge sharing and collaborative learning for AI-related skill development. Therein, they describe various practices, including learning from colleagues or experts and collaborative team initiatives that foster knowledge exchange among Company X's employees. In this vein, P10 points out: *"Anybody sharing their thoughts on their experience with any AI is a learning. And […] it doesn't only need to be success stories, but it could also be real failures, because as long as you learn from them, then it's fine".* This reflection indicates that knowledge sharing and collaborative learning are not about providing flawless content but about openness to share thoughts, no matter in what form.

Furthermore, participants also point to formats that promote collaborative team learning, such as knowledge sharing sessions. During these sessions, teams present projects and exchange ideas with each other (P2). Participants particularly appreciate new insights and practical knowledge gained in these sessions. For instance, P3 notes the role of such sessions in encouraging others to adopt effective solutions: *"If we spread that knowledge, that will encourage other people to start using [those services] too".* This indicates that knowledge sharing sessions not only foster collective learning but also provide an opportunity for knowledge transfer across teams. Another format offering knowledge sharing opportunities relates to *"lunch and learn"* gatherings, where *"every few weeks at least someone from usually within [Company X] gives like a mini lecture at lunch"* (P15). Similarly, P10 highlights that *"listening to experts, which we have plenty of in [Company X]",* is particularly advisable. These insights also extend to O2, where the participant intentionally follows a preferred expert on an internal learning platform, perceiving their explanations as considerably helpful.

Moreover, S4 highlights the development of an internal AI expert network, consisting of like-minded AI visionaries, aimed at fostering knowledge exchange related to AI. This in turn mirrors an assertion from P15: *"We should grow together and build this core of people who are a critical mass and drive the organization forward, because we're not going to be able to do it in our own little silos, in our little corners".* This demonstrates that knowledge sharing and collaborative learning occur in many forms and thrive when active exchange and mutual engagement across teams are encouraged. In summary, this section suggests that knowledge sharing and collaborative learning are not marginal but perceived as essential. Whether through informal conversations, team collaboration, or learning from experts, our findings indicate that collective learning is just as vital as individual learning efforts for building AI-related skills.

Self-directed Learning through External Platforms

Aside from the emphasis on experimentation and direct usage as well as knowledge sharing, participants highlight self-directed learning through external platforms as a central aspect within IL. Therein, interviewees stress the importance of staying *"on topic"* (P8), pointing to the need to proactively stay informed about current AI developments. P9 frames this aspect clearly in reflecting on their individual learning efforts besides official organizational initiatives: *"From a personal side, is staying up to date. […] You know, just taking part of news, what's happening in terms of the AI area".* Other participants also note utilizing podcasts to stay up-to-date and advance AI knowledge (P1 and P11). In this vein, P1 notes: *"I try to keep up to date on those sort of things. So, I listened to a lot of tech podcasts and, of course, AI is a huge buzzword right now. So they're always talking about different things happening with AI and different tools."* These reflections suggest that staying informed on the topic of AI through external providers appears as deliberate learning practice and notable foundation for developing AI-related skills, such as understanding the concept of AI.

Moreover, among the external platforms mentioned, YouTube stands out to the participants as a particularly helpful learning resource. Interviewees especially appreciate the platform's practical and hands-on manner in which learning content is delivered. For instance, P5 explains: *"I choose to learn from YouTube videos. I think those are really good resources because people actually like going over there, and then you can see what's actually working and what's not".* This perceived benefit from YouTube content also becomes visible during O2, where the participant proactively turns to YouTube in order to further explore insights gained from a formal training course. Overall, this section illustrates that participants actively choose external platforms to shape their IL pathways. Participants emphasize self-directed learning through external platforms as a key component of IL in the context of AI-related skill development. They deliberately engage with tools like podcasts, news and especially YouTube to stay up to date on AI trends and to access practical, hands-on content. This proactive information-seeking behavior reflects a personal commitment to continuous learning beyond organizational initiatives. Taken together, this aggregated dimension completes our analysis by illustrating the third building block in the realm of AI-related skill development. This dimension emphasizes workplace learning as dynamic mechanism through which employees respond to AI adoption and shifting skill demands. It closes the empirical findings by highlighting the dynamic interplay between the various FL and IL opportunities that shape AI-related skill development.

4.4. Summary of Empirical Findings

The empirical findings are structured around three aggregated dimensions that illustrate the way AI is adopted in the workplace, the transformation of knowledge and skills and dynamics within workplace learning. The first dimension highlights that AI adoption is perceived as a gradual and evolving process. Participants describe adapting through continuous exposure by gradually integrating AI into their workflows. Furthermore, AI is largely seen as a collaborative assistant that enhances productivity. While enthusiasm for AI's potential is evident, our findings reveal cautious engagement shaped by concerns around data privacy and trust. Hesitation and resistance are also present but vary across teams and roles, often linked to familiarity, generational differences, or organizational clarity. In addition, participants raise environmental concerns, reflecting a growing awareness of AI's broader impact.

Building on this, the second dimension captures the transformation of knowledge and skills through AI, showing that AI adoption is closely linked to evolving skill demands. Participants view AI knowledge as dynamic and differing among employees, yet foundational understanding of AI emerges as a necessary starting point for AI-related skill development. Moreover, participants emphasize the importance of prompting skills, domain knowledge and the need for human touch to use AI effectively and responsibly. This shows that AI-related skill development necessitates not only technical skills but also critical human involvement.

The third dimension illustrates the way employees respond to these shifting demands through workplace learning, encompassing both FL and IL opportunities. FL occurs through internal learning platforms, training sessions and collaborations with external providers. However, participants often experience these FL initiatives as fragmented, generic, or insufficiently tailored to their roles and levels of expertise. Calls for more role-specific, practical and continuous learning pathways suggest that current FL initiatives require further development to effectively support evolving skill demands. In the absence of fully satisfying FL opportunities, IL practices become central. Employees actively engage in experimentation, knowledge sharing and self-directed exploration using external platforms. These IL strategies often fill gaps left by FL and enable ongoing adaptation to AI advancements. Taken together, these three building blocks show that AI adoption, skill transformation and workplace learning are tightly interlinked. Our findings suggest that workplace learning is not a passive but a dynamic factor for employees' engagement with AI. Building on this, the following chapter discusses the empirical findings in relation to existing research on AI, skills and workplace learning.

5. Discussion

This chapter interprets and contextualizes the empirical findings in relation to existing research. We move beyond the presentation of results and focus the discussion on the way in which our findings contribute to existing literature on AI, skills and workplace learning. Finally, we present our conceptual framework, which builds the foundation for answering our research question.

5.1. Discussion of Findings on AI Literature

This section discusses the first building block of our empirical findings, *Adoption of AI in the Workplace*, by interpreting the way AI adoption initiates new learning requirements for employees' AI-related skill development. Our findings bring two central debates from literature into focus. First, we discuss the way augmentation is actively shaped by workplace learning. Second, we discuss automation in the context of AI adoption, suggesting that reactions such as fear or resistance are dynamic responses formed through various factors. By discussing these aspects, we build on current literature and highlight the dynamics of working with AI.

In line with the arguments raised by Anthony et al. (2023), participants frame AI primarily as a supportive tool that complements rather than replaces human capabilities. This, in turn, relates to the concept of augmentation, which emphasizes human-AI collaboration over task substitution (Raisch & Krakowski, 2021). Our findings show that AI helps free up routine tasks, enabling employees to focus on more creative aspects of their work. Anthony et al. (2023) describe this dynamic as *super teams*, where AI and humans collaborate to enhance performance. In our findings, this concept emerges in the form of AI being perceived as a collaborative assistant that complements, rather than competes with, human efforts. However, we add a nuanced perspective to the assumption that augmentation is a relatively stable outcome of AI adoption (Anthony et al., 2023), by highlighting that it is instead shaped by workplace learning efforts. In this vein, employees describe adopting AI gradually through experimentation and repeated application. This suggests that augmentation requires not only technical systems to be in place, but also workplace learning that helps employees adapt to new tools.

Existing research often frames automation as a source of anxiety and resistance, especially in connection with job displacement (Huang & Rust, 2018; OECD, 2019a). Authors argue that as AI evolves from handling routine tasks to more complex cognitive functions, workers may fear being replaced, leading to resistance to engage (Ångström et al., 2023). However, participants in our study rarely fear job displacement. Instead, they show awareness of potential changes, accompanied by curiosity and a sense of agency. These responses suggest that, rather than fearing replacement, employees focus more on practical concerns, such as the usefulness of tools, access to learning and environmental implications. This shift from fear toward practical engagement supports the view that AI-related skill development depends not only on technological change but also on the support and encouragement of employees to work with AI in their daily tasks.

While not fearing job displacement as such, some participants mention hesitation and resistance, which in turn suggests the potential of workplace learning to enhance clarity and build trust. This perspective resonates with Woo et al. (2024), who argue that trust in AI should be cultivated through exposure and training that addresses bias in AI tools. Interestingly, environmental concerns, largely unmentioned in our reviewed AI literature, also emerge as a source of hesitation in our findings. Participants question not only the way AI tools function, but whether to what extent they should be used, given their potential environmental impact. This focus on responsible usage, environmental impact and the ethical dimension of AI aligns with the idea that workplace learning should support not only technical skills but also reflective, value-oriented engagement with technology. This dynamic repositions AI adoption as more than a technical change, it becomes a trigger for shifts in skill requirements.

In summary, the discussion of our findings on augmentation and automation shows that AI adoption emerges as a gradual and ongoing process in which employees adopt AI through learning and experimentation. Augmentation, rather than being a result of using AI, is shaped by interactions and can be supported through workplace learning. At the same time, concerns around automation do not primarily revolve around job loss but reflect more practical and value-based questions, such as the trustworthiness and environmental impact of AI. This highlights that AI adoption creates both new opportunities and uncertainties and that workplace learning emerges as dynamic mechanism to support employees in responding to those changes.

5.2. Discussion of Findings on Skills Literature

This section discusses the second building block of our empirical findings, *Transformation of Knowledge and Skills through AI*, highlighting two central aspects of skill development in the context of AI. First, the increasing variety of skills required, and second, the diverse starting points from which employees engage in AI-related skill development. This section builds on both aspects and discusses in which way they relate to existing literature on AI-related skills.

In line with research by Stephany and Teutloff (2024) and Zirar et al. (2023), our findings reinforce the importance of fostering a variety of skills to work with and alongside AI. In this vein, participants emphasize that AI-related skill development does not require one single skill, but rather a variation of certain evolving skills. Looking at technical skills, our findings illustrate the importance of developing digital skills or AI literacy for the broad workforce, which relates to insights from Jaiswal et al. (2021) as well as Li and Kim (2024). Participants in our study show considerable awareness of such emerging technical skills and describe the way in which workplace learning initiatives directly target these skill areas, for instance, through formal courses or self-directed learning. Building on this, Chuang (2024) as well as Sanders and Wood (2023) emphasize fostering human skills in the age of AI. In this vein, our findings bring the relevance of prompting skills into focus. Although phrasing questions to AI may appear as a simple technical interaction at first glance, participants strongly highlight that asking proper questions and structuring prompts effectively is essential for achieving proper outputs from AI. Thus, prompting emerges as a complex skill that draws on several human capabilities simultaneously. Furthermore, participants highlight in-depth knowledge of their field as particularly relevant when working with AI tools. In this sense, our findings support prior research that argues for the irreplaceability of human involvement when working with AI (Sanders & Wood, 2023). Therefore, AI-related skill development includes a variety of skills that allow employees to work with and alongside AI, which in turn indicates that workplace learning should recognize this variety.

A repeatedly mentioned aspect within literature around skills emphasizes the strategic importance of considering both up- and reskilling, for successful employee development in the age of AI (Li, 2022; Tamayo et al., 2023; Tamayo et al., 2024). However, across interviews, observations and secondary data, we identified no indications of participants perceiving a need or expressing an inclination towards reskilling. Instead, our findings consistently show a focus on continuous upskilling, despite existing literature suggesting the broad applicability of

reskilling across industries (Tamayo et al., 2023; Tamayo et al., 2024; WEF, 2025). While upskilling is seen as essential, our study reveals that employees hold varying AI knowledge levels, indicating that AI-related skill development takes different departure points. This variation reinforces that, despite the broad importance of developing AI-related skills, employees' learning needs are shaped by their specific job roles, previous experience and individual learning preferences. In this light, our findings suggest that workplace learning requires diverse learning opportunities that recognize the various starting points among employees when fostering AI-related skills. Taken together, our study contributes to skills literature by showing that AI-related skill development does not pertain to a single skill but instead, it is about fostering several skills, indicating that workplace learning requires diverse learning opportunities that highlight skill variety and recognize diverse departure points among employees.

5.3. Discussion of Findings on Workplace Learning Literature

This section discusses the third building block of our empirical findings, *Dynamics within Workplace Learning*, highlighting the central role of both FL and IL in developing AI-related skills. While AI adoption reshapes skill requirements, it is through workplace learning that employees develop these skills. Our findings highlight two central aspects, first, the practical implementation of FL, which often appears fragmented and second, IL as self-directed, flexible strategy, especially when FL falls short. By discussing these aspects, we contribute to existing research by highlighting workplace learning as dynamic mechanism influencing AI-related skill development.

Discussion of Findings on FL Literature

Our findings contribute to current discussions on workplace learning by emphasizing the central, yet underdeveloped, role FL plays in AI-related skill development. While previous literature often frames FL as tool for skill acquisition (Manuti et al., 2015), our findings reveal that employees frequently experience formal offerings as fragmented, surface-level, or insufficiently tailored to their job roles. Structured training is often described as disconnected from actual work demands, suggesting that FL only impacts AI-related skill development when it is contextualized, continuous and responsive to employees' evolving needs. This also relates to the difficulty of scaling AI projects beyond isolated experiments (Hopf et al., 2023). Participants describe internal initiatives, such as hackathons or webinars, as beneficial but often disconnected, with little continuation or strategic framing. In this vein, participants stress the

importance of coordinated, long-term pathways that build knowledge over time. This complements and extends discussions from Zirar et al. (2023) and Engström et al. (2024), who argue that workplace learning processes should be strategically created to respond to AI's transformative impact. Our findings suggest that FL shapes employees' AI-related skill development not simply by existing, but by the way it is structured, customized and connected to employees' everyday work. Thus, FL emerges not as a passive background element but as an active condition that can either open or close possibilities for employees to engage meaningfully with AI tools. Overall, FL appears much less systematized than literature implies, exposing a gap between academic ideals of continuous workplace learning and the organizational, often fragmented FL initiatives experienced by employees. We contribute to workplace learning literature by suggesting that FL shapes AI-related skill development not merely by offering training modules, but through the perceived relevance, continuity and applicability of these offerings.

Discussion of Findings on IL Literature

Our findings contribute to existing research on IL by showing that, particularly in AI-impacted workplaces, IL becomes an individual strategic activity rather than a background process. Existing research emphasizes the importance of IL in workplace learning (Manuti et al., 2015), describing it as a flexible, often spontaneous complement to formal structures. However, our study refines that view by highlighting the way in which employees actively shape their IL efforts to adapt to technological change when formal opportunities fall short. Participants intentionally use IL opportunities, such as hands-on experimentation, knowledge sharing with various people and self-directed learning through external platforms, to build AI-related skills. This also links to the multidimensionality and continuous occurrence of IL during work activities (Clardy, 2018; Eraut, 2000; Jeong et al., 2018). Thereby, our findings show that participants draw on a multifaceted range of IL sources to develop AI-related skills across different situations and tasks, showing that IL is shaped by active problem-solving, collaboration across teams, continuous monitoring of external developments and a level of agency. This indicates that in the context of AI-related skill development, IL operates with a considerable degree of autonomy and frequently becomes the primary strategy through which employees build relevant skills. This perspective reinforces that employees appreciate and intentionally leverage the flexible and self-directed form of IL to build their AI-related capabilities. Overall, our findings contribute to literature on IL by suggesting that it emerges as a multifaceted, compensatory response when formal pathways do not fully meet employees'

evolving needs. This, in turn, suggests that flexibility and time are essential conditions for enabling IL and supporting the development of AI-related skills. Thus, IL appears less as an additional component to FL but more as a strategic necessity.

5.4. Conceptual Framework

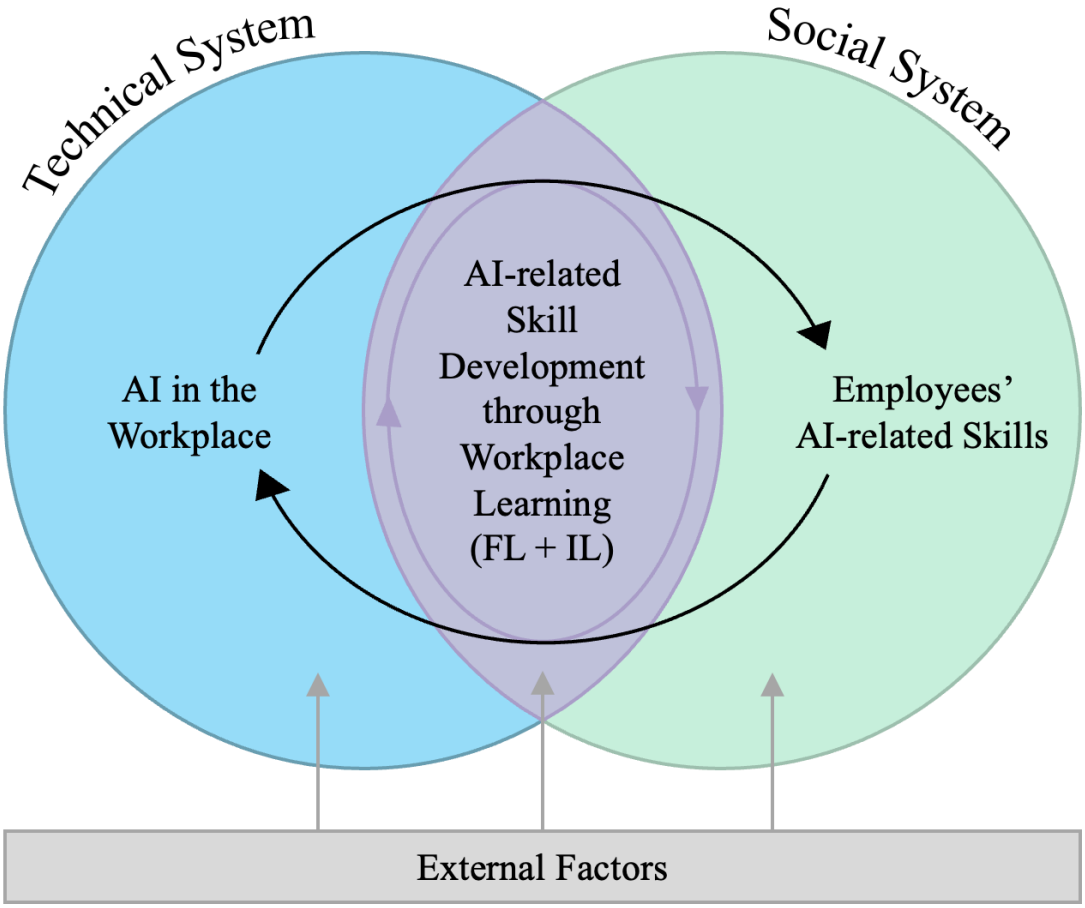


Figure 3: Conceptual Framework (own figure)

Building on the STS theory (Trist, 1981), our conceptual framework illustrates the dynamics between AI in the workplace, employees' AI-related skill development and workplace learning. The blue circle represents the technical system (AI in the workplace) and the green circle represents the social system (employees' AI-related skills). The technical system, in the context of our study, includes AI and its associated tools, systems and capacities within an organization. The social system includes employees' skills required to work with and alongside AI. These systems do not operate in isolation but intersect amidst AI-related skill development through workplace learning, shown through the purple overlapping section at the center.

This intersection is where workplace learning, including both FL and IL, takes place. FL reflects structured efforts to develop AI-related skills, such as security training, internal courses, or workshops. IL captures experiential and self-driven learning through peer collaboration, tool experimentation, or external platforms. FL and IL are not isolated, rather, they complement each other, resulting in dynamics within workplace learning, reflected through the inner arrows. This dynamic highlights the way FL and IL interact in practice, FL often providing a foundation, while IL fills gaps left by FL, creating a complementary relationship.

The outer arrows demonstrate the broader dynamics and relationships between the two systems. As AI technologies evolve and are adopted in the workplace (upper arrow), they create new learning demands for employees' AI-related skill development. In turn, employees' AI-related skills (lower arrow), which are developed through workplace learning, shape the way AI is interpreted, used and integrated into work, influencing adaptation, resistance, or engagement. Workplace learning, therefore, is a bidirectional process, AI drives learning needs to develop AI-related skills and those skills shape the way AI is used and accepted. Overall, the framework represents a dynamic process. Skill development is not a static endpoint, it evolves alongside the technologies that necessitate it. Workplace learning emerges as a dynamic mechanism that allows employees to navigate and respond to these shifts. The framework thus emphasizes that AI-related skill development is continuously evolving with workplace learning situated within changing socio-technical systems.

While the framework captures dynamics between AI integration, workplace learning, and employees' AI-related skills, several important factors remain outside its visual scope and are illustrated as external factors in the conceptual framework. This aspect connects to environmental factors within the STS theory (Trist, 1981), emphasizing that socio-technical systems continuously interact with and are impacted by their environment. Within our study, this relates to time constraints and competing work demands that may limit employees' ability to adapt to AI, develop AI-related skills and engage in workplace learning, reducing the opportunities to pursue consistent learning efforts. Broader issues, such as job displacement or shifting role expectations, particularly in response to automation due to AI, may affect the motivation of employees to pursue workplace learning. Similarly, skill erosion, where unpracticed or outdated knowledge fades over time, is not reflected. The framework also does not show the way in which the absence or inadequacy of FL can create imbalances, placing disproportionate pressure on IL to compensate. These factors could be considered for future research, further developing the framework.

The framework offers practical guidance by offering a visualization of the relationships and dynamics surrounding AI-related skill development. By illustrating the way AI in the workplace, employees' AI-related skills and workplace learning interact, it can help organizations to identify where interventions are needed, whether that is improving access to role-specific FL, fostering IL environments, or addressing external barriers that hinder engagement in learning efforts. Furthermore, organizations can use the framework to assess if current workplace learning efforts are balanced and aligned with the way AI is reshaping skills. This synthesis can act as starting point for providing targeted learning efforts that evolve alongside technological and social systems.

6. Conclusion

This chapter summarizes the key insights of our study and answers the research question. First, we outline the societal, theoretical and practical implications of our findings. Second, we acknowledge our study's limitations and suggest directions for future research. Together, these elements highlight the influence of workplace learning on employees' AI-related skill development.

6.1. Answer to the Research Question

The purpose of our study is to explore how workplace learning influences employees' AI-related skill development. Our empirical findings show that the influence of workplace learning is multifaceted and depends on individual engagement, organizational efforts, as well as a combination of contextual factors. Three main aspects emerge from our analysis:

First, FL provides a foundation for employees to develop AI-related skills, but its influence depends on relevance, depth and accessibility. FL initiatives help to acquire essential knowledge about AI, data handling and ethical use. However, our findings show that FL is currently perceived as fragmented and should be complemented with more practical, role-specific, shared and continuous pathways to meet the evolving skill demands of working with and alongside AI. Second, IL plays a critical role in influencing AI-related skill development, especially when FL is incomplete or too generic. Employees actively engage in experimentation, peer learning and self-directed exploration through external platforms to develop AI-related skills. In this vein, IL often becomes the primary individual strategy through which employees adapt to AI in their workplace. Our findings indicate that IL thrives when collaboration is encouraged, opportunities for experimentation and usage are provided and self-initiated knowledge acquisition is motivated. Third, our findings emphasize that workplace learning, in both its formal and informal forms, influences AI-related skill development by acting as a dynamic mechanism balancing technological change through AI and transformation of employees' skills, in line with the STS theory. Within this, AI-related skill development emerges not as a final outcome, but as part of a continuous, evolving process. It adapts through workplace learning as AI technologies and skill requirements shift.

In summary, workplace learning influences AI-related skill development by providing both foundational knowledge through FL and self-directed opportunities through IL, in response to technological change. IL often drives continuous learning when FL initiatives fall short. Together, workplace learning emerges as dynamic mechanism that helps employees develop AI-related skills as AI technologies and skill demands evolve.

6.2. Theoretical Implications

Our thesis provides theoretical implications to advance knowledge on how workplace learning influences employees' AI-related skill development. Therein, we address academic and practical calls for conducting research on employee training (OECD, 2023; Zirar et al., 2023). By conducting an exploratory, single case study within the rapidly evolving ICT industry, we advance the underexplored research area of AI-related skill development and provide an outset for future studies. Our study offers four theoretical contributions at the intersection of AI, skills and workplace learning.

First, we offer a nuanced perspective to the literature on augmentation by highlighting that it is shaped by employees' learning experiences in the workplace, rather than being a stable outcome of AI adoption (Anthony et al., 2023). This, in turn, contributes to the STS theory (Trist, 1981) by showing that the interplay of technical and social systems is highly dynamic. These aspects point to a need for theory to more explicitly incorporate learning processes as integral part of human-AI collaboration and the way augmentation is approached in the workplace. Furthermore, we nuance existing automation literature by showing that fear of displacement is not necessarily the dominant response to AI. While existing research emphasizes fear of automation (Huang & Rust, 2018), our findings reveal that employees are more concerned about cautious and responsible AI usage. This implies a need for research to shift the focus from fear to organizational conditions that enable critical reflections as part of workplace learning. Second, we contribute to skills literature by showing that AI-related skill development is not about mastering one specific skill, but about developing a variety of skills. Our findings support and expand existing research (Stephany & Teutloff, 2024; Zirar et al., 2023) by demonstrating that prompting skills, domain knowledge and conceptual understanding are key aspects of AI-related skill development. Furthermore, we advance research on skill development by highlighting the differing knowledge levels regarding AI. This has implications for research, which should acknowledge the diversity of starting points for developing AI-related skills, evolving skill demands and context-specific learning pathways.

Third, we refine workplace learning literature by emphasizing the conditions under which FL and IL influence AI-related skill development. While FL is often treated as a structured mechanism for skill development (Clardy, 2018; Manuti et al., 2015), our findings suggest that its impact depends on perceived relevance, depth and accessibility. IL, in contrast, emerges not merely as complementary but as a strategic necessity when FL falls short. This implies for research that workplace learning requires closer attention to the way learning formats are perceived and used in practice, rather than assuming their impact based on structure alone. Fourth, we add a nuanced perspective to the STS theory (Trist, 1981) by showing that workplace learning, in both formal and informal ways, acts as a dynamic mechanism in balancing the technical and social systems in organizations for AI-related skill development. Our findings illustrate that AI technologies, as part of the technical system, and employees' AI-related skills, as part of the social system, interact continuously. Given the rapid and continuous developments on the technical as well as the human side, our study suggests that contextualized and practical workplace learning functions as a dynamic mechanism in keeping the social and technical systems aligned. This implies for theory that the alignment of social and technical systems should be seen as an ongoing and dynamic process.

Overall, our study advances the current research landscape of AI, skills and workplace learning, by highlighting their intersection and answering our research question of how workplace learning influences employees' AI-related skill development.

6.3. Societal Implications

Our findings suggest that the way organizations structure workplace learning for AI-related skill development carries broader societal implications beyond the internal perspective. As AI integration transforms workplaces, the unequal distribution of learning opportunities within companies risks widening existing skill gaps. When workplace learning remains inaccessible, too generic, or poorly aligned with evolving technologies, certain groups of employees, especially those without a prior technical background, may be left behind. This dynamic highlights digital inequalities and may contribute to broader social segregation.

Moreover, our findings show that while employees value AI for its potential to enhance productivity, concerns about data security and environmental impact remain present. Without a workplace learning strategy that allows employees to critically reflect on the use of AI, there is a risk of normalizing practices that threaten privacy or increase environmental harm through

uncontrolled energy consumption. Workplace learning, in this case, can accelerate unsustainable AI adoption without allowing employees to question or improve these processes.

Given these implications, organizations should not treat AI-related skill development only as an internal efficiency project. They should design workplace learning initiatives that emphasize ethical AI usage, environmental responsibility and social inclusion. In detail, this entails providing accessible, practical and critical AI education for all roles, embedding sustainability principles centered around AI into workplace learning, consciously selecting AI providers, and creating a culture where questioning and improving AI tools is valued alongside their application.

6.4. Practical Implications

Our findings offer several practical implications for organizations that want to support AI-related skill development through workplace learning.

First, companies should move beyond offering isolated FL opportunities and provide learning initiatives that are role-specific, hands-on and adaptive to technological changes. These FL initiatives will be essential to maintain employees' long-term engagement and motivation. Second, organizations should recognize the strategic importance of IL. Providing designated time, resources and platforms for experimentation, peer learning and self-directed exploration will not only complement FL but also encourage innovation and knowledge sharing. In this vein, organizations should take an active role in creating IL opportunities, for instance through accessible sandboxes for AI experimentation, open communication forums and collaborative internal networks. Third, companies should avoid fragmentation of learning initiatives and instead embed workplace learning into their broader strategic vision. AI-related skill development should not be treated as an isolated initiative but fully aligned with AI adoption strategies and organizational goals. At the same time, organizations should offer pathways to develop those AI-related skills for all employees, regardless of their technical background.

In summary, our findings suggest that organizations should view workplace learning as a continuous, evolving process that is closely aligned with technological change, employee needs and broader strategic goals.

6.5. Limitations

While our study provides insights into the influence of workplace learning on employees' AI-related skill development, several limitations need to be acknowledged.

First, our study captures a specific moment in the evolving and dynamic technological environment. As AI technologies, regulations and workplace norms continue to change, some findings may lose relevance or require adaptation over time. We address this by focusing on employees' current perceptions and practices, offering a snapshot of workplace learning under ongoing transformation. Additionally, our study does not observe the actual unfolding of AI-related skill development. Capturing the way skills emerge or advance would require longitudinal studies, which is beyond the scope and timeframe of our thesis. However, we recommend longitudinal studies to explore the way these dynamics evolve over time and the way AI-related skill development progresses alongside technological change. Second, our study focuses on the individual employee's perspective on learning. Broader organizational and team-level factors, such as leadership support or cultural norms, while touched upon, are not analyzed. We include questions in the interview guideline that touch upon these topics and reference them when necessary, but they are not the primary focus. Future research could integrate interviews with managers or team leaders to better understand structural impacts on workplace learning. Third, from a methodological perspective, another limitation lies in the voluntary participation of interviewees, which may have led to include more engaged or AI-interested employees in our research. To address this, we interview employees across departments and roles to reflect a range of perspectives. We encourage future research to incorporate random sampling for capturing less vocal or more resistant viewpoints. Fourth, access to participants, as well as observational and secondary data, is mediated by the company, which limits the scope and depth of insight into workplace learning. To address this, we triangulate the available material to strengthen validity and reduce reliance on a single data source. Future studies could benefit from broader access to internal platforms, documents, or anonymized usage data to better capture learning processes in context.

Overall, this section acknowledges limitations of our study, outlines the way we address them and points to alternative approaches that future studies could take to respond to them. Therefore, these reflections highlight boundaries of our study and underscore the need for future research.

6.6. Future Research

In the following section, we propose several avenues for future research emerging from our thesis. First, given our time constraints in conducting our research as well as considering the rapidly evolving developments within contemporary workplaces, the area of AI and AI-related skills, we encourage future research to conduct a longitudinal study investigating how AI-related skills develop over time. This could provide more detailed insights into the actual process of AI-related skill development and identify contextual factors that further contribute to the process. Second, conducting a multiple case study across organizations, industries, or countries with differing technical maturities could offer insights into factors such as industry norms or cultural influences. Therefore, while our thesis focuses on capturing depth and richness through a single case study, a multiple case study could uncover patterns across several contexts, which in turn would further advance the currently limited research on AI-related skill development. Third, given the novelty of the research phenomenon, we focus on the entire workforce within one company for our investigation. However, future studies could narrow the focus to specific job roles, such as managers, or compare the perceptions of multiple roles. This could highlight whether AI-related skill development differs across job roles or whether notable similarities appear. Fourth, considering the environmental and societal impact of AI technologies, future research could explore how environmental awareness can be integrated into workplace learning. This could present insights into whether such awareness increases the conscious use of AI and in which way AI-related skill development is influenced. Fifth, building on our conceptual framework and the STS theory, we believe a particularly interesting avenue for future research could be to investigate our framework in the light of systems thinking, utilizing a causal-loop diagram to illuminate the different feedback loops emerging from this context. This could considerably advance knowledge on the intricate dynamics within this research phenomenon.

As these avenues for future research mark the final part of our thesis, we return to the wider implication that first sparked our interest. Looping back to the beginning of our thesis, if nearly half of all jobs are expected to disappear or transform (OECD, 2019a), then developing AI-related skills is no longer optional. Therefore, our thesis underlines the importance of workplace learning in building those skills, so all employees are equipped to surf the wave of AI, rather than drown in the flood.

7. Reference List

Alekseeva, L., Azar, J., Giné, M., Samila, S., & Taska, B. (2021). The demand for AI skills in the labor market. *Labour economics*, *71*, 102002. https://doi.org/10.1016/j.labeco.2021.102002

Ångström, R. C., Björn, M., Dahlander, L., Mähring, M., & Wallin, M. W. (2023). Getting AI Implementation Right: Insights from a Global Survey. *California Management Review*, *66*(1), 5-22. https://doi.org/10.1177/00081256231190430

Anthony, C., Bechky, B. A., & Fayard, A.-L. (2023). "Collaborating" with AI: Taking a System View to Explore the Future of Work. *Organization Science*, *34*(5), 1672-1694. https://doi.org/10.1287/orsc.2022.1651

Bell, E., Harley, B., & Bryman, A. (ed.) (2022). *Business research methods* (Sixth edition). Oxford University Press.

Blume, B. D., Kevin Ford, J., & Huang, J. L. (2024). Transfer of informal learning: The role of manager support in linking learning to performance. *Business Horizons*, *67*(2), 125-136. https://doi.org/https://doi.org/10.1016/j.bushor.2023.12.001

Brown, O., Davison, R. M., Decker, S., Ellis, D. A., Faulconbridge, J., Gore, J., Greenwood, M., Islam, G., Lubinski, C., MacKenzie, N. G., Meyer, R., Muzio, D., Quattrone, P., Ravishankar, M. N., Zilber, T., Ren, S., Sarala, R. M., & Hibbert, P. (2024). Theory-Driven Perspectives on Generative Artificial Intelligence in Business and Management. *British Journal of Management*, *35*(1), 3-23. https://doi.org/https://doi.org/10.1111/1467-8551.12788

Cerasoli, C.P., Alliger, G.M., Donsbach, J.S., Mathieu, J. E., Tannenbaum, S. I., & Orvis, K. A. (2018). Antecedents and Outcomes of Informal Learning Behaviors: A Meta-Analysis. *J Bus Psychol 33*, 203–230. https://doi.org/10.1007/s10869-017-9492-y

Chalutz-Ben Gal, H. (2023). Person–Skill Fit: Why a New Form of Employee Fit Is Required. *Academy of Management Perspectives*, *37*(2), 117-137. https://doi.org/10.5465/amp.2022.0024

Chartered Association of Business Schools. (2024). *Academic Journal Guide 2024*. C. ABS.

Choudhary, V., Marchetti, A., Shrestha, Y. R., & Puranam, P. (2025). Human-AI Ensembles: When Can They Work? *Journal of Management*, *51*(2), 536-569. https://doi.org/10.1177/01492063231194968

Chuang, S. (2021). An empirical study of displaceable job skills in the age of robots. *European journal of training and development*, *45*(6/7), 617-632. https://doi.org/10.1108/EJTD-10-2019-0183

Chuang, S. (2024). Indispensable skills for human employees in the age of robots and AI. *European journal of training and development*, *48*(1/2), 179-195. https://doi.org/10.1108/EJTD-06-2022-0062

Chuang, S., Shahhosseini, M., Javaid, M., & Wang, G. G. (2024). Machine learning and AI technology-induced skill gaps and opportunities for continuous development of middle-skilled employees. *Journal of Work-Applied Management*. https://doi.org/10.1108/JWAM-08-2024-0111

Clardy, A. (2018). 70-20-10 and the Dominance of Informal Learning: A Fact in Search of Evidence. *Human resource development review*, *17*(2), 153-178. https://doi.org/10.1177/1534484318759399

Collis, J., & Hussey, R. (2021). *Business research: A practical guide for undergraduate & postgraduate students* (Fifth edition). Macmillan Education.

Davenport, T. H., & Ronanki, R. (2018). Artificial Intelligence for the Real World. *Harvard Business Review*, *96*(1), 108-116.

Denzin, N. K., & Lincoln, Y. S. (2017). *The SAGE Handbook of Qualitative Research* (Fifth edition). Sage Publications.

Easterby-Smith, M., Jaspersen, L. J., Thorpe, R., & Valizade, D. (2021). *Management and business research* (Seventh edition). SAGE.

Engström, A., Pittino, D., Mohlin, A., Edh Mirzaei, N., & Johansson, A. (2024). Artificial intelligence and work transformations: Integrating sensemaking and workplace learning perspectives. *Information Technology and People*, *37*. https://doi.org/10.1108/ITP-01-2023-0048

Eraut, M. (2000). Non-formal learning and tacit knowledge in professional work. *British Journal of Educational Psychology, 70*, 113-136. https://doi.org/10.1348/000709900158001

European Parliament and Council of the European Union. (2024). Regulation (EU) 2024/1689 of the European Parliament and of the Council of 13 June 2024 laying down harmonised rules on artificial intelligence and amending Regulations (EC) No 300/2008, (Artificial Intelligence Act). *Official Journal of the European Union,* (L 1689). http://data.europa.eu/eli/reg/2024/1689/oj

Gallagher, P. T., Mathieu, J. E., & Reilly, G. (2023). Deploying to Develop Unit Human Capital Resources. *Journal of Management*, *49*(8), 2805-2830. https://doi.org/10.1177/01492063221113541

Glaser, B. G., & Strauss, A. L. (1967). *The discovery of grounded theory: strategies for qualitative research*. Aldine.

Goel, S., Puckett, J., Claver, P., & Kovacs-Ondrejkovic, O. (2022). 6 Strategies to Upskill Your Workforce. *Harvard Business Review*, 1-7.

Gray, A. (January 19, 2016). *The 10 skills you need to thrive in the Fourth Industrial Revolution*. World Economic Forum. https://www.weforum.org/stories/2016/01/the-10-skills-you-need-to-thrive-in-the-fourth-industrial-revolution/

Guba, E. G. (1981). Criteria for assessing the trustworthiness of naturalistic inquiries. *ECTJ*, *29*(2), 75-91. https://doi.org/10.1007/BF02766777

Hillebrand, L., Raisch, S., & Schad, J. (2025). Managing with Artificial Intelligence: An Integrative Framework. *Academy of Management Annals*, *19*(1), 343-375. https://doi.org/10.5465/annals.2022.0072

Hopf, K., Müller, O., Shollo, A., & Thiess, T. (2023). Organizational Implementation of AI: Craft and Mechanical Work. *California Management Review*, *66*(1), 23-47. https://doi.org/10.1177/00081256231197445

Huang, M.-H., & Rust, R. T. (2018). Artificial Intelligence in Service. *Journal of Service Research*, *21*(2), 155-172. https://doi.org/10.1177/1094670517752459

Jaiswal, A., Arun, C. J., & Varma, A. (2021). Rebooting employees: Upskilling for artificial intelligence in multinational corporations. *The International Journal of Human Resource Management*, *33*(6), 1179-1208. https://doi.org/10.1080/09585192.2021.1891114

Jeong, S., Han, S. J., Lee, J., Sunalai, S., & Yoon, S. W. (2018). Integrative Literature Review on Informal Learning: Antecedents, Conceptualizations, and Future Directions. *Human resource development review*, *17*(2), 128-152. https://doi.org/10.1177/1534484318772242

Katz, R. L. (1974). Skills of an effective administrator. *Harvard Business Review*, *52*(5), 90-102.

Krakowski, S., Luger, J., & Raisch, S. (2023). Artificial intelligence and the changing sources of competitive advantage. *Strategic Management Journal. 44*(6), 1425-1452. https://doi.org/10.1002/smj.3387

Li, H., & Kim, S. (2024). Developing AI literacy in HRD: competencies, approaches, and implications. *Human resource development international*, *27*(3), 345-366. https://doi.org/10.1080/13678868.2024.2337962

Li, J., & Yeo, R. K. (2024). Artificial intelligence and human integration: A conceptual exploration of its influence on work processes and workplace learning. *Human resource development international*, *27*(3), 367-387. https://doi.org/10.1080/13678868.2024.2348987

Li, L. (2024). Reskilling and Upskilling the Future-ready Workforce for Industry 4.0 and Beyond. *Information Systems Frontiers*, *26*(5), 1697-1712. https://doi.org/10.1007/s10796-022-10308-y

Manuti, A., Pastore, S., Scardigno, A. F., Giancaspro, M. L., & Morciano, D. (2015). Formal and informal learning in the workplace: A research review. *International Journal of Training and Development*, *19*(1), 1-17. https://doi.org/https://doi.org/10.1111/ijtd.12044

Marsick, V. J., & Volpe, M. (1999). The Nature and Need for Informal Learning. *Advances in Developing Human Resources*, *1*(3), 1-9. https://doi.org/10.1177/152342239900100302

Matthews, M. J., Su, R., Yonish, L., McClean, S., Koopman, J., & Yam, K. C. (2025). A Review of Artificial Intelligence, Algorithms, and Robots Through the Lens of Stakeholder Theory. *Journal of Management*. https://doi.org/10.1177/01492063241311855

Northouse, P. G. (2018). *Leadership: theory and practice* (Eighth Edition). SAGE Publications.

OECD. (2019a). OECD Employment Outlook 2019: The Future of Work. https://doi.org/10.1787/9ee00155-en

OECD. (2019b). OECD Future of Education and Skills 2030: Conceptual learning framework. Skills for 2030. https://www.oecd.org/content/dam/oecd/en/about/projects/edu/education-2040/concept-notes/Skills_for_2030_concept_note.pdf

OECD. (2023). OECD Employment Outlook 2023: Artificial Intelligence and the Labour Market. https://doi.org/10.1787/08785bba-en

Omrani, N., Rejeb, N., Maalaoui, A., Dabic, M., & Kraus, S. (2022). Drivers of Digital Transformation in SMEs. *IEEE Transactions on Engineering Management*. https://doi.org/10.1109/TEM.2022.3215727

Ostmeier, E., & Strobel, M. (2022). Building skills in the context of digital transformation: How industry digital maturity drives proactive skill development. *Journal of Business Research*, *139*, 718-730. https://doi.org/10.1016/j.jbusres.2021.09.020

Peterson, T. O., & Van Fleet, D. D. (2004). The ongoing legacy of R.L. Katz: An updated typology of management skills. *Management decision*, *42*(10), 1297-1308. https://doi.org/10.1108/00251740410568980

Raisch, S., & Fomina, K. (2024). Combining Human and Artificial Intelligence: Hybrid Problem-Solving in Organizations. *Academy of Management Review*. https://doi.org/10.5465/amr.2021.0421

Raisch, S., & Krakowski, S. (2021). Artificial Intelligence and Management: The Automation–Augmentation Paradox. *Academy of Management Review*, *46*(1), 192-210. https://doi.org/10.5465/amr.2018.0072

Rajaram, K., & Tinguely, P. N. (2024). Generative artificial intelligence in small and medium enterprises: Navigating its promises and challenges. *Business Horizons*, *67*(5), 629-648. https://doi.org/10.1016/j.bushor.2024.05.008

Rinta-Kahila, T., Penttinen, E., Salovaara, A., Soliman, W., & Ruissalo, J. (2023). The Vicious Circles of Skill Erosion: A Case Study of Cognitive Automation. *Journal of the Association for Information Systems*, *24*(5), 1378-1412. https://doi.org/10.17705/1jais.00829

Saldaña, J. (2015). *The coding manual for qualitative researchers* (Third edition). Sage Publications.

Sanders, N. R., & Wood, J. D. (2023). The Skills Your Employees Need to Work Effectively with AI. *Harvard Business Review*, 1-7.

Saunders, M., Lewis, P., & Thornhill, A. (2016). *Research methods for business students* (Seventh edition). Pearson Education.

Shao, Y., Huang, C., Song, Y., Wang, M., Song, Y. H., & Shao, R. (2024). Using Augmentation-Based AI Tool at Work: A Daily Investigation of Learning-Based Benefit and Challenge. *Journal of Management*. https://doi.org/10.1177/01492063241266503

Sousa, M. J., & Wilks, D. (2018). Sustainable Skills for the World of Work in the Digital Age. *Systems research and behavioral science*, *35*(4), 399-405. https://doi.org/10.1002/sres.2540

Sparr, J. L., Knipfer, K., & Willems, F. (2017). How Leaders Can Get the Most Out of Formal Training: The Significance of Feedback-Seeking and Reflection as Informal Learning Behaviors. *Human Resource Development Quarterly*, *28*(1), 29-54. https://doi.org/https://doi.org/10.1002/hrdq.21263

Stake, R. E. (1995). *The Art of Case Study Research*. SAGE Publications.

Stephany, F., & Teutloff, O. (2024). What is the price of a skill? The value of complementarity. *Research policy*, *53*(1). https://doi.org/10.1016/j.respol.2023.104898

Suddaby, R. (2006). From the Editors: What Grounded Theory is Not. *Academy of Management Journal*, *49*(4), 633-642. https://doi.org/10.5465/AMJ.2006.22083020

Tamayo, J., Doumi, L., Goel, S., Kovacs-Onarejkovic, O., & Saaun, R. (2023). Reskilling in the Age of AI. *Harvard Business Review*, *101*(5), 56-65.

Tamayo, J., Doumi, L., Goel, S., Kovács-Ondrejkovic, O., & Sadun, R. (2024). Designing a Successful Reskilling Program. *Harvard Business Review*, 1-10.

Thomas, G. (2017). *How to Do Your Research Project: A Guide for Students*. SAGE Publications.

Trist, E. L. (1981). *The Evolution of Socio-technical Systems: A Conceptual Framework and an Action Research Program*. Ontario Quality of Working Life Centre.

Watkins, K. E., & Marsick, V. J. (2023). Rethinking Workplace Learning and Development Catalyzed by Complexity. *Human resource development review*, *22*(3), 333-344. https://doi.org/10.1177/15344843231186629

WEF. (2016). *Future of Jobs Report: Employment, Skills and Workforce Strategy for the Fourth Industrial Revolution*. W. E. Forum. https://www3.weforum.org/docs/WEF_Future_of_Jobs.pdf

WEF. (2025). *Future of Jobs Report 2025: Insight Report*. W. E. Forum. https://reports.weforum.org/docs/WEF_Future_of_Jobs_Report_2025.pdf

Woo, S. E., Tay, L., & Oswald, F. (2024). Artificial intelligence, machine learning, and big data: Improvements to the science of people at work and applications to practice. *Personnel Psychology*, *77*(4), 1387-1402. https://doi.org/https://doi.org/10.1111/peps.12643

Yin, R. K. (2014). *Case Study Research: Design and Methods* (Fifth edition). SAGE.

Yin, R. K. (2018). *Case Study Research and Applications*. SAGE Publications Ltd.

Zirar, A., Ali, S. I., & Islam, N. (2023). Worker and workplace Artificial Intelligence (AI) coexistence: Emerging themes and research agenda. *Technovation*, *124*. https://doi.org/10.1016/j.technovation.2023.102747

Appendices

Appendix 1: GDPR Thesis Study Consent Form

JÖNKÖPING UNIVERSITY
Jönköping International Business School

GDPR Thesis Study Consent Form

Required by European Union General Data Protection Regulation 2016/679

GDPR Consent for the thesis "A Single Case Study Investigation on AI-related Skill Development"

Please tick the appropriate boxes	**Yes**	**No**
Taking part in the study I consent to JIBS processing my personal data in accordance with current data protection legislation and the data delivered.	☐	☐
I consent voluntarily to be a participant in this study and understand that I can refuse to answer questions and I can withdraw from the study at any time, without having to give a reason.	☐	☐

My signature below indicates that I choose to take part in the thesis study and consent to JIBS treating my personal data in accordance with current data protection legislation and the data delivered.

Name of participant	Signature	Date

Version: January 2020

JÖNKÖPING UNIVERSITY
Jönköping International
Business School

Participant Information Sheet

'It is entirely up to you to decide whether or not to take part in this study. If you decide to do so, you will be given this information sheet to keep and will be asked to give your consent. All the information that we collect about the company and interviewees during the research will be kept strictly confidential. You will not be able to be identified in any ensuing reports or publications.'

Under GDPR you have the following rights over your personal data:

- ***The right to be informed**. You must be informed if your personal data is being used.*
- ***The right of access**. You can ask for a copy of your data by making a 'subject access request'.*
- ***The right to rectification.** You can ask for your data held to be corrected.*
- ***The right to erasure**. You can ask for your data to be deleted.*
- ***The right to restrict processing**. You can limit the way an organisation uses your personal data if you are concerned about the accuracy of the data or how it is being used.*
- ***The right to data portability**. You have the right to get your personal data from an organisation in a way that is accessible and machine-readable. You also have the right to ask an organisation to transfer your data to another organisation.*
- ***The right to object**. You have the right to object to the use of your personal data in some circumstances. You have an absolute right to object to an organisation using your data for direct marketing.*
- ***How your data is processed using automated decision making and profiling**. You have the right not to be subject to a decision that is based solely on automated processing if the decision affects your legal rights or other equally important matters; to understand the reasons behind decisions made about you by automated processing and the possible consequences of the decisions, and to object to profiling in certain situations, including for direct marketing purposes.*

***You should also know that you may contact the data protection officer if you are unhappy about the way your data or your participation in this study are being treated at** dpo@ju.se*

Thank you for reading this information sheet and for considering whether to take part in this research study.'

Contact details for further information:

Thesis supervisor: Anup Banerjee

Thesis student 1: Katharina Ebner

Thesis student 2: Jorina Baltzereit

Version: January 2020

Appendix 2: Interview Presentation

Research Purpose

- **Bridging the research gap**: Exploring workplace learning's influence on AI-related skill development.
- **Workplace learning**: Formal & informal learning for AI-related skills.
- **AI-related skills:** Skills that are necessary to work directly with AI, but also complementary skills.
- **Practical insights**: Understanding training methods, challenges and key focus areas.

Data Utilization

Anonymity
All collected data, including company and participant names, will be fully anonymized.

Recording
Interviews may be recorded with consent for transcription and analysis; data will be used only for research and deleted afterward.

Data Processing
Tools used include MS Word, MaxQDA, MS Teams and QuickTime Player; all data is stored securely on OneDrive and deleted post-research.

Appendix 3: Interview Guideline

General Questions and Rapport Building

1. First, could you please introduce yourself to us - What is your name, age, nationality and gender?
2. Can you describe your current role and responsibilities at [Company X]?
    - Have you worked in other departments within [Company X]? If yes, which?
3. Since when have you worked for [Company X]?
4. In terms of an average working week, how much time do you allocate for meetings and individual work?

AI and Workplace Transformation

5. Can you walk us through how you first got involved with AI-related tasks or tools at work?
    - What was this experience like for you?
6. Which AI tools do you usually use within your workplace?
    - *(If not answered already)* How do you use these AI tools and how often? Can you give us some concrete examples?
    - *(If not answered already)* Which is your most frequently used tool?
7. Do you face any challenges when using AI?
8. Have you encountered resistance or fear among employees regarding AI adoption?
9. In your experience, how has AI changed the way you and your team work?
10. How confident do you feel in using AI tools in your work?
    - What are the reasons for that?
11. If you had to sum up your professional relationship with AI in one word, what would it be?
    - Why did you choose that word, what experiences or interactions have shaped your perspective?
12. How do you decide when to rely on AI and when to rely on human input?
13. How would you describe the current AI vision or AI strategy of [Company X]?

AI and Skill Requirements/ Skill Development

14. When you think of situations where you are using AI, can you describe the skills needed in those situations?
15. Besides working directly with AI, what skills do you believe are needed in a workplace where AI is present?
16. Do you feel the need to develop any skills more now that you use AI and that AI is present in your workplace?
17. Do you feel there are certain skills missing when it comes to working with AI in your organization?
18. What core skills do you believe are becoming obsolete due to AI, and how should organizations plan for that transition?
19. Can you describe a specific situation where you learned an AI-related skill at work?

Workplace Learning

20. How does [Company X] approach workplace learning for AI?
    - How do you typically find out about available AI-related learning or training opportunities within [Company X]?
21. Did you participate in any learning initiatives to develop AI-related skills?
    - If yes, what did this initiative look like?
        - What did you learn from it?
    - If not, why not?
22. Besides official learning initiatives offered by the company, do you engage in any other form of learning AI-related skills?
    - If yes, can you walk us through what this learning approach looks like?
    - If not, why not?
23. When you think of all the learning you did for AI, what helps you most in developing AI-related skills?
    - Can you recall a situation where something was particularly helpful or particularly disappointing?
24. In your view, what distinguishes someone who thrives in learning AI-related skills from someone who struggles?
25. If a colleague asked for advice on developing their skills while using AI and working in an AI-integrated workplace, what would you tell them?

26. If you were CEO for one day, what decision for AI-related skill development and workplace learning would you take?
27. What's a radical idea or experiment in AI-related workplace learning that you wish more organizations would try?
28. If you had to sum up workplace learning related to AI in your current role in one word, what would it be?
    - Why did you choose that word, what experiences or interactions have shaped your perspective?
29. What organizational blind spots do you see when it comes to supporting employees in AI-related skill development?
30. How do you apply the AI-related skills you have learned in your daily tasks?
31. Do you exchange the knowledge you learn with your colleagues?
    - If yes, can you give us an example?
32. What role does feedback play in your learning at work?
33. How much time do you allocate for learning activities?
34. How would you describe your workplace culture when it comes to learning or asking for help?
35. How do you evaluate whether an AI learning initiative has truly impacted behavior and performance on the job?

Outro

36. Is there anything else that we haven't covered yet that you would like to touch upon?
37. To summarize our interview, we identified that X, X and X are especially relevant to you. Did we understand that correctly?
38. If we have any follow-up questions, is it okay if we reach out to you again via the email address we currently have?