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The Role of AI in the Digital Skill Development of Employees in SMEs

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ABSTRACT

This thesis explores the transformative role of Artificial Intelligence (AI) in the digital skill development of employees within Small and Medium-sized Enterprises (SMEs), a sector that often faces unique constraints and opportunities in adopting emerging technologies. In the context of ongoing digital transformation, SMEs are increasingly pressured to equip their workforce with relevant digital competencies. AI, widely recognized for its potential to transform work processes, is also emerging as a tool for informal learning and skill enhancement. This study investigates how AI contributes to the digital skill development of employees and assists them in adapting to the ongoing digital transformation.

A qualitative research approach has been adopted, with data collected through semi-structured interviews conducted with employees, managers, and executives from five SMEs in Finland. These case firms span industries such as software development, consulting, and manufacturing. The study draws from thematic analysis to identify key patterns and interpret the human-centered dynamics of AI integration in workplace learning. The research is grounded in a theoretical framework that links employee skills development to technological advancement, emphasizing digital literacy, organizational readiness, and ethical AI governance.

The study reveals that AI functions primarily as an informal, supportive learning tool rather than a formal training system. Employees use AI applications such as generative models, chatbots, and code assistants to enhance productivity, access just-in-time learning, and foster self-directed development. This has reduced reliance on traditional mentorship models and encouraged independent problem-solving. However, effective integration is closely linked to foundational digital literacy and a willingness to engage in continuous learning. Furthermore, concerns regarding data privacy, algorithmic bias, and ethical usage highlight the importance of governance frameworks in supporting responsible AI adoption.

The study contributes to the literature by extending theoretical discussions on workforce upskilling in the AI era and emphasizing the need for inclusive, adaptive learning environments. The research highlights the importance of top management support, investment in digital literacy, and the implementation of ethical AI practices. The findings underscore the need for future studies to explore the long-term impacts of AI-facilitated skill development. Ultimately, the study concludes that while AI is a powerful enabler of digital skills, its success hinges on strategic alignment with technological advancement and a human-centered approach to workforce development.

KEYWORDS: Artificial Intelligence (AI), Digital Skill Development, Small and Medium Enterprises (SMEs), Digital Literacy, AI Adoption.

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1 Introduction

1.1 Motivation for the Study

The synergy between digital and innovative skills and business environmental support significantly impacts the adoption of AI in SMEs (Arroyabe et al., 2024). The same study stated that internal resources have a bigger impact on SMEs' adoption of AI than does business environment support.

The association between AI integration and SMEs' sustainable competitive advantage is moderated by managers' increased digital literacy (Alzaghal et al., 2024). Hence, in a country like Finland, where digital literacy is one of the best in the world, a study on the role of artificial intelligence in digital skill development is crucial. Finland has surpassed the overall target for the European Union (EU) 2030 goal, which seeks to have 80% of the EU population possess at least basic digital abilities, by achieving 82% coverage of basic digital skills, compared to the EU average of 55.6% (Digital Decade Country Report 2024: Finland 2 Finland Contents, n.d.).

The study by Istudor et al. (2024) discusses the potential for Central and Eastern European (CEE) countries, particularly Romania and Poland, to experience short-term economic growth due to technological advancements, but also warns about the risk of falling into a "middle-income trap" over time. This trap arises because, despite having capable programmers and growing AI development, a large portion of the population lacks basic digital skills, which limits broader technological adoption (Istudor et al., 2024). As a result, progress in AI may be confined to certain urban areas with better infrastructure and education, creating a divide between more developed regions and poorer, digitally underdeveloped areas. To avoid this, these countries need to focus on retaining talent, funding research and development, and attracting multinational companies to foster AI adoption more widely and reduce the risk of a brain drain and start-up loss.

However, in Nordic countries like Finland, where income-level and socio-economic differences are low (with a Gini coefficient value of 27.9 in 2023 according to Statistics

Finland), digital literacy starts at a young age. A study by Kumpulainen et al. (2020) in Finland highlights that children's digital literacy practices at home are diverse and involve a mix of digital tools, such as videos, interactive games, and apps on devices like tablets and smartphones. These digital practices are not isolated but often blend with non-digital activities, creating a hybrid approach to learning and playing. Additionally, these practices are shaped by the daily routines of the families, meaning digital and non-digital activities are interwoven into the children's everyday lives (Kumpulainen et al., 2020).

SMEs are more likely to use AI technology if their owners or managers have a university degree or other advanced professional training, if they have IT specialists on staff, or if they provide IT-related training to their workers (Huseyn et al., 2024). Additionally, SMEs that collaborate with universities and research centers and have excellent digital management abilities (using marketing analytics tools and ERP systems) are more likely to integrate AI into their operations (Huseyn et al., 2024). Finland is a pioneering country for technology and adopting new trends in technology. With a high rate of literacy, the SMEs of the country have an inclination towards adopting AI; however, from the perspective of employees, how satisfying are the different courses and trainings in their practical job experience.

Enhancing professional development programs and hard skills is crucial, as they together account for over half of reaching the goal of labor force adaptation to AI (Istudor et al., 2024). Thus, it has become extremely common among employees already in the workforce to join different executive and study methods to attain additional knowledge about AI. These courses have various scopes ranging from the functions to ethical backgrounds and government policies. This study will try to fill the gap on how different courses help employees to improve and navigate through this transition.

Muehlemann(2024) stated that production worker skill development and training are affected in different ways by the use of AI in the workplace. As AI decreases the amount of continuous training given to existing employees, there is a greater emphasis on hiring high-skilled new hires and less medium-skilled ones, which leads to "skill polarization" (a growing divide between low and high skill occupations). However, the adoption of AI also results in a rise in apprenticeship contracts, especially in small and medium-sized businesses (SMEs). This underscores the ongoing significance of apprenticeships in equipping future workers with the necessary skills to work with AI in production environments. Hence, reinforcing the necessity to study the effectiveness of AI training programs in upskilling employees and managers in SMEs.

The study aims to examine the effectiveness of AI training programs in upskilling employees and managers in SMEs. The study will research how AI tools assist workers in developing digital skills necessary for navigating the digital transition. Lastly, throughout the findings, it is possible to analyze the impact of such skill development on business performance and employee satisfaction.

Research Question 1: What is the Role of AI in the digital skill development of employees in small and medium enterprises (SMEs)?

Research Question 2: How do AI tools assist workers in developing digital skills necessary for navigating the digital transition?

1.2 Thesis Structure

This thesis is organized into five chapters that collectively build a comprehensive examination of the role of AI in the digital skill development of employees within SMEs. Chapter 1 introduces the study by outlining the motivation, identifying the research gap, and defining the main research questions. It also highlights the theoretical contributions of the study and provides context for the rest of the thesis.

Chapter 2 presents the literature review, covering core concepts such as artificial intelligence, digital skill development, and AI adoption in SMEs. This chapter synthesizes prior research to frame the study's theoretical background and culminates in formulating a conceptual framework that guides the research design and analysis.

Chapter 3 details the methodological approach of the study. It explains the rationale for selecting a qualitative case study method and describes the data collection process, including semi-structured interviews with employees and managers from five SMEs in Finland. The chapter also outlines the thematic analysis technique used to analyze the interview data.

Chapter 4 presents the findings of the study, structured according to the two research questions. It identifies and explains key themes that emerged from the interviews, including how AI is currently used as a tool for learning and how it supports the broader digital transition within SMEs.

Chapter 5 provides a discussion of the findings in relation to existing literature and the conceptual framework. It outlines the theoretical and managerial implications of the study, offers suggestions for future research, and discusses the limitations of the current research.

2 Theoretical Background

In the current era of exponential extension in massive data sets, or "big data," and a shift in technical innovation, artificial intelligence (AI) has transitioned from a theoretical concept to widespread practical implementation on an unprecedented scale (Helm et al., 2020).

The table below lists the key definitions that have been used in this thesis.

Table 1 Key Definitions.

Term	Definition	Source
Artificial Intelligence (AI)	AI is defined as the ability of machines to mimic human cognitive functions such as learning, reasoning, problem-solving, and language understanding.	Mueller and Massaron (2018)
Generative AI	A subset of AI that can generate new content, such as text, images, or code based on learned patterns from large datasets.	Dwivedi et al. (2021)
Digital Skills	A range of abilities needed to use digital devices, communication tools, and networks to access and manage information. These include both basic digital literacy and more advanced competencies.	Chaker(2020)
Employee Skill Development	The process through which workers acquire new knowledge or capabilities that improve their performance and adaptiveness in the workplace	Jagannathan et al. (2019)
Workplace Digital Competence	Employees’ ability to use digital technologies effectively and ethically in their professional roles, including communication, problem-solving, and data handling.	Kemendi et al. (2022)

2.1 Artificial Intelligence

Artificial intelligence (AI) definitions are highly context-dependent (Caluori, 2024). According to the study, AI definitions are shaped by disciplines, policy needs, and business strategies.

AI has been defined by Mueller & Massaron (2018) by categorized into four ways: acting humanly, thinking humanly, thinking rationally, and acting rationally. AI is the result of successful algorithmic programming. These algorithms seek to attain results of some sort (Mueller & Massaron, 2018).

Firstly, acting humanly means seeking intelligence/data elsewhere, reasoning with it, and acting accordingly to attain the desired result. Secondly, thinking humanly includes performing tasks that require intelligence (Mueller & Massaron, 2018) and can also include cognitive modeling to perform the task. Thirdly, thinking rationally involves studying how humans think through programming and following that thinking pattern since humans are rational beings, that is, humans use standard of thinking and decide accordingly to approach and solve problems in a manner that ought to be logical. Lastly, AI also acts rationally like humans. Programming of AI is done in a manner that it provides a baseline for negotiating to successfully conclude a task. It is different from human behavior in that human behavior involves aptitude, emotion, and other variables (Mueller & Massaron, 2018).

AI research methodologies need to evolve (Masters-Wheeler & Bay, 2024). The study explores how AI models blur the lines between human and machine agency. The study focuses on theoretical perspectives using literature review and theoretical analysis. According to Masters-Wheeler and Bay (2024) new methodologies should include user-centered perspectives alongside social justice. The study provides insights into the challenges of traditional research methods in human-computer interaction (HCI) and technical and professional communication (TPC) through AI.

However, educators see AI as beneficial but feel unprepared to integrate it effectively (Gayed, 2025). The study, using surveys, interviews, and thematic analysis, highlights the gaps in AI training for educators. On the other hand, the study also states that though teachers want more AI education, they see ethical concerns. This study suggests structured AI training for educators. The study considers “teacher attitudes toward AI adoption” as the dependent variable and “AI training” and “availability of resources” as the independent variables. A total of 132 educators from various countries and educational levels took part in the survey and interview. Gayed (2025) suggests that AI-assisted language learning and automated assessments may be used in the education system.

Digital tools and methodologies enhance STEM learning outcomes (Boltsi et al., 2024). The study concludes that universities need to digitize infrastructure and adopt new pedagogical approaches to prepare students for Industry 4.0. Though there are barriers to overcome, the integration of IoT and AI in traditional curricula requires significant investment. For example, smart campuses, remote labs, and STEM education enhancement (Boltsi et al., 2024). The study used a literature review and case study analysis of educational technologies to come to this conclusion.

2.2 Employee Skill

Human resource management (HRM) is shifting towards digital processes to improve efficiency and employee experience (Zhang & Chen, 2024). The study uses literature review and qualitative analysis to provide a structured view of HR digital transformation. The independent variables of the study are digital HRM strategies and technological advancements, while the dependent variable is employee performance.

Automating HR processes improves accuracy and reduces workload (Elena Turcu & Octavian Turcu, 2021). Case studies on Romanian SMEs and literature review provide a roadmap for robotic process automation (RPA) applications in HR. The study states that RPA enhances HR efficiency in SMEs.

Digital skills influence professional social capital, impacting workplace integration (Chaker, 2020). Chaker (2020) used social capital as the dependent variable, and ICT use and digital literacy as the independent variables. The study is guided by a theoretical framework that leads to two key research questions addressing how digital skills influence the recognition of professional and social competencies and any connection between recognition and social capital. To explore these questions, the study develops measurement tools that connect the concepts of linkage and integration with recognition. Research into an active working population employed in an organization is necessary to investigate these aspects. Hence, employees with varying digital skill levels were surveyed to conduct a quantitative study using regression analysis. Chaker (2020) develops a tool to examine the connection between recognition, skills, and interactions. The study explores how these concepts relate to factors like gender, age, and job roles. Structural equation modeling has been used to answer research questions.

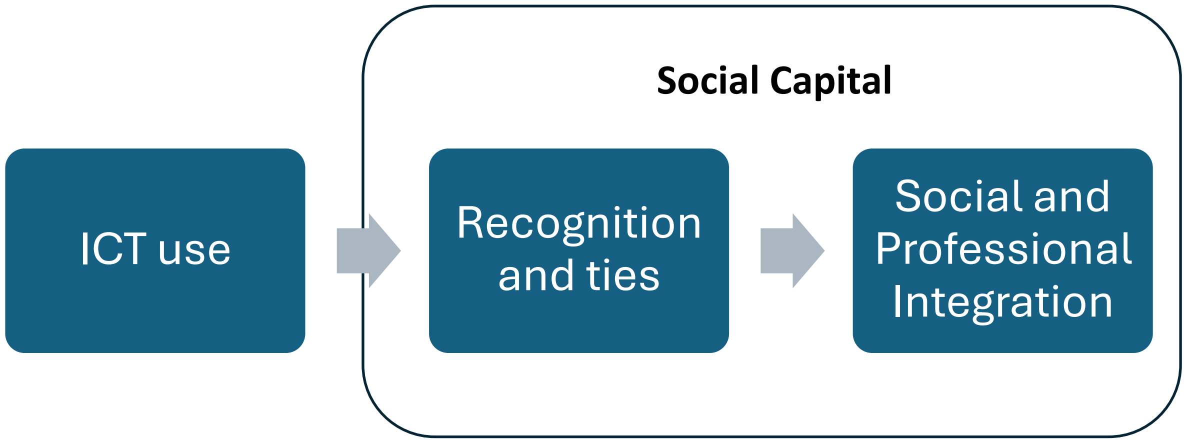

Figure 1 Recognition and ties are the link between ICT use and social and professional integration (Chaker, 2020).

Chaker (2020) states that digital skills mediate social and professional integration, affecting career success, and emphasizes digital literacy as critical for professional growth. Figure 1 illustrates the study’s findings that social capital exists both as a potential resource (through recognition and connection) and as the realization of that potential, seen in social and professional integration.

Digital skills are crucial for workforce adaptation (Mazurchenko & Zelenka, 2022). A survey of construction and automotive industries in the Czech Republic and statistical analysis concludes that many employees lack digital literacy. According to the study, digital training enhances productivity. Mazurchenko and Zelenka (2022) considered workforce digital readiness as the dependent variable, and training programs and technology adoption as the independent variables. The study states there is resistance to change and a high workload to overcome the situation.

Industry 4.0 reshapes the job market and skills requirements (Jagannathan et al., 2019). The study concludes that skills development must align with technological advancements. The study tries to discuss the global trends in job market evolution by reviewing labor market trends and Industry 4.0. Jagannathan et al. (2019)state that policymakers must focus on reskilling and lifelong learning. The study analyzed workforce adaptability as the dependent variable and digital skills and automation trends as independent variables.

Industry 4.0 demands new skills, but training programs lag behind (Marmier et al., 2021). The study uses a multi-phase methodology to assess the skills required for Industry 4.0 and design training programs accordingly. First, a diagnostic tool is developed to categorize the required skills in an organization. The second phase involves the identification of the skills development objectives. Third, the training, identification, and internal recruitment of employees are completed. The fourth step includes the identification of the training courses necessary for the recruited employees. Lastly, employees are trained, and new employees are recruited according to the skill requirements.

The study further states that workforce upskilling is critical for Industry 4.0 success and proposes tailored learning paths for Industry 4.0 training. The study utilizes industry workforce training data and concludes that Industry 4.0 requires a mix of technical and soft skills. The study highlights the need for continuous learning, emphasizing adaptable training models that incorporate simulation-based learning, e-learning platforms, and real-world applications. Moreover, companies that adopt proactive training strategies show improved workforce adaptability. It may be difficult to bridge the skills gap in digital manufacturing; however, implementing adaptive learning pathways is essential(Marmier et al., 2021)

Digital skills drive manufacturing growth (Chenoy et al., 2019). With a population sample of the Indian manufacturing sector workforce, the study highlights skill gaps in the industry. Chenoy et al. (2019) The study listed workforce readiness as the dependent variable and digital literacy and training programs as the independent variables.

Figure 2 Drivers impacting manufacturing industry (Chenoy et al., 2019).

Through policy analysis and a literature review, Chenoy et al. (2019) state that the industry must align training programs with digital transformation. The study deduces the drivers of manufacturing trends gathered by Microsoft (2019) and concisely presented in the following figure. As the figure summarizes, alongside the management of the global value chain, new-age technological advances, demographic shifts, and consumption trends drive the manufacturing industry in India.

A positive relationship exists between learning abilities, market changes, and technology development in shaping future skills (Gouda, 2022). Gouda conducted a quantitative study using online survey distribution among the managers and workers working with Generation Z (those born between 1996 and 2012) and millennial employees (those born between 1980 and 1996) in 3 industries (FINTECH, FMCG, and Industrial/production) in Egypt. The study examines how learning abilities, technological advancements, and shifts in the market influence the demand for future skills. The research aims to answer two research questions. Firstly, how has the labor market changed due to technology and the impact of Corona Virus Disease 2019 (COVID-19)? Secondly, in what ways do learning capabilities, market transformations, and technological progress shape the skills required for the future?

Though the study is limited to quantitative data and lacks qualitative insights, it concludes that the future job market requires continuous upskilling and digital transformation. Learning abilities, technology growth, and market change significantly influence the need for future skills (Gouda, 2022). Since it is challenging for educators and policymakers to adapt to rapid technological shifts and evolving job market demands, the study provides insights on designing future-ready curricula.

2.3 Adoption of AI

Internal capabilities drive AI adoption more than external business support (Arroyabe et al., 2024). The study highlights synergy between digital and innovation capabilities, though findings are limited to the European SMEs and may not be generalized. As mentioned earlier, SMEs with strong digital skills integrate AI more effectively. The study further says that external support has a limited impact on AI adoption, rather digital capabilities play the most vital role. The study used survey analysis and regression modeling using the Eurobarometer dataset. While the AI adoption rate is the dependent variable, digital capabilities, innovation capabilities, and external business support have been the independent variables (Arroyabe et al., 2024).

The study can be backed by another study that concludes that digital literacy indirectly affects the tendency of using technology via habit and performance expectations(Jang et al., 2021). The study used structural equation modeling and multigroup analysis. This comparative study among young people of Finland and Korea has been such cross-country study linking literacy skills to technology adoption for learning. The results show that while Finnish students prefer laptops for educational purposes, Korean students rely more on personal computers (PC) and tablets. The study considered the intention to use digital technology for learning as the dependent variable, while the independent variables were digital literacy and information literacy.

Another study (Ciarli et al., 2021) mentioned that AI and automation impact employment differently across industries. While this study used literature review and industry case study analysis it also states that fast-evolving technological advancement makes it hard to predict future job impacts. Ciarli et al. (2021) examine the relationship between digital technology, firm routines and skill formation.

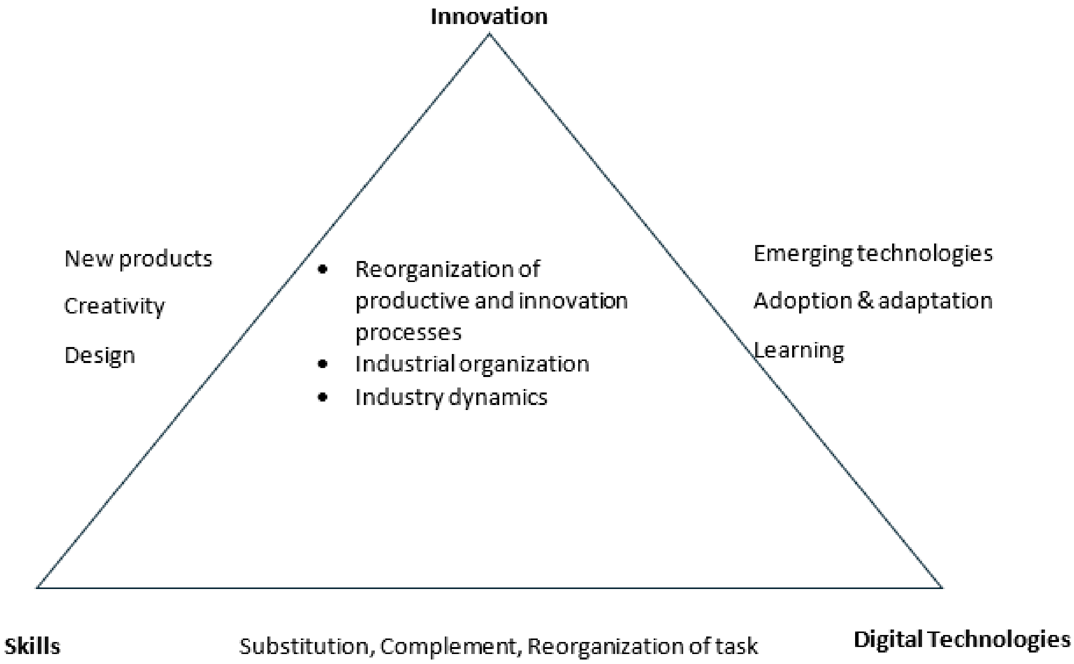

Figure 3 The interconnected nature of innovation, skills, and digital technologies (Ciarli et al., 2021).

Each point of the triangle represents a pairwise relationship between these elements, which are often examined in isolation. However, their full impact emerges through a systematic interaction that necessitates and is also shaped by the transformation of production and innovation processes within and across firms (Ciarli et al., 2021)

The study concluded that though digital technology increases productivity it requires new skills. The study considered the employment shifts due to digitalization as the dependent variable while the independent variables were digitalization and innovation adoption.

AI adoption enhances SME sustainability and digital literary plays a crucial role in AI adoption (Alzaghal et al., 2024). The study further states that AI integration with moderation of digital literary strengthens competitive advantage. The argument of linking digital literacy to a competitive edge highlights the importance of comprehending and integrating digital tools. Owning technology without the expertise to utilize it effectively is pointless. The extent of digital literacy within the company greatly influences how broadly and flexibly SMEs adopt AI (Alzaghal et al.,). With higher digital literacy AI can be transformed from a basic operational tool to a strategic asset.

Alzaghal et al. (2024) considered AI integration as the independent variable of interest which has been subdivided into 4 categories: decision-making, customer service, operational procedures, and data analysis. Factors used by the study to measure SMEs' long-term competitive advantage are, for example, customer loyalty, market share, and sustainability.

This leads to thinking that the workforce skill gaps must be addressed through policy and training. Singh Sidhu et al.,(2024) states that AI adoption outpaces workforce skill development. Emerging economies face training challenges. The study suggests that workforce training and government intervention are necessary. The study is built on 3 hypotheses.

Alzaghal et al. (2024) point out the research gap that while many studies highlight AI's impact on different industries and operations, few of them explore how SMEs gain a long-term competitive advantage through AI utilization. A cross-sectional study surveying SMEs affiliated with the Palestinian Information Technology Association (PITA) has been conducted. The study used Partial Least Squares-Structural Equation Modeling (PLS-SEM). Supported by robust statistical evidence, the analysis confirmed that AI integration positively influences sustainable competitive advantage The research highlights the opportunities and challenges SMEs face in the AI-driven era, particularly in the context of Palestine.

In summary, integrating AI into SMEs can lead to improved decision-making, market share, and environmental sustainability. Alzaghal et al. (2024)encourages training to enhance digital literacy. The study emphasizes SMEs face challenges like resource limitations, lack of technological infrastructure, and low digital literacy among managers. Besides providing insights relevant to developing economies, the study contributes to policymakers' and business leaders' efforts to promote AI adoption.

Central and Eastern European (CEE) countries face a different kind of problem. These countries face digital talent migration(Istudor et al., 2024). The study concludes that AI adoption must align with workforce skills to be effective. Multiple-criteria decision-making (MCDM) was used as a methodology of study. One of the critical findings of the study is that AI integration is hindered by workforce readiness.

SMEs with digitally skilled managers, IT experts, and ERP/marketing analytics tools are more likely to adopt AI (Huseyn et al., 2024). The study also claims that collaboration with universities also fosters AI adoption. Logistic regression analysis, survey data from Spanish SMEs, and Generative Adversarial Networks (GANs) were used to balance data. However, since most of the variables are dichotomous it limits the study scope.

AI accelerates job polarization and reduces demand for intermediate-skilled workers (Understanding the Impact of Artificial Intelligence on Skills Development, 2021). The study highlights that to cope with the changing ecosystem, education systems must rapidly adapt to equip workers with AI-related skills. This study came to its conclusion through policy analysis, case studies, and surveys. One of the crucial limitations of the study was the lack of quantitative analysis of AI's specific effects on separate industries. However, the study provides a global perspective on AI-driven skills development. The study by UNESCO (2021) suggests that stronger policy frameworks are necessary to address AI-driven skills shifts through the examination of AI's role in shaping education and labor market skills. From a global perspective, AI demands more adaptability and continuous learning in the education sector.

However, due to differences in economies, the study failed to define "intermediate skills" (2021). It suggests future research on ethical AI governance in education. The dependent variable of the study is "Skill levels in the workforce," and the independent variable is "AI adoption." While one of the challenges is the ethical concerns about AI-driven inequalities, the results of the study are essential for educational reform and AI integration(2021).

Table 2 Common Values and Principles of Ethical AI *(*Understanding the Impact of Artificial Intelligence on Skills Development*, 2021).*

Values and Principles	Explanations
Responsibility	Human oversight or legal accountability (must be agreed upon), i.e. someone has the power to make changes should fix problems caused by AI algorithm.
Explainability	Linked to the idea of accountability, how and why an algorithm made a certain decision.
Accuracy	It's important to find and track errors from algorithms and take steps to fix or reduce them.
Auditability	The possibility of external experts or public checking and review helps to build trust and can uncover problems.
Fairness	Checking for discrimination and ensuring equal access to AI and its benefits is important to eliminate human biases, especially from past or social data.
Safety and Security	When handling personal data it must be protected and whether on purpose or by accident, AI must not cause harm. Harm can include factors like discrimination, privacy violation, or emotional and social damage.
Wellbeing	AI should be used as a means to benefit people, society, and the economy.

A variety of stakeholders, including international organizations, governments, research institutions, private companies, non-profits, and professional associates, are actively shaping ethical AI frameworks and principles(Jobin et al., 2019). While the approaches and definitions may differ, many share common values. Table 1 highlights a list of widely recognized principles.

Morandini et al. (2023) concluded that companies need to implement proactive strategies to help employees adapt to AI-driven transformations. While the study conducted a systematic review of literature and corporate training programs, it has limited empirical data on actual implementation success. The study provides insights into how companies are addressing AI-driven skill shifts. AI increases the importance of transversal (soft) skills alongside technical skills (Morandini et al., 2023). While the study recommends exploring Industry 5.0's impact on job market skill demands, it provides recommendations for industry-specific training approaches. The independent variable of the study is "employee skills," and the dependent variable is "AI integration."

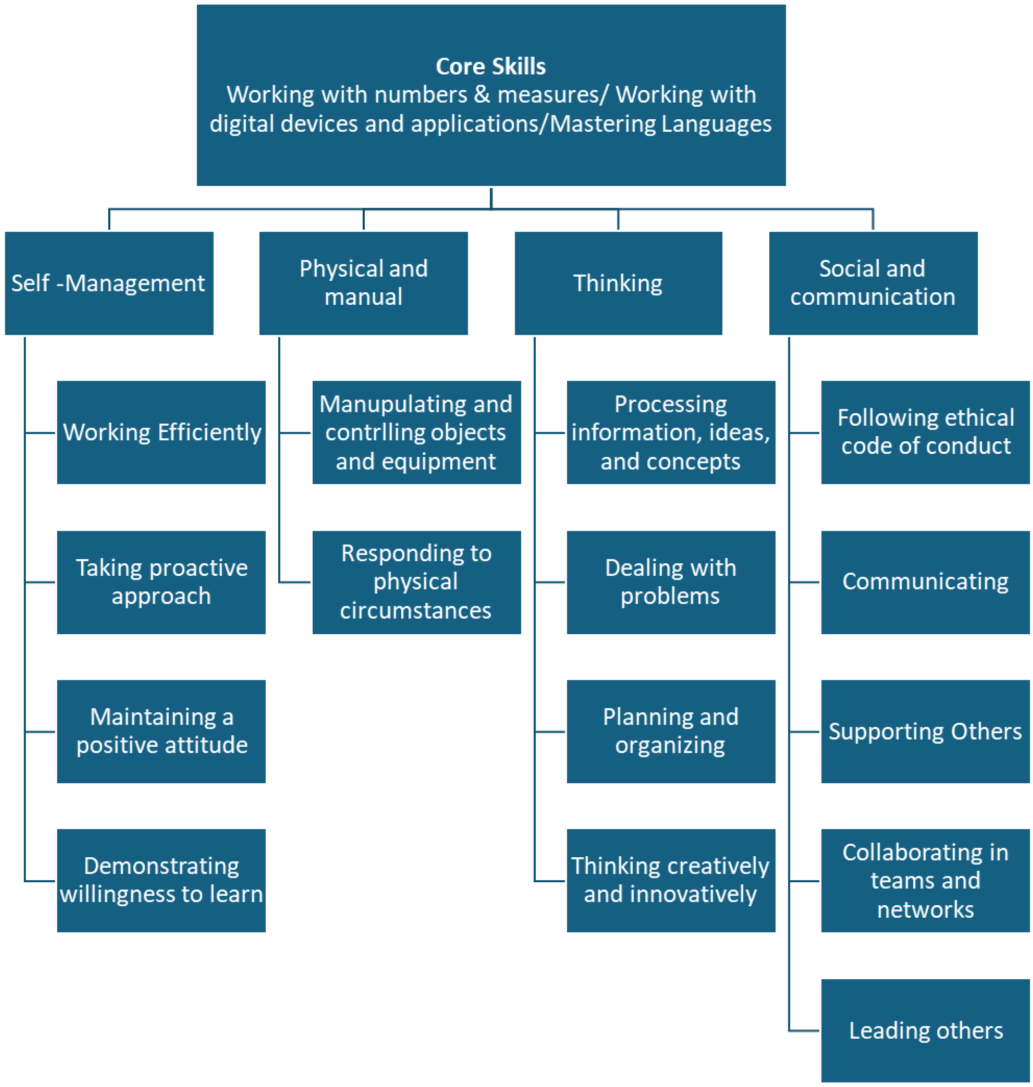

Figure 4 Transversal Skills and Competencies Model(Hart et al., 2021).

The adoption of AI systems in organizations has highlighted the need to recognize and develop transversal skills within the workforce. These skills are sometimes called transferable skills or soft skills and are useful across different roles and sectors(Hart et al., 2021).

Core skills are foundational abilities involving understanding, speaking, reading, and writing in one or more languages, managing numerical and measurement-related tasks, and using digital tools and applications. They are essential for communication, learning, and personal growth. Core skills comprise self-management skills, physical and manual skills, thinking skills, and social and communication skills (Hart et al., 2021).

The ability to recognize and regulate one's strengths and weaknesses to guide actions across different situations is a self-management skill. It includes acting responsibly and reflectively in line with one's values, responding to feedback, and pursuing growth in both personal and professional domains (Morandini et al., 2023). Physical and manual skills include the ability to carry out tasks requiring coordination, agility, strength, or endurance. They may involve using one's hands, physical effort, or operating tools, machinery, or instruments. The mental capacity to gather, interpret, assess, and summarize information from experiences, observations, reasoning, or communication is referred to as thinking skills (Morandini et al., 2023). These skills enable individuals to plan, reach objectives, solve problems, and handle both routine and unfamiliar tasks using various forms of information. Social and communication skills are needed to engage constructively with others. They include sharing ideas with empathy, collaborating towards shared goals, resolving conflicts, building trust, leading activities, and supporting the well-being and advancement of others.

Bogoslov et al. (2024)concludes that digital skills development is crucial for AI adoption among the elderly, and countries with stronger digital infrastructures foster better AI adoption. The study used bibliometric analysis, cultural analysis using Hofstede's model, and statistical data analysis. Considering the demographic representation issues, the study provides strategies to bridge the digital divide for elderly AI adoption. Bogoslov et al. (2024) suggest that while there is growing interest in the adoption of AI among the elderly, digital skills are lacking. The study used "AI adoption rates" as the independent variable and "digital literacy" and "cultural background" as the dependent variables. The sample population included elderly individuals in the EU above the age of 65 years.

Digital Intelligence Assistants (DIAs) can support cognitive task loads in SMEs, although usability can be challenging (Wellsandt et al., 2023). Using literature reviews and case study of WASABI project the study concluded that DIAs aid SMEs, but they require better business models and cost-reduction strategies. The WASABI project (White-label shop for digital intelligent assistance and human-AI collaboration in manufacturing) envisions the development of intelligent digital assistance solutions that empower workers to achieve their objectives while maintaining their central role in manufacturing. The project’s primary focus is to enable seamless human-AI collaboration, ensuring that technology supports workers rather than replacing or marginalizing them.

Wellsandt et al. (2023) envisions that AI-driven digital assistants and conversational tools will play a key role in helping manufacturers achieve sustainability and other goals. Workers will use them to explore ways to repurpose waste, streamline processes, and reduce environmental impact. These solutions will be easy to access and configure as apps from an online store, ensuring flexibility and preventing dependence on a single provider. AI training programs will become a common practice (Wellsandt et al., 2023) allowing employees to test solutions firsthand and understand AI’s strengths and weaknesses, risks, and limits in workability.

A white-label online shop may allow one to overcome the barrier of a lock-in product design model Wellsandt et al., 2023). The current use of the assistance framework uses a vendor lock-in where customers are forced to buy separate skills for each platform, while developers must maintain multiple versions, increasing costs and limiting the usefulness of new digital assistants. DIAs improve knowledge acquisition, decision-making, and sustainability.

The study considers SMEs in the manufacturing industry. AI assistance implementation is regarded as the independent variable, and cognitive workload reduction is the dependent variable. The results of the study can be used for implementing AI-driven workforce augmentation(Wellsandt et al., 2023).

Workplaces are currently transitioning into Industry 5.0, a movement led by the European Commission that emphasizes sustainability, human-centered work, and resilience in European industries. This shift is bringing unforeseen changes to how work will look in the future. As digital technologies become more integrated and sustainability becomes a priority, job roles, required skills, and qualifications are evolving across all sectors, including SMEs (Zare et al., 2024).

Zare et al (2024) explore the skills and abilities that workers will need in the future as industries transition into Industry 5.0, preliminary focusing on SMEs. The study addresses two research questions looking at the competencies employees must develop to work effectively in a more technology-driven and sustainable environment, and how SMEs will adapt to new technologies, sustainability goals, and changing work structures.

A detailed analysis of past studies was carried out to gather essential insights into the skills and competencies required for employees working in SMEs. The research highlights the critical skills SMEs need to embrace digital innovation and environmentally friendly practices. These skills cover different areas, including broad, transferable abilities, specialized technical knowledge, and expertise in sustainability (Zare et al., 2024). SMEs need to upskill workers in technical, transversal, and green competencies (Zare et al., 2024). Additionally, SMEs should implement competency-based training programs.

AI adoption in SMEs depends on technological, organizational, and environmental factors (Lai et al., 2025). Like other studies, the study concludes that though AI improves efficiency and competitiveness, SMEs struggle with implementation barriers. The study employs the Technology-Organization-Environment (TOE) framework for its analysis.

The study uses a mixed-method approach. A structured survey collects quantitative data on technological, organizational, and environmental factors. The survey aims to address five research questions, including the relationship between AI adoption intention and sustained use. The survey also collects data on the types of AI technologies used, the areas where AI has been implemented, and the overall extent of AI adoption in SMEs (Lai et al., 2025). Additionally, the survey pinpoints the main factors that encourage or hinder AI adoption.

Deeper insights into the barriers and drivers of AI adoption have been mined through qualitative semi-structured interviews among SME owners and managers (Lai et al., 2025). Data analysis techniques like structural equation modeling (SEM) are used to uncover connections between different factors besides thematic analysis to identify recurring patterns and key insights. The research investigates nine propositions related to AI adoption in Malaysian SMEs. The study considers organizational, technological and environmental factors as independent variables and AI adoption intention as dependent variable. The key themes include perceived benefits, complexity challenges, top management support, and technological readiness as critical to adoption intentions.

Lai et al. (2025) concludes that SMEs are more likely to adopt AI if it clearly improves the current ways of working. The bigger the advantage AI offers, the more willing they are to use it. Additionally, if AI is too complicated and businesses lack technical know-how, they may struggle to adopt it (Lai et al., 2025). Providing support, like training programs, can help to make the transition easier for SMEs.

From an organizational viewpoint, having strong support from top management is key to overcoming pushback and ensuring resources are allocated effectively for AI initiatives (Lai et al., 2025). Additionally, the study proves that the financial considerations, for example, the setup of AI and ongoing maintenance, are a big factor in whether businesses choose to adopt it. Government incentives can help reduce financial barriers through incentives.

External environmental factors include competitors and market trends. If competitors and market trends demand the adoption of AI, to stay competitive and meet customer expectations, SMEs might feel pushed to keep up with the new technology. As per the Malaysian SME context, the study suggests that via policy support and training, SMEs must overcome AI adoption barriers. To gain long-term benefits from AI, businesses need to consistently adjust and adapt (Lai et al., 2025).

Though the lack of empirical data on SME-specific AI adoption strategies made the study difficult, Lai et al. (2025) concluded that AI benefits include cost savings, efficiency, and improved decision-making. AI adoption among Malaysian SMEs is influenced by technological, organizational, and environmental factors (Lai et al., 2025).

One field to constantly study the effect of AI in the working implications is the healthcare. AI may enhance precision in medication and diagnostics, though there are ethical and legal concerns. AI-driven tools enhance early disease detection and reduce costs (Horgan et al., 2020). The study mentions the lack of unified AI regulation in healthcare. Horgan et al.(2020) state that AI can reduce costs and improve medical outcomes.

AI awareness and implementation drive SME performance (Senadjki et al., 2023). The study concludes that the relationship between competitiveness and AI in the context of awareness, empowerment, and implementation is positively significant. The study suggests that SMEs should integrate AI to improve market competitiveness since AI significantly boosts SME growth. Additionally, competitiveness and AI awareness have a partial mediating influence (Senadjki et al., 2023).

The conceptual model of the study considers AI as the independent variable, which considers the awareness, knowledge, empowerment, and implementation of AI. Technological innovation has been used as the mediation variable while SME competitiveness has been considered as the dependent variable. Senadjki et al. (2023) tries to prove three hypotheses relating to AI and technological innovation, social innovation, and environmental innovation of SMEs in Malaysia.

The study uses Partial Least Squares (PLS-SEM) based structural equation modelling to comprise a variance-based way of data analysis. Survey-based research using SmartPLS focused on Malaysian SMEs and successfully extends Open Innovation Theory (OIT) in AI research. According to OIT, businesses can and should develop their technological capabilities through both internal and external routes and ideas to successfully compete in the market (Chesbrough, 2003).

Senadjki et al. (2023) state external factors include environmental and social impact, and their effects on investor attractiveness. Businesses' social and environmental initiatives rely on suitable regulations and investments in the adoption of advanced technologies. In consideration of the expanding sustainability movement, businesses that ignore environmental and social agenda practices are less attractive to investors and relevant stakeholders (Senadjki et al., 2023). The study concludes that, AI awareness and implementation drive SME performance.

SMEs adopt digital business models to enhance competitiveness (Teoh et al., 2023). The study concludes that digital transformation supports business sustainability. Using semi-structured interviews with SMEs the study explores value creation through digital models. Teoh et al. (2023) conducted semi-structured virtual interviews with the top management of four SMEs.

The purposive sampling method has been used to ensure that the interviewees have experience with digital transformation. Each interview lasted between 60-80 minutes and was recorded with permission. The collected data has been thematically analyzed to identify the key elements of digital business model innovation (DBMI).

The study claims that digitalization enhances SME growth and cost efficiency (Horgan et al., 2020). Teoh et al. (2023) examine DBMI adoption in SMEs in Malaysia and conclude DBMI helps SMEs to survive in volatile markets. Despite being in the early stages of adoption the companies demonstrated different strategies to integrate digital technologies into their business models.

For instance, value-creating innovations like new digital systems (accounting, human resource management, and customer relationship management) have been implemented(Teoh et al., 2023). Additionally, SMEs adopted value proposition innovation models through the introduction of new products and services like digital payment schemes and live-streaming sales events. Moreover, companies leveraged online marketing tools, search engine optimization (SEO), and social media platforms to reach broader audiences to implement value delivery innovation(Teoh et al., 2023). SMEs in Malaysia use digital tools to optimize operations, reduce costs, and generate new revenue streams, including collaborating with online platforms and third-party logistics services to minimize expenses. Such innovative actions can be referred to as value-capture innovation.

The study highlights that SMEs struggle with resource limitations, requiring collaborations with research institutions and technology providers to enhance their digital capabilities. One of the opportunities in adopting DBMI was the COVID-19 pandemic. It accelerated digital adoption since businesses were forced to find ways to sustain operations(Teoh et al., 2023). Furthermore, the study emphasizes the importance of strategic planning, upskilling employees, and continuously adapting to new digital trends to remain competitive. Thus, DBMI is becoming a necessity for SMEs to survive and thrive in the modern business landscape (Teoh et al., 2023).

Zhang and Chen (2024) investigate how human resource management (HRM) is digitally transforming in the modern digital economy. The researchers use a combination of literature review and theoretical analysis to explore key drivers, transformation directions and the impact of digital HRM. Zhang and Chen (2024) identify five major drivers of HRM digital transformation: digital needs of internal customers, innovation within industry, competitive challenges, digital innovation governance, and the requirements of the digital era.

The study focuses on how HRM processes such as recruitment, training, and performance evaluation are adapting to digital advancements like AI, big data, and cloud computing. HRM processes are evolving since digital technologies enable more efficient employee selection, training, and assessment (Zhang & Chen, 2024). Digital workplaces integrating HRM technology improve productivity by fostering collaboration, transparency, and efficiency in organizations (Zhang & Chen, 2024). Personalized training and self-service HR portals improve employee engagement and enhance experience. However, there are challenges in the transitioning systems: the shift from traditional HR practices to digital models must be carefully managed. Additionally, ethical concerns regarding data privacy, security risks, and fairness in AI-driven decision-making are critical concerns in digital HRM implementation.

Zhang and Chen (2024) conclude that digital transformation in HRM is inevitable and necessary for businesses to remain competitive. But the transition must be maneuvered carefully to ensure a balance between automation and human involvement. The study reinforces that organizations should invest in upskilling employees, improving data security, and adopting a phased approach to HRM digital transformation. The study states that digital HRM is more than adopting new technologies; it is about strategically reshaping HR functions to align with the demands of the digital era.

Human-machine collaboration improves productivity (Kemendi et al., 2022). The study uses a combination of literature review, cluster analysis, and statistical methods to define Industry 5.0 and its workforce impact. Kemendi et al. (2022) identify the key differences between the two industrial revolutions (Industry 4.0 and Industry 5.0), focusing on technology, human resources, and security risks. European Union (EU) countries are categorized based on digital and computer skills using k-means methods for cluster analysis. Moreover, key digital skill indicators are determined through variance analysis, and a dynamic analysis compares the percentage of enterprises employing ICT specialists in 2020 versus 2012. Kemendi et al. (2022) consider workforce adaptability as the dependent variable, and digital skills and automation trends as the independent variables.

The study identifies the skill gaps in digital competencies among EU countries: Western and Northern European nations have higher digital literacy than Eastern and Central European ones.

Kemendi et al. (2022) conclude that Industry 4.0 focuses on automation and efficiency, while Industry 5.0 integrates human creativity with intelligent systems. The percentage of companies hiring ICT specialists remains low across the EU, especially among small enterprises (Kemendi et al., 2022). Data breaches and system vulnerabilities are some of the security risks associated with Industry 4.0 and 5.0.

Industries must invest in digital skills development (Kemendi et al., 2022). The study suggests that productivity may be improved through effective human-machine collaboration, for example, with smart manufacturing cobots. Industry 5.0 seeks to enhance human collaboration with smart machines. The study concludes alongside investing in digital tools and security systems, organizations must invest in workforce training to remain competitive in the evolving industrial landscape.

Bettoni et al. (2022) use a combination of literature review and empirical analysis to develop and validate a conceptual model for AI adoption in SMEs. The study examines existing digitalization and AI readiness models and identifies the complexity as a barrier to SME adoption. A survey of 39 companies (30 SMEs and 9 large enterprises) assesses the various aspects of AI readiness, such as data strategy, digital skills, and organizational structure. Assessment methods were refined by interviewing two SME managers from Poland and Italy.

Bettoni et al. (2014) claim several key barriers to AI adoption in SMEs. Many SMEs lack sufficient data collection and storage processes essential for AI implementation. Additionally, SMEs struggle to evaluate the return on investment for AI and perceive it as expensive (Bettoni et al., 2021). SMEs have specific needs regarding AI solutions however, most available AI solutions in the market are designed for larger enterprises, while customization may require a hefty investment. Moreover, employees in SMEs require significant training to work effectively with AI technologies. Complex AI tools are often difficult to integrate and use without specialized knowledge and as Kemendi et al. (2022) state SMEs tend not to hire specialist ICT employees for such purposes.

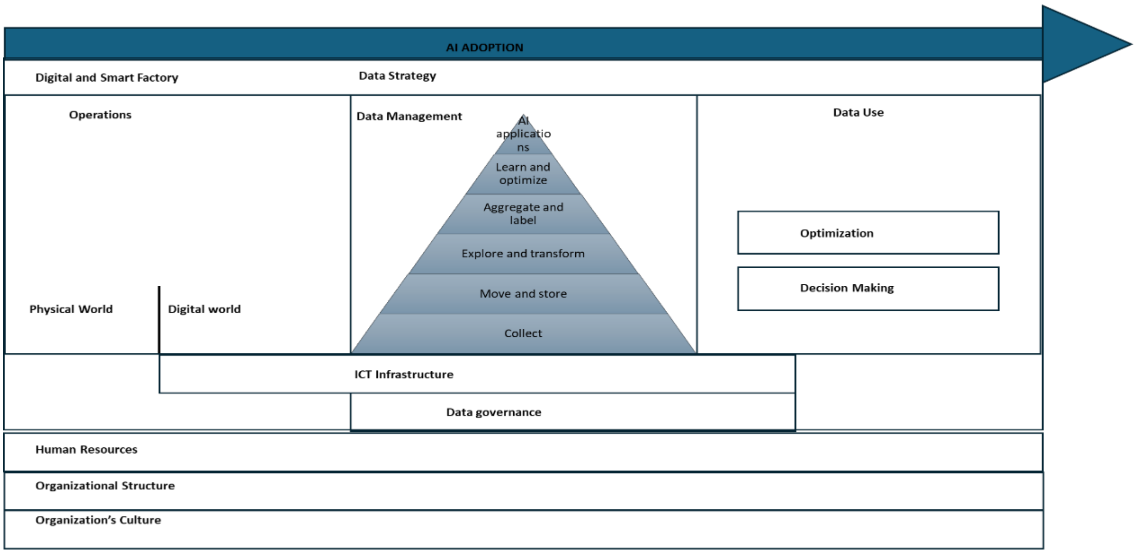

Figure 5 AI Maturity and Adoption Model (Bettoni et al., 2021).

As shown in Figure 5, the model addresses not just the operational side of AI integration but also examines how a company's internal organization and culture enable it to fully harness AI's capabilities. It is built around five key pillars, each corresponding to a critical area within the business that must evolve to support AI adoption(Bettoni et al., 2021). These pillars were established by examining the fundamental functions of a company and identifying which ones are either impacted by or have an impact on AI. The five pillars include: digital and smart factory; data strategy; human resources; organisational structure; and company culture (Bettoni et al., 2021).

Though large enterprises are more AI-ready than SMEs, SMEs perform better in data strategy, indicating a growing awareness of AI's potential (Bettoni et al., 2021). The study highlights the need for a structured, easy-to-use AI adoption model tailored for SMEs. Bettoni et al. (2021) propose a framework that provides a self-assessment tool that aids SMEs in evaluating their AI readiness and identifying improvement areas. Bettoni et al. (2021) also suggest further research to refine the model, expand the sample size, and explore AI adoption trends across different industries, particularly incorporating ethical concerns and additional metrics for AI readiness. To bridge the AI adoption gap, supportive policies, funding opportunities, and skill development programs are necessary (Bettoni et al., 2021).

2.4 Theoretical Framework: Employee skill development must align with technological advancement

A theoretical framework is important to lay a structured foundation for understanding and analyzing a study's key concepts, relationships and assumptions. A theoretical framework guides research design, methodology and analysis, and enhances the study's validity and reliability (Grant & Osanloo, 2014). This theoretical framework will try to answer the research questions.

Research Question 1: What is the Role of AI in the digital skill development of employees in small and medium enterprises (SMEs)

Research Question 2: How do AI tools assist workers in developing the digital skills necessary for navigating the digital transition?

Jagannathan et al. (2019) argues that to stay competitive, companies as well as employees must adapt to the trending technological advancements. In this case, we can take AI as the most influential technological advancement. Digital literacy, to some extent, is necessary for AI adoption in digital skill development. Without basic digital literacy, it is baseless to expect improvement (Singh Sidhu et al., 2024). To successfully and effectively utilize AI to develop employee skills, top management support is essential (Arroyabe et al., 2024; Lai et al., 2025). All three aspects impact how AI influences digital skill development. Figure 6 illustrates the relationship between AI and digital skill development.

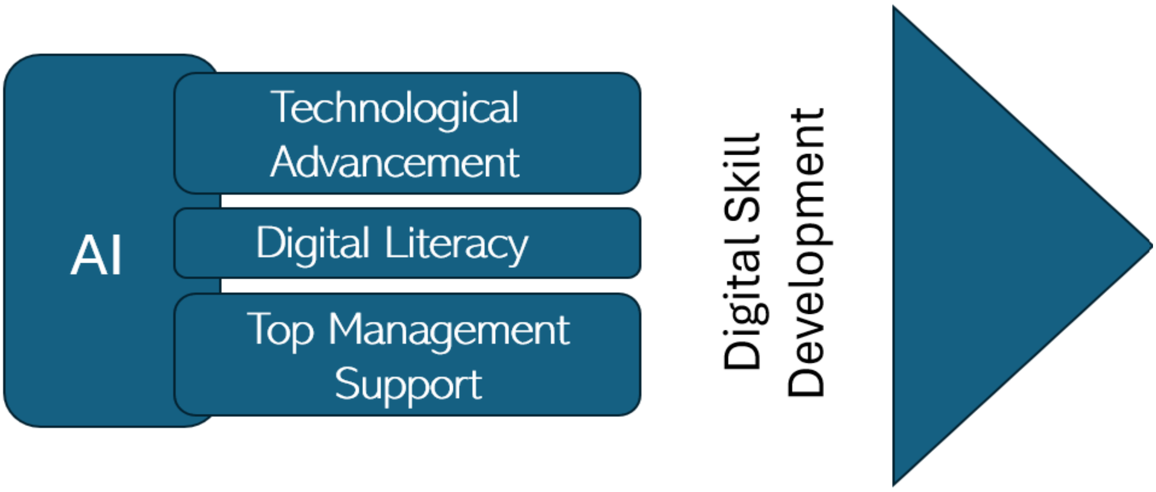

Figure 6 Illustration of Theoretical Framework.

Digital skills influence social capital, impacting workplace integration (Chaker, 2020). Thus, if employees want to stay competitive, they must adopt AI in their daily work life to sustain and remain competitive. Arroyabe et al. (2024) mention internal capabilities drive AI adoption more than external business support. When companies have experts in AI in their top management, they are more likely to utilize it for training and development programs.

Employee skill development must align with technological advancements (Jagannathan et al., 2019).With the radical use of generative AI among ordinary people, it has become necessary to learn the proper use of generative AI. People working with AI for years, for example, in software development companies, may be well-trained and aware of the usage and advantages of AI. But if we consider SMEs that are not very technologically advanced AI adoption for them may prove to be too fast for them to gain sufficient knowledge and skill development. Hence, workforce training and government intervention may be necessary (Singh Sidhu et al., 2024).

Having strong support from top management is the key to overcoming barriers and effective allocation of resources (Lai et al., 2025). The top management of a company decides the strategies to stay competitive in the market. Therefore, the companies must be able to adopt the technologies being adopted by the market to thrive in the competition. SMEs struggle with implementation barriers to adopting AI (Lai et al., 2025) though it improves efficiency and competitiveness.

3 Methodology

3.1 Research Approach

This section outlines the research design and methodological approach employed to explore the role of AI in the digital skill development of employees, particularly within SMEs. In a time marked by rapid technological transformation, AI has emerged not only as a driver of business innovation but also as a critical enabler of workforce development (Bessen, 2018)

The growing digitalization of work environments presents both challenges and opportunities for employee upskilling. AI-powered platforms, such as adaptive learning systems, chatbots, and virtual training assistants, are increasingly integrated into learning and development strategies to enhance employee capabilities (Dwivedi et al., 2021). Given the resource constraints typically faced by SMEs, understanding how these tools are deployed and perceived in a smaller organizational context is vital.

AI adoption and digital skill development involve nuanced human experiences, such as employee perceptions of AI, resistance to new technologies, or managerial attitudes towards training. Hence, a qualitative research method was chosen as it allows to capture the depth and richness of these experiences, which quantitative data alone cannot provide. Additionally, SMEs operate under unique constraints, like limited resources, informal structures, and diverse levels of digital maturity. Qualitative research helps to understand these contextual factors in detail, shedding light on how AI impacts skill development differently across SMEs.

To explore these dynamics further, semi-structured interviews were employed as the primary data collection method. This approach balances structure with flexibility, allowing for a consistent framework of core questions while also enabling participants to elaborate on their unique experiences, perceptions, and challenges. This method is particularly effective when investigating topics that are complex or sensitive, such as workforce adaptation to AI or internal organizational resistance. The open-ended nature of semi-structured interviews encourages deeper reflection, which can uncover underlying motivations, attitudes, and meanings that standardized surveys might miss.

Moreover, qualitative research allows for capturing the human-AI interaction. AI is often perceived as impersonal, but its impact is deeply human. Semi-structured interviews provide the opportunity to examine how employees interact with AI tools in a real-world context, including their emotional and behavioral responses, trust in automation, and concerns around job security or skills relevance. This perspective is crucial for human-centered innovation and training design.

Furthermore, with limited resources in SME settings, it was difficult to access large datasets. The use of qualitative methods, and in particular, semi-structured interviews is ideal for small, targeted samples and allows deep dives into a few cases to generate valuable, theory-rich insights.

Through semi-structured interviews, the current situation regarding AI at SMEs has been analyzed, focusing on five SMEs operating in diverse sectors, including software development, management consulting, and manufacturing. This method is well-suited to capturing the complex, context-dependent dynamics of technology adoption and its impact on workforce skills. Information was gathered through semi-structured interviews with employees and managers. The cross-industry analysis aims to identify patterns and divergences in the use of AI for skill development across different organizational contexts.

Four out of five companies where the interview participants work have their origins in Finland, reflecting the country’s strong presence in digital innovation and technology-driven services. Finland consistently ranks among the most digitally advanced countries in the world (The Digital Economy and Society Index (DESI), 2023)). Finland has a highly digitalized economy with strong public support for tech-driven innovation, and the country has successfully built an ecosystem that embraces emerging technologies, including AI.

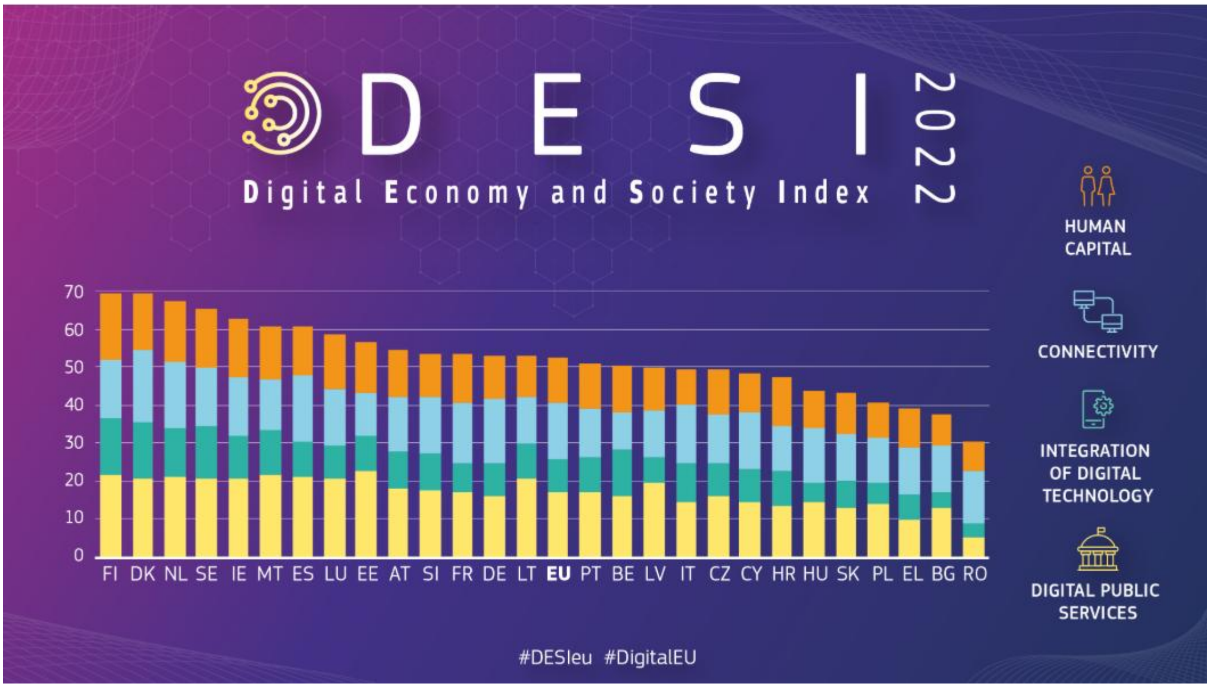

Figure 7 Significant resources to support digital transformation (The Digital Economy and Society Index (DESI), 2023).

3.2 The sample/case firms

Five representatives from five SMEs have been interviewed. From the Finnish context, these firms are considered SMEs because they have less than 250 employees, less than Euro (EU) 50 million turnover, or a balance sheet of less than 43 million (Tilastokeskus, 2025).

Among the five companies analyzed, three operate within the software industry, specializing in enterprise solutions, event management, and application development. One firm is engaged in management consulting, offering strategic advisory and business optimization services, while the fifth company belongs to the manufacturing sector, focusing on the production of wind power facilities. The following table gives a short introduction of the operations and the core business of the companies.

Table 3 Brief introduction of the interviewees' workplace.

Company Case	Industry	Core Business and Operation
A	Software	Development of software for production planning, production management, customer relationship management, and material management. As well as working with Internet of Things (IoT) and different possibilities for machine learning and AI.
B	Software	Develop and manage solutions mainly for events. This includes effective point of sales (POS) systems, access control, smartcards, and wristbands equipped with RFID technology, visitor counting, event network solutions, e-commerce platforms, app builder, and event management integration.
C	Software	Develops software and technology to support industrial design, mechanical design, technical analysis, electrification, technical documentation, packaging design, additive manufacturing, project management, and sustainable product design.
D	Manufacturing	Manufactures, installs, and services wind turbines. This includes the development of automated solutions and different sort of sustainable product development
E	Consulting	Consultancy and advocating workshops on implementing AI, generating prompts, AI ethics and legislation, creating and tailoring AI strategies and solutions.

Appendix 2 illustrates the interviewees' age of work experience, and job position. All participants are professionals actively engaged in companies where AI integration plays a significant role in daily operations and strategic decision-making. These individuals were carefully selected from SMEs that are either currently implementing AI solutions or are in the process of adapting to AI-driven workflows. The purpose of choosing such participants was to capture practical experience-based insights from those who are directly witnessing and shaping the transformation driven by AI technologies.

To recruit participants, I employed network sampling (also known as snowball sampling). This method involves starting with a few known and relevant individuals and asking them to refer others within their professional network who fit the research criteria. Network sampling is especially useful in reaching experts in niche fields like AI implementation in SMEs, where such individuals may not be easily identified through random sampling. Since referrals come from existing contacts, it reduces the time and cost involved in screening large populations. Additionally, the engagement and response rate of participants were high due to the reference.

However, this sort of sampling may lack diversity, as participants tend to refer people within similar professional or social circles, which may lead to homogeneous viewpoints. As in this case, we see 3 out of 5 participants work in the software industry. Due to dependence on the initial contact, the results may have limited generalizability. Despite these limitations, this sort of sampling aligns well with the exploratory nature of the research, where the goal is to gather in-depth quantitative insights, rather than statistically generalizable results.

3.3 Data collection

Data were collected through semi-structured interviews with key informants from five selected companies to investigate the role of AI in digital skill development among employees in SMEs. These firms were purposefully sampled to ensure sectoral and geographical diversity, representing industries such as software development, management consulting, and manufacturing, and originating from Finland and Denmark. Participants included employees, managers, and CEO involved in digital upskilling initiatives or AI tool implementation within their organizations.

Analyzing data collected from participants with diverse backgrounds, such as different industries, job roles, education levels, and age groups, adds significant depth, validity, and richness to the study. Including participants from varied backgrounds allowed capturing different experiences, interpretations, and needs related to AI and digital skill development (Patton, 2015). Additionally, diverse participant input supports data triangulation (Denzin, 2009). This allows comparing and contrasting perspectives from different types of participants to validate patterns or contradictions. This is particularly helpful in this study as it enables cross-checking of employee, managerial, and organizational-level views.

Since this is qualitative research, it does not aim for statistical generalization. However, it does aim for thematic generalizability through the identification of common themes recognized across contexts (Maxwell, 2013) and unique insights tied to specific groups. By involving different demographic and professional backgrounds, a better identification of barriers and opportunities in AI-driven skill development strategies has been possible. Diversity in data sourcing can help reveal inequalities in access to digital skill development that may affect certain groups of people (Van Deursen & Helsper, 2015). For example, older versus younger workers or high-skilled versus low-skilled roles.

Interviews were conducted remotely via Microsoft Teams. Prior to each session, participants were contacted to confirm their availability and schedule a mutually convenient time. The decision to use Microsoft Teams was driven by several factors, most notably its accessibility and practicality in accommodating participants from various geographic locations. Given that the participating companies operated across different regions and were influenced by hybrid work policies, remote interviews offered a flexible and efficient solution that minimized logistical constraints and supported timely engagement.

Each interview session lasted between 25 to 47 minutes, providing ample opportunity to delve into participants' individual experience, professional insights, and subjective perceptions regarding the integration of AI into skill development practices. This time frame allowed for a rich and meaningful dialogue while being respectful of participants' time constraints.

A semi-structured interview format was employed, offering a balance between consistency and adaptability. Predetermined themes, such as AI implementation strategies, employee training mechanisms, user interaction with AI tools, and the perceived influence of AI on skill acquisition, guided the interviews. However, this format also permitted flexibility to probe deeper into unanticipated topics or insights that emerged organically during the conversations. This methodological choice enriched the data, enabling a more nuanced understanding of the complex ways in which AI technologies intersect with human learning and professional development.

All interviews were audio-recorded with the informed consent of the participants. The recordings were then transcribed verbatim to maintain accuracy and support detailed qualitative analysis. The transcriptions provided a solid foundation for thematic coding, interpretation, and pattern identification across cases.

To augment the interview data and enhance the robustness of the findings, publicly available secondary sources were also reviewed. These included materials such as company websites and official press releases. No internal or confidential documents were accessed, as such data was not available to the researcher. The secondary materials ranged from brief web pages to multi-page reports (typically between 2-20 pages) and were selected based on their relevance to specific SMEs involved in the study. These sources served two main purposes: first, to provide contextual background for understanding each organization's digital initiatives; and second, to support triangulation by corroborating or contrasting the insights gathered through interviews. This approach contributed to building a more comprehensive and credible analysis of how AI is influencing digital skill development in SME settings.

In summary, this data collection strategy of combining semi-structured interviews with publicly available organizational materials has been deliberately chosen to capture both the individual and organizational dimensions of AI adoption in skill development. This approach enabled a more holistic understanding of how employees experience digital upskilling initiatives, while also situation those experiences within the broader context of each SME's strategic direction. By integrating diverse data sources, the study ensured methodological rigor, supported data triangulation, and adhered to ethical standards throughout the research process.

3.4 Data Analysis

The qualitative data collected from the semi-structured interviews were analyzed using a thematic analysis approach, following the guidelines of Braun and Clarke (2006).This method was chosen for its flexibility and systematic approach to identifying, analyzing and reporting patterns (themes) within data, particularly in exploratory research contexts. Thematic analysis enabled the study to uncover both explicit and implicit meanings in participants' narratives, aligning well with the exploratory nature of the research questions:

1. What is the Role of AI in the digital skill development of employees in small and medium enterprises (SMEs)?
2. How do AI tools assist workers in developing the digital skills necessary for navigating the digital transition?

The data analysis followed the six-step framework proposed by Braun and Clarke (2006):

1. Familiarization with the data through repeated reading of interview transcripts and notes.
2. Generating initial codes to capture notable features relevant to the research questions.
3. Searching for themes by collating codes into potential thematic categories.
4. Reviewing themes to ensure they accurately reflected the dataset.
5. Defining and naming themes to capture the essence of each category.
6. Producing the report by integrating thematic findings with representative quotes and theoretical insights.

This iterative and reflective process ensured a rigorous and transparent approach to data interpretation. Thematic categories were developed both inductively (emerging from the data) and deductive (informed by existing literature on digital transformation and workplace learning).

3.4.1 Informal Integration of AI in Workplace Learning and Skill Development

The interviews revealed that AI is not yet formalized as a structured tool for employee digital skill development across the studied SMEs. Instead, AI is primarily used informally to support daily tasks, encourage self-directed learning, and enhance work efficiency. Tools such as GitHub, Copilot, and OpenAI's GPT were frequently cited as practical assistants for coding, writing, prototyping, and information retrieval, suggesting that AI acts as a "silent partner" in the development of digital competencies, offering on-demand support that mimics informal peer learning (Boud & Hager, 2012).

> "*Even with basic digital skills, you can enhance your AI skills and develop on it… and vice-versa"*- one of the interviewees.

This finding is consistent with the concept of workplace learning in the flow of work, where employees acquire knowledge and skills through real-time problem solving rather than formal instructions (Bersin, 2018).

3.4.2 AI Reducing Dependency on Traditional Mentorship

Several participants highlighted how AI tools can reduce the dependency on senior mentors for junior employees by offering immediate guidance, solutions, or code generation support. While human mentorship remains valuable, AI enables junior employees to work more independently, suggesting a shift in how digital knowledge is acquired within organizations.

> "*In addition to having like actual human mentor, there is also this kind of possibility to have AI assistants or mentors who are able to assist people along their way."*- one of the interviewees.

This reflects emerging trends in AI-enhanced learning ecosystems, where human-computer collaboration facilitates faster knowledge transfer (Chenoy et al., 2019; Marmier et al., 2021)

3.4.3 Efficiency, Stress Reduction, and Productivity

AI's role in improving work efficiency and reducing cognitive load was another theme. Interviewees noted that AI assistance in repetitive and technical tasks allows them to focus on more complex, creative aspects of their work, thus enhancing overall productivity and reducing stress. Furthermore, AI use was linked to lower workplace stress, especially when employees were under pressure to meet deadlines or multitask.

> *"So, for example, in my work, I used almost 30% AI. So now I can complete more tasks than previously…It increases productivity…"*-said one of the interviewees. Another interviewee stated that, *"…we want to increase efficiency and productivity in a sustainable way using AI, we also need to look at the stress factor."*

This suggests that when appropriately integrated, AI tools can contribute to digital well-being by reducing task overload (Tarafdar et al., 2015)

3.4.4 Necessity of Basic Literacy and Continuous Learning

Participants emphasized that while AI can accelerate skill development, a basic level of digital literacy remains essential. Workers must possess fundamental technical skills and an openness to learn to successfully integrate AI tools into their workflows. Additionally, existing workers need to learn and upgrade their skills in a fast-changing environment.

> *"It (AI) increases the productivity, and at the same time, one should remember that the basics are important,"- one of the interviewees. "..that's probably also the biggest hurdle is that the people actually that people don't want to want… and in the long term they may not be as successful..."- said one of the interviewees.*

Hence, it is important to change and adapt to new digital technologies to keep up in the market. This echoes findings from the literature emphasizing the importance of lifelong learning in the digital age (Ciarli et al., 2021; Masters-Wheeler & Bay, 2024)

3.4.5 Concerns Around Data Security and Ethical Considerations.

Concerns about data leakage, information security, and ethical use of AI also emerged prominently. Some companies were cautious about allowing unrestricted AI use, particularly due to the risks associated with handling sensitive information and the potential for AI misuse (for example, using AI for social scoring). Participants also raised apprehensions about data leakage, bias in algorithms, and the broader ethical misuse of AI technologies. Even if the concerns do not arise from within the companies, there may be clients who strictly prohibit the use of AI when handling client information.

> "*They (customers) can say that anything, any of their IPs or information, cannot be used with the AI."*- one of the interviewees.

These insights reflect ongoing debates around AI governance, emphasizing the need for clear policies and ethical frameworks to ensure responsible usage (Ciarli et al., 2021; Masters-Wheeler & Bay, 2024; Understanding the Impact of Artificial Intelligence on Skills Development, 2021)

3.4.6 Societal and Organizational Impact

Finally, participants discussed broader implications, such as the need for legislative frameworks to govern AI usage, the potential for innovation or societal inequalities arising from uneven access to AI skills, and the importance of preparing employees at all skill levels to interact with AI technologies responsibly. Interviewees highlighted that innovation can exacerbate gaps if AI literacy is unevenly distributed.

> *"Difference in innovation and societal breakthrough-threat comes from the lack of knowledge and information,"*-one of the interviewees. Another interviewee stated, *"…Basics are important… basics and domain knowledge is important…"*

These findings suggest that for AI to be a force for inclusive digital transformation, SMEs must proactively address disparities in access and invest in organizational readiness (Bettoni et al., 2021; Teoh et al., 2023; Zhang & Chen, 2024)

3.5 The assessment of the quality of the data

This chapter evaluates the quality and trustworthiness of the data gathered for this thesis. The research employed a qualitative approach, utilizing semi-structured interviews, analyzed thematically, to understand how AI tools support digital skill development in SMEs. To ensure methodological rigor, the quality of data is assessed across four key criteria: internal validity, construct validity, external validity, and reliability.

Internal validity relates to the soundness of interpretations and the alignment of findings with the theoretical framework. This study was grounded in a well-developed conceptual model that integrated perspectives from digital transformation, AI adoption in SMEs, and employee skill development theories (Chaker, 2020; Jagannathan et al., 2019; Lai et al., 2025). The framework helped to guide the formulation of research questions and informed the coding process during the thematic analysis. As the data were analyzed, a revised framework emerged that reflected observed patterns between AI tool usage, informal learning, self-directed development, and organizational context. The framework was not applied rigidly but evolved iteratively, allowing theoretical triangulation through the combined lenses of skill acquisition theory, workplace learning, and organizational innovation readiness. Thematic analysis followed Braun and Clarke’s (2006) six-step process. This allowed for the identification of recurring patterns and relationships, supported by direct participant quotes, enabling logical and consistent interpretation of data.

Construct validity assesses whether the study accurately measures what it claims to investigate. In the data collection procedure, construct validity has been ensured by interviewing five professionals from diverse SMEs in Finland, ranging from a software engineer and project manager to a CEO. The participants were selected using snowball sampling, beginning with known industry contacts and expanding to other relevant professionals within AI-integrated organizations. Data triangulation enhanced construct validity by corroborating evidence across different sources. All interviews were recorded with consent and transcribed verbatim. The data coding and analysis process was driven by both participant responses and the initial theoretical framework. This ensured that emergent codes remained grounded in the research focus while allowing space for new insights to surface. Throughout the findings, verbatim quotes are used to express participant experiences before interpreting or “telling” what they mean in the broader theoretical context. This creates a transparent chain of evidence from raw data to interpretation, increasing traceability of conclusions.

External validity, or analytical generalizability, refers to the extent to which findings can be extended to broader theoretical concepts. While this qualitative study does not seek statistical generalizability, it does aim for thematic generalizability by identifying cross-case patterns relevant to SMEs in technologically advanced environments like Finland. The five SMEs represented a mix of sectors with differing digital maturity levels. This diversity enhances the ability to generalize key themes to other SMEs in similar environments facing AI integration pressures. The organizational and geographic context has been described using demographic and operational data from each firm, supported by national digital indexes (The Digital Economy and Society Index (DESI), 2023) For example, Finland’s high digitalization level helps contextualize how readily SMEs integrate AI into daily workflows. Additionally, firms were not selected randomly, but because they met theoretical relevance criteria, such as active or emerging AI adoption, and involvement in employee upskilling initiatives. This sampling strategy supports robust theoretical inference (Patton, 2015).

Reliability in qualitative research is achieved through transparency and replicability in the research process. To enhance reliability, standardized procedures with detailed case documentation and maintenance of bias awareness have been adapted. An interview protocol (Appendix 1) was used consistently across participants. This protocol included open-ended questions aligned with key themes such as AI adoption, digital skills, productivity impact, and ethical considerations. The thesis includes a clear explanation of how participants were recruited, which companies they represent, and their roles within those organizations (Appendix 2). Each interview’s duration and demographic details are also provided, further supporting transparency. The limitations of snowball sampling and potential interviewer bias have been acknowledged. Measures such as verbatim transcription, cross-referencing of data, and systematic coding helped reduce these risks.

By grounding the research in a solid theoretical framework, adopting a structured yet flexible data collection process, and applying rigorous analytical procedures, the study achieves methodological credibility. While the limited sample size and sectoral concentration impose certain constraints, the study’s analytical generalizability provides valuable insights for theory development and future research on AI-driven skill development in SMEs.

4 Findings

The analysis of the interview data provides insight into how AI influences digital skill development in SMEs and how it assists employees in adapting to the ongoing digital transformation. The results are closely aligned with the conceptual framework, which emphasizes that digital skill development must continually adapt to technological advancements and that internal capabilities, such as managerial support and employee readiness, play a crucial role in successful AI adoption.

4.1 The Role of AI in the Digital Skill Development of Employees in SMEs

The findings reveal that AI plays an increasingly supportive role in employee skill development within SMEs, but it has not yet been formalized as a structured learning tool. Instead, AI tools such as GitHub, Copilot, GPT models, and other AI-driven platforms are integrated informally into daily workflows to assist with coding, information retrieval, writing, and problem-solving tasks. This reflects AI's function as a facilitator of on-the-job learning and micro-skilling, allowing employees to enhance their digital competencies in a flexible and demand-driven manner, rather than as a replacement for traditional training programs.

The findings of this study strongly align with Jagannathan et al. (2019), who emphasize that employee skill development must evolve in tandem with ongoing technological advancements. As digital technologies, particularly AI, continue to reshape the workplace, the ability of employees to keep pace with these innovations becomes a fundamental determinant of their relevance and productivity. AI tools such as language models, code generators, and intelligent search functions offer users dynamic, real-time assistance. When employees actively engage with these tools, they develop new digital competencies organically, often through self-directed learning embedded in day-to-day tasks rather than through formal training structures.

This insight was powerfully echoed by one participant, who stated:

> *"In order to stay competitive, they must adopt the use of AI, otherwise their colleagues who are willing to change will take their place."*

Another participant stated something similar as well:

> *"There are, of course, people who are really,… taking into things (AI). But then, on the other hand, people are lazy …So I don't need to learn. but then suddenly it happens that OK, you are really outdated, if you are not like all the time trying to improve in this area."*

This quote reflects a growing recognition that digital transformation is not optional, but imperative for both individual and organizational survival. In competitive, fast-paced environments, those who fail to adapt risk being displaced by peers who demonstrate greater technological adaptability. The participant's observation highlights that AI tools are not only enablers of productivity but also act as barometers of adaptability in a rapidly evolving job market.

Another interviewee emphasized the acceleration of the learning cycle brought on by AI:

> *"So that is like making the learning cycle a lot, lot faster… if you are not (learning faster), then you are a bit like dropping from the base… It's quite a tough business area… AI is helping. If you are using it."*

This candid reflection captures the dual-edged nature of AI integration: it can empower employees to learn and grow rapidly, but it also imposes pressure to adapt at an accelerated pace. The metaphor of "dropping from the base" illustrates the risk of professional obsolescence in globally competitive sectors where technological change is constant and unrelenting.

However, the study also revealed a critical condition for realizing the benefits of AI: foundational digital literacy. While AI can democratize access to knowledge and lower skill acquisition barriers, those lacking even basic digital competencies are unable to capitalize on these opportunities.

One of the participants stated that:

> *"Like the standard sort of school told knowledge still work... but you do need to have some sort of basic knowledge to stand on to be able to kind of take that step out into AI over. To use AI in your daily work."*

This finding substantiates the argument made by Chaker (2020), who posits that digital skills are not only a means to professional integration but are increasingly central to an individual's capacity to remain competitive in the workforce. Without these foundational capabilities, employees are less likely to engage confidently with AI tools, thereby exacerbating skill gaps and digital exclusion.

In short, the findings show that AI can be a powerful accelerator for skill development, but only for those who are already digitally literate and open to change. As such, the study underlines the importance of organizational investment in foundational training as a prerequisite for leveraging advanced technologies. This supports a broader theoretical view that effective AI adoption in SMEs requires a strategic alignment between technology, workforce capabilities, and continuous learning structures (Chaker, 2020; Jagannathan et al., 2019).

The findings of this study reveal that AI plays a multifaceted role in enhancing workplace performance, particularly in increasing efficiency, reducing employee stress, and accelerating learning processes. Participants consistently emphasized AI's ability to provide instantaneous feedback, support, and task-based solutions, particularly in technical domains such as coding, prototyping, and data handling. This capacity for real-time assistance minimizes the trial-and-error cycles typical in manual problem-solving, enabling workers to resolve challenges more efficiently and with greater autonomy.

One participant illustrated this point with a compelling example:

> *"So for code reviewing and for code generation and for fast prototyping, we are using AI as much as we can… it takes five hours to build some kind of a feature in the web application. With AI, it's possible to do within an hour or less."*

This quote underscores the tangible impact of AI on time efficiency, particularly in repetitive or modular development tasks such as web applications. AI enables developers to access and customize pre-generated code, eliminating the need to build everything from scratch. This not only speeds up output but allows employees to allocate more time to creative problem-solving and innovation, functions that are less automatable and more cognitively enriching.

A particularly noteworthy outcome of this shift is the diminished reliance on senior mentorship. Traditionally, junior employees would turn to experienced colleagues for guidance and problem-solving. However, with the integration of AI tools, such as code-generating assistants and intelligent writing platforms, employees at earlier stages in their careers can access on-demand instructional support, mimicking the effect of mentorship but without human dependency. This fosters a more self-directed and independent learning culture, as highlighted in this observation by one interviewee:

> *"..You can use in addition to having like actual human mentor there also this kind of like AI like assistants or mentors who… Are able to assist people along their way."*

One firm's approach to implementing Fridays off as a way to combat burnout, maintain focus, and promote creativity speaks to a holistic view of productivity, where efficiency is not achieved at the expense of mental health. This perspective reinforces a growing body of literature suggesting that technology must be embedded within sustainable human systems, particularly in knowledge-intensive and creative sectors. The interviewee's concerns is highlighted hereby:

> *" If we want to increase efficiency and productivity in a sustainable way using AI, we also need to look at the stress factor."*

This comment sheds light on a deeper organizational concern: the balance between technological acceleration and human well-being. In rapidly evolving digital environments, employees face heightened pressure to remain productive, innovative, and competitive. While AI can certainly enhance performance metrics, the psychological costs associated with continuous adaptation, especially stress and burnout, must be acknowledged. The respondent emphasizes the importance of creating systems that honor employee values such as freedom, rest, and creativity, recognizing that genuine innovation stems not only from smart tools but also from a healthy, well-supported workforce.

This finding directly supports Chakers's (2020) assertions that AI fundamentally alters the style and pace of digital skill development. Rather than linear, top-down knowledge transfer, learning has become fluid, responsive, and personalized, with AI acting as both a cognitive scaffold and a learning catalyst. Employees are not only required to learn faster but must also continuously reskill and realign their capabilities in sync with emerging technologies. The statement by another participant:

> *"…you need to run faster because the others are running as well. But the AI is helping. If you are using it."*

Captures this dynamic succinctly. In a globalized, high-speed digital economy, AI is both an enabler and a demand driver. It assists in closing the skill gap but also raises the bar for how quickly individuals must adapt. This duality reflects the need for organizations to not only equip their workers with AI tools but also cultivate supportive environments that mitigate stress and foster resilience, creativity, and sustained engagement. To fully harness AI's potential, SMEs must not only adopt the technology but also reconfigure work structures, values, and expectations in a way that supports sustainable human-machine collaboration.

Another key finding of this study concerns the critical role of organizational context, particularly leadership attitudes and top management support, in shaping how AI is utilized for digital skill development. While much emphasis in digital transformation discourse focuses on technological capability or individual readiness, this study reinforces that organizational endorsement is often the key catalyst that determines whether AI adoption becomes meaningful or remains superficial.

Participants consistently described how leadership encouragement provided legitimacy or confidence for experimenting with AI tools. One interviewee described the moment AI became integrated into their professional development:

> *"…when the GPT has released its first version… our CTO (Chief Technology Officer) recommended trying to use that ethically and responsibly for gaining knowledge. Then the GPT has influenced a lot of work."*

This quote captures a pivotal shift, not only in tool usage but in organizational mindset. The fact that the Chief Technology Officer (CTO) personally advocated for AI use signals a top-down endorsement that helped embed AI as a legitimate learning and productivity tool. This aligns with findings from Lai et al. (2025) and Arroyabe et al. (2024), who argue that leadership support directly influences employee engagement with digital tools, and is especially important in SMEs where digital maturity varies.

The participant also reflected on practical AI use cases, such as simplifying complex code and accelerating learning:

> *"It is really hard to understand… it takes a lot of time. So then I can copy and paste the code into GPT and ask for a simple explanation… from there it started."*

This reflects a recurring pattern in the data: AI tools, once sanctioned by leadership, allow employees to overcome knowledge bottlenecks independently, especially in highly technical fields. By removing reliance on senior team members for every clarification, AI not only saves time but also cultivates self-directed learning habits. This autonomy, empowered by leadership and AI together, becomes essential for thriving in fast-paced digital environments.

However, organizational openness to AI must also grapple with ethical and regulatory complexities, which several participants were quick to highlight. One interviewee expressed concern over data ownership and the long-term implications of training models on third-party data:

> *"… what is really important nowadays is who owns the data? So what if someone says that… if you trained your data, you need to pay us royalties?... then it gets a bit more expensive."*

This quote surfaces an often-overlooked barrier to AI integration in professional development: data governance and ethical liability. Even when AI tools are technically accessible and organizationally encouraged, their use may still be constrained by concerns over intellectual property, data provenance, and legal risks. This highlights that leadership support must go beyond verbal endorsement. It must involve the development of internal policies, training, and ethical frameworks that clarify the boundaries of responsible AI use.

Moreover, these insights are consistent with the literature that emphasizes the importance of internal capabilities, data stewardship, and ethical readiness as foundational to digital transformation. For instance, Arroyabe et al. (2024) note that effective AI deployment requires organizations to balance openness with internal governance mechanisms.

Taken together, the findings suggest that leadership influences AI-driven skill development on three critical levels:

1. Culture- by creating psychological safety for experimentation.
2. Strategic- by aligning AI use with broader learning and innovation goals.
3. Ethical- by setting guardrails for responsible, secure application of AI tools.

While AI technologies hold substantial promise for enhancing skill development, the findings of this study also reveal a critical caveat: employees cannot fully harness AI's potential without possessing foundational digital literacy. In other words, although AI tools offer intuitive interfaces and real-time support, they still demand a baseline level of digital competence to be effectively utilized. This creates a paradox: AI is both an accelerator of learning and a gatekeeper, setting a new threshold for minimum skills in the modern workplace.

This insight aligns with the argument made by Singh Sidhu et al.(2024), who emphasize that as AI becomes more embedded in workplace practices, the digital divide may widen, not just between organizations but within them, unless proactive efforts are made to upskill all members of the workforce. This highlights the increasing need for both organizational training initiatives and public policy interventions to ensure that employees at all levels are equipped to work alongside intelligent systems.

As one participant noted:

> *"Even with basic digital skill, you can enhance your AI skills and develop on it."*

This quote affirms the idea that AI can support incremental learning, building new capabilities on top of existing skills. However, it also subtly underscores that even basic digital familiarity is a prerequisite. Without this foundation, employees may struggle to engage meaningfully with AI tools, much less leverage them for advanced tasks like automation, optimization, or data interpretation.

Another participant reinforced the fluid and reactive nature of skill development within organizations:

> *"Employee skill development plans frequently change according to employee need, market, competition, etc."*

This statement reflects a reality in many SMEs: skill development is often unstructured and opportunistic, rather than strategic or standardized. In such environments, the integration of AI further complicates the learning curve because the tools are evolving rapidly. This creates a need not only for individual adaptability but also for systemic interventions that provide clear guidance and consistent access to learning resources.

Taken together, these findings suggest that while AI can democratize access to knowledge and support self-directed learning, it also risks exacerbating inequality if certain employees are left behind due to a lack of digital fluency. A such, the study supports the view that AI adoption must go hand in hand with foundational upskilling efforts, particularly in industries or regions where digital literacy is uneven. Government policies, education systems, and organizational training programs must align to ensure inclusive digital transformation.

Table 4 Summary of Key Themes and Supporting Participant Quotes (RQ1).

Theme	Description	Supporting Participant Quote
AI as a Catalyst for Learning and Efficiency	AI speeds up coding, prototyping, and task execution, allowing faster upskilling.	"So for code reviewing and for code generation and for fast prototyping, we are using AI as much as we can… with AI, it's possible to do (tasks) within an hour."
Leadership Support Enables AI Integration	Endorsement from top management legitimizes AI use and boosts adoption.	"Our CTO has recommended trying to use (GPT) ethically and responsibly for gaining the knowledge. Then the GPT has influenced a lot of work."
Ethical and Data Concerns	AI use raises concerns about data privacy, ownership, and responsible practices.	"Who owns the data? What if someone says that… you need to pay us royalties?... then it gets a bit more expensive."
Reduction in Mentorship Dependency	AI reduces reliance on senior colleagues for knowledge transfer.	"I can copy and paste the code into GPT and ask for a simple explanation…from there it started."
Stress Reduction and Well-being	AI boosts productivity, but must be implemented with attention to employee health.	"If we want to increase efficiency and productivity in a sustainable way using AI, we also need to look at the stress factor."
Digital Literacy as a Prerequisite	Foundational digital skills are necessary to benefit from AI tools.	"Even with basic digital skill you can enhance your AI skills and develop on it."
Dynamic Skill Planning in SMEs	Learning strategies evolve with market needs and AI integration.	"Employee skill development plans frequently change according to employee need, market, competition, etc."

4.2 How AI Tools Assist Workers in Developing the Skills Necessary for Navigating the Digital Transition

The findings of this study indicate that AI tools function as powerful accelerators for digital upskilling, particularly in the context of ongoing digital transformation. These tools do not merely support task execution; they fundamentally reshape how learning occurs in the workplace by lowering entry barriers, enabling employees at varying skill levels to engage complex digital practices. As such, AI helps democratize access to previously high-skilled domains, allowing non-specialists to perform tasks such as coding, prototyping, and data interpretation with minimal prior training.

This insight is well illustrated by one participant's reflection on how large language models (LLMs) like GPT impacted their software development workflow:

> *"... when the GPT has released its first version... Our CTO recommended trying to use that ethically and responsibly... GPT has influenced a lot of work... For development, prototyping, and explaining code."*

This quote highlights how organizational encouragement and accessible AI tools converged to open new learning pathways. The participant described using GPT to understand unfamiliar code, an example of real-time knowledge acquisition that previously required expert mentorship or formal instruction. By simply pasting complex code into GPT and receiving human-readable explanations, the employee was able to engage in self-directed learning, converting passive exposure into active skill-building.

Moreover, the participant's experience demonstrates that AI tools enhance comprehension and accelerate problem-solving. Especially in technical areas like programming and software development. This reflects the broader argument made by Singh Sidhu et al. (2024) That AI can only reach its full developmental potential when embedded within structured training ecosystems, particularly in SMEs where technical capacity may be limited. AI alone does not replace the need for workforce development; it amplifies the need for foundational training so that all employees can use AI meaningfully and safely.

In another interview, a participant commented on the limitations of AI when dealing with highly specialized or context-specific tasks:

> *“...you can get a lot of generic things from the internet, but that doesn’t necessarily help... then you need to start building on top of the AI engine... Skilled guys doing stuff on that.”*

This insight is crucial because it reveals the dual nature of AI in skill development. On one hand, AI tools provide accessible entry points for digital engagement; on the other, they serve as platforms for advanced learning where skilled professionals build custom applications and domain-specific solutions.

This Layered model of AI engagement suggests that the digital transition is not only about access but also about scalability, providing tools that grow with the user’s expertise.

By supporting a continuum of learning, from foundational to advanced, AI fosters both horizontal and vertical skill development, enabling employees to build breadth and depth in digital competencies. However, to fully capitalize on these opportunities, SMEs must ensure foundational readiness, both in terms of infrastructure and human capital. Without basic digital skills, employees may be unable to engage with AI tools meaningfully, thus widening internal skill gaps. The findings support Singh Sidhu et al.’s(2024) call for public-private collaboration, where government interventions (e.g., national digital literacy programs, SME grants) complement organizational strategies to ensure inclusive and equitable access to AI-enabled skill development.

A key theme that emerged from the findings is that AI tools contribute not only to technical upskilling but also to the development of adaptive learning habits. Through frequent and meaningful interactions with AI systems, employees are encouraged to engage in problem-solving, iterative inquiry, and experimentation, all of which foster a growth-oriented mindset. This process supports the development of soft skills such as critical thinking, self-direction, adaptability, and digital resilience. These capabilities are increasingly essential for navigating digital transformation in dynamic work environments.

These adaptive skills evolve organically through daily engagement with AI tools, especially when employees use AI not just for execution, but as a collaborative partner in learning and decision-making. One participant illustrated this shift toward a more inquisitive, continuous learning culture by describing how their team uses AI during meetings:

> *“We take AI notes from every meeting… and then we ask lots of questions… because we get good answers.”*

This quote reflects a workplace culture that uses AI tools not passively, but actively and strategically to deepen understanding, record knowledge, and stimulate critical inquiry. The routine use of AI for information synthesis and reflection creates an environment where asking questions and seeking answers become normalized, thereby reinforcing self-directed learning behaviors and cognitive engagement.

Another interviewee emphasized the importance of helping employees “crawl” forward in their skill progression, a metaphor that suggests gradual, continuous improvement rather than a one-time leap:

> *“So I think that (it’s the) responsibility of the companies to keep it in a way that we are able to help people to crawl within their skills… (AI is) definitely helping on that one.”*

This insight is significant. It acknowledges that AI can scaffold early-stage learning, making the development process less intimidating and more accessible. When companies adopt the mindset of using AI as a facilitator rather than just a productivity booster, they help nurture resilience and learner autonomy, particularly among less experienced staff.

Furthermore, employees are also required to continuously reinterpret and realign their skillsets to stay relevant in a landscape where digital tools and expectations evolve rapidly. One participant captured this dynamic succinctly:

> *"But then, combining that with your skills and understanding of the customer... that's where the value is… It's like a changing thing. What people need to be able to do all the time."*

This comment points to a crucial shift: technical knowledge alone is no longer sufficient. Instead, the value lies in the integration of human judgment, contextual understanding, and adaptive thinking. As AI automates more routine and commodity-level tasks, employees must focus on complex problem-solving, cross-functional collaboration, and creative applications of digital tools. These are not static skills but evolving competencies that require constant reflection and flexibility. Taken together, these findings suggest that AI not only enhances what employees know but also how they learn and adapt. Through this lens, AI becomes a cognitive and behavioral catalyst, shaping a workforce that is not only more digitally competent but also more agile, curious, and proactive.

While the findings underscore the transformative potential of AI in fostering digital upskilling, they also reveal a set of critical challenges that could hinder or even reverse these benefits if left unaddressed. These challenges, particularly related to data privacy, overreliance, and ethical misuse, highlight the urgent need for structured, responsible AI training within organizations.

One of the most frequently mentioned concerns is data privacy and security in some organizations, or when working with sensitive client projects, employees face strict limitations or prohibitions on AI use one participant remarked:

> *"Some customers are different... maybe not even allowing using the AI or they have strict policies... Because there's the issue that some AI tools are leaking the source code..."*

This statement reflects a real-world constraint, While AI tools may be available and capable, their use is not always permissible due to concerns about data leakage, intellectual property exposure, or compliance violations. For example, using AI models like ChatGPT or GitHub Copilot in software development might unintentionally transfer proprietary to externals servers. This creates tension between AI enabled skill development and the necessity of maintaining client trust and legal compliance.

Moreover, these concerns contribute to a broader ethical dilemma, as employees become more reliant on AI tools for decision making, coding, writing, or communication, there's a risk overreliance, where users begin to accept AI outputs without critical scrutiny. In high shakes industries such as finance, healthcare, or cybersecurity, this can lead to complacency or algorithmic bias becoming embedded in workflows.

In addition to the technical risks, the findings also suggest a growing awareness of ethical and surveillance-related concerns. In environments where AI is used for performance evaluation, behavior tracking, or productivity scoring, employees may perceive the tools as instruments of control rather than empowerment. This can lead to resistance, stress, and even disengagement from AI facilitated learning opportunities.

These insights align with the study's theoretical framework, which emphasizes that AI integration into workplace learning must be not only functional but also ethical and inclusive. The success of AI as a tool for digital upskilling depends on embedding it within responsible learning ecosystems, where employees are trained not just in usage, but also in the implications, limitations, and best practices of AI deployment.

The findings suggest a clear need for structured training programs that go beyond technical tutorials. Such training would empower employees to engage with AI tools confidently and safely while preserving accountability, accuracy, and trust. It would also support organizations in building a culture of ethical digital innovation, where Ai enhances skill development rather than compromising integrity or autonomy.

Overall, AI assists workers by creating new pathways for skill acquisition and encouraging adaptability and continuous learning. At the same time, it demands that companies and governments implement supportive structures to ensure employees can keep pace with technological changes and that AI is used ethically and responsibly.

Table 5 Summary of Key Themes and Supporting Participant Quotes (RQ2).

Theme	Description	Supporting Participant Quote
AI as a Learning Accelerator	AI helps employees learn faster through real-time feedback, reducing the complexity of technical tasks.	"Then the GPT has influenced a lot of work…development, prototyping, and explaining code…I can copy and paste the code into GPT and ask for a simple explanation."
Democratization of Digital Skills	AI allows non-experts to perform tasks like coding, lowering entry barriers to digital competencies.	"Even with basic digital skill you can enhance your AI skills and develop on it."
Support for Adaptive Learning Habits	AI promotes self-direction, inquiry, and adaptability, fostering digital resilience.	"We take AI notes from every meeting… and then we ask lots of questions…because we get good answers."
Organizational Role in Skill Progression	Companies are expected to scaffold growth and encourage digital upskilling through AI.	"It's the responsibility of the companies… to help people to crawl within their skills.. AI is definitely helping on that one."
Integration of Soft and Technical Skills	Value is created when AI skills are combined with critical thinking and customer understanding.	"Combining that with your skills and understanding of the customer… that's where the value is… it's a changing thing people need to be able to do all the time."
Awareness of AI Limitations	AI has limits in customized applications; users must build on top of models for deeper value.	"You get to a certain point with this like LLM models. Then you need to start building on top… a lot of skilled guys doing stuff on that."
Ethical and Data Privacy Concerns	Client and company policies may restrict AI use due to privacy, legal, or IP concerns.	"There are customers who are maybe not even allowing using the AI… because there's the issue that some AI tools are leaking the source code."
Need for Responsible AI Training	Structured programs should address both usage and ethical literacy.	"Responsibilities of the companies… is to help people crawl… but also use it ethically and responsibly for gaining the knowledge."

4.3 Summary of the Findings and Revised Theoretical Framework

The results support the thesis's theoretical framework: AI does shape digital skill development by providing new pathways for learning, enhancing efficiency, and broadening access to digital competencies. However, successful skill development depends heavily on employees' ability to align their learning processes with evolving technological advancements. Without a solid foundation in digital literacy and ethical awareness, employees may struggle to realize the potential benefits of AI-driven upskilling. SMEs risk falling behind in the digital transition, further highlighting the importance of internal capabilities emphasized by Arroyabe et al. (2024) and Lai et al. (2025).

The study reaffirms the central idea from Jagannathan et al. (2019) That digital skill development must evolve in parallel with technological advancements. AI technologies, particularly large language models and code generation platforms like GPT and GitHub Copilot, serve as accelerators of informal, on-the-job learning. They allow employees to perform tasks that traditionally required high levels of technical expertise, thereby democratizing access to digital skills. This dynamic supports a shift from traditional, top-down training to fluid, micro learning embedded in daily workflows.

However, as Chaker (2020) and Singh Sidhu et al. (2024)argue, and as the findings affirm, this democratization has a threshold. Employees without basic digital literacy struggle to benefit from AI tools, highlighting the risk that AI could widen digital divides within and between organizations. While AI reduces technical barriers for some, it raises the minimum entry requirement for all. Thus, baseline digital competence and critical awareness are essential preconditions for successful AI enabled upskilling.

The findings extend the framework by revealing AI's role in fostering adaptive learning behaviors, including self-direction, critical thinking, and digital resilience. Through real-time feedback, AI encourages experimentation and problem-solving, nurturing not only technical expertise but also soft skills that are vital in fast-evolving, AI driven environments. This redefines the scope of "digital skills" to include behavioral and cognitive capacities, not just technical knowledge.

Consistent with Arroyabe et al. (2024) and Lai et al. (2025), the study shows that top management support and internal capabilities are key enablers of effective AI integration. Leadership endorsement legitimizes AI experimentation, promotes ethical awareness, and facilitates employee buy-in. Moreover, organizational culture influences whether AI is perceived as a tool for empowerment or control particularly relevant in contexts involving data privacy, surveillance, or performance monitoring.

Another dimension added by the study is the ethical and governance layer. Findings reveal that concerns over data privacy, proprietary information leakage, and algorithmic surveillance limit AI adoption in some SMEs. This reinforces the need for structured, responsible AI training programs that educate employees not only how to use AI tools, but also on how to use them ethically, securely, and critically.

Thus, AI is not merely a tool for enhancing existing skills; it acts as a transformative agent that redefines what skills are needed and how they must be developed to remain aligned with technological progress. To provide a clearer summary of the research findings, the key insights have been organized concerning the research questions and the conceptual framework of the study. The following table presents an overview of how AI contributes to digital skill development in SMEs and how AI tools assist employees in navigating the digital transition. This table also highlights how the findings align with the broader conceptual understanding that digital skill development must continuously adapt to technological advancements(Jagannathan et al., 2019).

Table 6 Research questions in relation to the Theoretical Framework.

Research Question	Main Findings	Relation to theoretical framework
RQ1: What is the role of AI in digital skill development of employees in SMEs?	▪ AI is primarily used informally for learning (e.g. coding, writing, problem-solving). ▪ Supports self-directed microlearning. ▪ Foundational digital literacy remains essential. ▪ Top management support influences AI adoption.	▪ AI affects skill development directly. ▪ Skill development must align with technological advancements (Jagannathan et al., 2019). ▪ Internal capabilities drive successful AI integration (Arroyabe et al., 2024; Lai et al., 2025)
RQ2: How do AI tools assist workers in developing the digital skills necessary for navigating the digital transition?	▪ AI democratizes access to complex digital skills. ▪ Encourages adaptive learning behaviors (self-direction, problem-solving). ▪ Raises ethical, security, and misuse concerns. ▪ Need for structured training and support programs.	▪ AI enables new pathways for learning but demands ethical and responsible integration. ▪ Government intervention and workforce training needed especially for less technologically advanced SMEs (Singh Sidhu et al., 2024).

In summary, the findings highlight the multifaceted role AI plays in digital skill development within SMEs and the various ways AI tools facilitate employees' adaptation to the digital transition. These results are closely aligned with the theoretical background and underline the importance of technological alignment, internal capabilities, and continuous learning. The following figure tries to illustrate the relationship and the factors impacting between AI and Digital Skill Development.

As Figure 8 illustrates, alongside digital literacy and top management support, organizational adaptability and willingness to adopt AI for informal learning material are essential for utilizing AI for digital skill development. Organizational adaptability involves cultivating a culture that embraces change, encourages experimentation with new technologies, and supports continuous learning among employees.

Without a flexible and open mindset at the organizational level, even the most advanced AI tools may be underutilized or met with resistance. Furthermore, a proactive approach to integrating AI into daily workflows, rather than relying solely on structured training programs, can foster more organic skill acquisition. This informal, experimental learning often enables employees to engage with AI tools in ways that are context-specific, practical, and immediately applicable to their roles. Therefore, aligning strategic leadership, digital competence, and cultural readiness is crucial for embedding AI-driven learning within the fabric of the organization.

Figure 8 Revised Theoretical Framework: The Role of AI in Digital Skill Development.

5 Discussions

5.1 Theoretical Implications

This study advances current understanding of the relationship between AI adaptation and digital skill development in SMEs by demonstrating that AI is not only a technological tool but also a learning ecosystem and behavioral catalyst. Theoretically, the findings challenge and expand upon prior work in major ways.

Firstly, unlike many earlier studies that treat AI as a separate intervention requiring structured deployment (e.g. formal training programs or IT-led rollouts), this research shows that AI is becoming organically and code generators in real time to perform tasks, solve problems, and interpret information, turning the work environment into a continuous learning space. This aligns with Jagannathan et al. (2019), who emphasize the dynamic interplay between work and learning in the digital age, but this study expands that view by demonstrating how AI reduces friction in the skill acquisition process by collapsing the distance between learning and doing.

Secondly, the findings confirm and extend Chaker's (2020)proposition that AI fosters micro learning. However, this study provides concrete evidence that employees do not require structured programs to begin developing digital competencies. Instead, they navigate AI tools with autonomy, learning in short cycles based on specific needs, e.g., understanding unfamiliar code, wrong documentation, or troubleshooting design flaws. This suggests that AI acts as a just-in-time knowledge interface, reinforcing theories of adult learning and workplace learning where autonomy, relevance, and problem-orientation are key drivers of skill acquisition.

Thirdly, the findings complicate the assumption that AI universally democratizes access to skills. While AI makes advanced digital tasks more accessible, it raises the floor: a minimum threshold of digital literacy is needed to use AI meaningfully. This duality, AI as gateway and gatekeeper, challenges Muehlemann's (2024) view that AI necessarily deepens skill stratification, while supporting Singh Sidhu et al.(2024) , who argue that the digital divide now exists not just in access to tools but in the ability to use them effectively. This insight carries strong implications for policy and HR development in SMEs, which must provide foundational training before AI can truly empower workers.

Fourthly, This study reinforces the theoretical claims made by Lai et al. (2025) and Arroyabe et al. (2024) that internal capabilities, notably leadership vision, culture, and governance structures, determine the trajectory of AI adoption. Where top management was proactive in recommending AI use, employees reported deeper engagement and more creative applications of AI. Where caution prevailed, especially due to data privacy or client restrictions, AI use was fragmented or absent. This confirms that internal leadership, not just technological infrastructure, shapes whether AI becomes a learning enabler on an organizational liability.

Lastly, a novel thermotical contribution of this study is its exploration of the emotional and ethical terrain of AI use. The findings suggest that employees not only contend with how to use AI but also with how they feel about it, stress, fear of obsolescence, uncertainty about surveillance, and discomfort with opaque systems. These emotional dimensions point to a socio-technical framework of AI adoption, where affect, trust, and well-being are as important as functional. This extends current AI and learning theories, which often underemphasize the humanistic and ethical dimensions and transformation.

5.2 Managerial Implications

The Practical implications of this study for SME managers are multifaceted. They involve not only the selection of AI tools but also how managers embed these tools into culture, workflows, and professional development systems.

5.2.1 Treat AI as a Learning Partner, not just a productivity tool

Managers must shift from viewing AI solely as a means to enhance efficiency toward recognizing it as a continuous learning interface. Employees are using AI tools like GPT not just to learn new skills as they go. Leaders should encourage experimentation and curiosity by framing AI as a co-worker or coach, not a replacement or supervisor.

5.2.2 Build Digital Foundations before scaling advanced tools

Findings show that without basic digital literacy, employees struggle to unlock AI's potential. SMEs must map existing skill levels and other foundational programs in areas like digital navigation, data awareness, and basic coding logic. Only then can more advanced AI tools like generators or prompt=based automation be introduced meaningfully and equitably.

5.2.3 Embed AI ethics and Governance in onboarding and practice

Ethical concerns, especially around data leakage and algorithmic dependence, were prevalent. SMEs need clear, practical ethical guidelines, covering what can be shared with AI systems, how AI outputs should be verified, and what constitutes misuse. Governance frameworks should be tailored to the SME context and communicated through onboarding, manager training, and AI usage policies.

5.2.4 Create a culture of Psychological Safety around AI

Employees expressed anxiety about falling behind, being replaced, or being judged through AI tools. Managers must foster a psychologically safe environment where questions, experimentation, and even skepticism are welcomed. This includes allowing space from failure, supporting informal peer learning, and recognizing that AI fluency is a journey, not a benchmark.

5.3 Suggestions for Future Studies

The findings of this study open multiple avenues for further academic inquiry. While the qualitative data gathered provides rich, in-depth insight into how AI tools influence digital skill development in SMEs, future research would benefit from adopting quantitative and mixed method approaches. By using large-scale surveys and statistical techniques, future studies can validate the patterns identified here and determine the generalizability of these findings across broader populations. For instance, exploring correlations between AI tool usage frequency and perceived skill growth, or testing the influence of leadership support on AI integration, could bring empirical rigor to themes highlighted in this study.

Additionally, cross-country comparative studies would be particularly valuable in identifying how contextual factors such as national digital infrastructure, policy framework, and cultural attitudes towards technology influence AI adoption and digital learning outcomes. Given that SMEs operate under vastly different regulatory and economic conditions globally, such comparative studies could reveal important disparities in readiness, access, and ethical perceptions of AI in workforce development.

Sector-specific investigations also offer a promising direction for further research. While this study focused primarily on SMEs within technology and consulting domains, other industries such as healthcare, agriculture, education, or manufacturing may encounter distinct challenges and opportunities in leveraging AI for skill development. Understanding the sectoral nuances in AI integration would provide a more refined view of how workplace learning ecosystems adapt based on industry demands, digital maturity, and employee profiles.

Moreover, longitudinal studies that track employees' digital capabilities and attitudes over time would offer a more comprehensive understanding of the sustainability and long-term effects of AI-enabled skill development. Such studies could help determine whether early engagement with AI leads to enduring changes in learning behavior, professional growth, or job satisfaction, or whether these benefits diminish without sustained organizational support and policy alignment.

5.4 Limitations

While this study contributes meaningful insights to the literature on AI adoption and workforce learning, it is not without limitations. The first limitations pertain to the sample size and scope. Interviews were conducted with a relatively small number of participants from five SMEs, predominantly within the technology and digital consulting sectors. As a result, the findings may reflect the experiences of firms that are already somewhat familiar with digital tools and may not fully capture the perspectives of more traditional or digitally lagging SMEs in other industries.

A Second limitation concerns the self-reported nature of the data. Participants' descriptions of their experiences with AI tools were subjective and based on personal perceptions, which may not always reflect actual behavior or measurable learning outcomes. Although care was taken to triangulate themes across participants and include verbatim quotations, there remains the possibility that participants over, or under stated their engagement with AI tools due to optimism, misunderstanding, or social desirability bias.

Furthermore, the study took place within a rapidly evolving technological landscape, where AI tools are frequently updated or replaced. As such, some of the platforms and practices referenced by participants may become outdated within a short time frame. This temporal limitation challenges the longitudinal validity of the findings and calls for continued research to keep pace with evolving AI capabilities and workplace norms.

Finally, while the study focused extensively on employee experience and included some managerial perspectives, it did not deeply analyze broader systemic or organizational variables such as national education policies, labor market dynamics, or strategic business models that might influence AI adoption and skill development trajectories. Incorporating these wider macro-level considerations in future research would allow for a more comprehensive understanding of how AI impacts human capital across different environments.

In conclusion, this study investigates how AI influences digital skill development among employees in SMEs and how AI tools assist workers in adapting to the digital transition.

The findings confirm that AI serve not only as a technological enabler but as a transformational learning agent that alters how, when, and what employees learn. By providing real-time support, automating repetitive tasks, and scaffolding learning, AI fosters both technical skill acquisition and behavioral competencies such as adaptability, self-direction, and critical thinking.

However, the transformative potential of AI is not automatic. It is deeply dependent on organizational readiness, leadership vision, foundational digital literacy, and ethical integration. Without these enablers, AI may reinforce existing skill gaps or introduce new risks around overreliance and data misuse.

The study refines and extends existing theories of digital transformation and AI adoption by emphasizing the co-evolution of tools, people, and systems. For SME managers, the findings underline the importance of fostering a culture of responsible innovation and continuous learning. AI should not be viewed as a threat or a mere efficiency booster, but as a strategic partner in building a digitally resilient and empowered workforce.

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Appendices

Appendix 1. Semi-structured Interview Guide

Opening Questions:

1. Can you briefly introduce yourself and your role in the company?
2. How long have you been working in this organization?

AI Adoption and Skill Development:

3. Tell me how your company utilizes AI.
4. What motivates your company to encourage skill development through AI?
5. What are the key digital skills that your company focuses on developing using AI? (E.g., data analytics, automation, cybersecurity, programming, AI literacy)

AI's effectiveness in Digital Skill Development

6. Tell me about the effectiveness of AI in digital skill development.
7. Can you share any examples of how AI-based learning tools have impacted employees' performance or efficiency?

Challenges and Barriers

8. What do you think are the barriers/challenges in adoption of AI (esp for training and skill development)?

Future Perspectives on AI & Digital Skills

9. How do you see AI evolving in the future of digital skill development of SMEs in Finland?
10. Are you aware of the new AI regulations? What is your say about it?

Closing Question:

11. Is there anything else you'd like to share about AI's role in digital skill development?

Appendix 2. Interviewees' Profile

Interviewee	Industry	Years in the organization	Designation	Interview Duration (hh:ss)
1	Software	5	Software Engineer	47:00
2	Software	3	Head of Finland	28:28
3	Software	15+	Business Unit Director	36:30
4	Manufacturing	2+	Project Coordinator	40:37
5	Consulting	2+	CEO	25:34