UNIVERSITY OF TURKU
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How deep is your GenAI use?

Studying role-based differences of GenAI literacy in business organizations

Information Systems Science
Master's thesis

Author:
Nikolas Rawlins

Supervisor(s):
Senior researcher Jani Koskinen
Research fellow Salla Westerstrand

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Student’s statement regarding the use of Artificial Intelligence (AI) for preparing and/or writing this thesis:

☐ **I have not used any AI-based tools.**

☒ **I have used AI-based tools**. Their use is documented in the Appendix. The AI tools were used in a way that complies with academic integrity guidelines.

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Abstract

This thesis examines how Generative Artificial Intelligence (GenAI) literacy is perceived across organizational roles and how these perceptions compare with existing AI and GenAI literacy frameworks. As the adoption of GenAI systems increases, employees and managers are expected to keep up with the pace of technological change while developing the skills and competencies required to use these tools effectively. However, existing research remains fragmented and heavily focused on educational settings with comparatively few studies exploring literacy in the workplace and business environments.

The study adopts a qualitative approach with ten semi-structured interviews with experts, managers and users from four large organizations in Finland. The interview data were subsequently analyzed using Reflexive Thematic Analysis (RTA) to identify patterns in participants' experiences and viewpoints. Moreover, the literature review draws on multiple fields of study in order to establish a broader understanding of how GenAI literacy is currently conceptualized.

The findings indicate that GenAI literacy is primarily viewed as a set of practical competencies rather than having theoretical or technical knowledge. Responsible use, critical evaluation and validation emerged as individual-centered themes whereas clear guidelines, company culture, the role of management and the need for training and support highlighted the importance of organizational dimensions. At the same time, clear differences were identified between roles suggesting literacy misalignment. Taken together, a key observation was that GenAI literacy is shaped by individual factors as well as their workplace environment.

Similarly, the comparison with existing frameworks revealed substantial alignment with many practical individual competencies, but considerably less emphasis on personal attitudes, confidence, organizational or role-based requirements. Consequently, contemporary frameworks do not sufficiently capture the complexity of GenAI literacy in the workplace. This thesis contributes to the surrounding literature by demonstrating how GenAI literacy extends beyond individual competencies and is shaped by personal, contextual and organizational factors. This in turn provides a variety of opportunities for future research.

Keywords: Generative artificial intelligence, AI literacy, GenAI literacy, role-based literacy, organizational literacy, GenAI adoption, reflexive thematic analysis.

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Tiivistelmä

Tämä opinnäytetyö tutkii miten generatiivisen tekoälyn (GenAI) lukutaito ymmärretään eri organisaatioroolien näkökulmasta ja miten nämä käsitykset vertautuvat olemassa oleviin sekä tekoälyn että generatiivisen tekoälylukutaidon viitekehyksiin. GenAI:n yleistyessä yrityksissä sekä työntekijöiden että esihenkilöiden odotetaan pysyvän teknologisen kehityksen tahdissa samalla kun he kehittävät ja ylläpitävät omaa osaamistaan. Aiempi tutkimus on kuitenkin hajanaista ja keskittyy pitkälti koulutusympäristöihin, kun taas työelämään ja liiketoimintaympäristöihin keskittyvät selvitykset ovat jääneet vähäisemmälle huomiolle.

Tutkimuksessa hyödynnetään laadullista tutkimusotetta puolistrukturoitujen haastattelujen avulla. Aineisto koostuu kymmenestä haastattelusta, joka toteutettiin asiantuntijoiden, esihenkilöiden ja käyttäjien kanssa, jotka työskentelevät neljässä suuressa Suomessa toimivassa organisaatiossa. Haastatteluaineiston analysoinnissa sovellettiin refleksiivistä temaattista analyysia (Reflexive Thematic Analysis, RTA), jonka avulla tunnistettiin toistuvia teemoja osallistujien kokemuksissa ja näkemyksissä. Lisäksi kirjallisuuskatsauksessa yhdistetään useita tutkimussuuntauksia laajemman käsityksen muodostamiseksi siitä, miten GenAI-lukutaito tällä hetkellä ymmärretään kirjallisuudessa.

Tulokset osoittavat, että työelämässä GenAI-lukutaito nähdään ensisijaisesti käytännöllisinä taitoina ja valmiuksina teoreettisen tai teknologisen tietämyksen sijaan. GenAI-järjestelmien vastuullinen käyttö, kriittinen arviointi ja tuotosten validointi korostuivat tärkeinä yksilötason taitoina, kun taas selkeät ohjeistukset, yrityskulttuuri, johtamisen rooli sekä koulutuksen ja tuen tarve painottivat organisaatioiden roolia lukutaidon kehittämisessä. Samalla eri roolien välillä havaittiin selkeitä eroja, jotka viittaavat lukutaidon epätasaisuuteen. Kokonaisuudessaan nämä viittaavat siihen, että GenAI-lukutaitoon vaikuttavat sekä yksilölliset että ympäristölliset tekijät.

Vastaavasti, vertaaminen olemassa oleviin viitekehyksiin osoitti huomattavaa yhteneväisyyttä käytännön läheisiin osaamisiin ja kompetensseihin, mutta merkittävästi vähemmän liittyen yksilöiden asenteisiin, itsevarmuuteen sekä organisaatio- ja roolikohtaisille vaatimuksille. Tämän perusteella, olemassa olevat viitekehykset eivät riitä selittämään GenAI-lukutaitoa monimutkaisuutta työelämässä. Näin ollen tutkielma täydentää olemassa olevaa kirjallisuutta osoittamalla, ettei GenAI-lukutaito koostu vain yksilöllisitä kompetensseista ja osaamisista ja se rakentuu henkilökohtaisten, kontekstuaalisten ja organisaatioon liittyvien tekijöiden vuorovaikutuksessa. Tämä vuorostaan avaa monia mahdollisuuksia jatkotutkimuksille.

Avainsanat: Generatiivinen tekoäly, tekoälylukutaito, generatiivisen tekoälyn lukutaito, rooliperustainen lukutaito, organisatorinen lukutaito, generatiivisen tekoälyn käyttöönotto, refleksiivinen temaattinen analyysi.

TABLE OF CONTENTS

FIGURES

TABLES

1 Introduction

1.1 Overview

What is artificial intelligence? Today, this technology is present everywhere from schools to the workplace, but not necessarily in an obvious way. There is a high level of awareness around social media algorithms, but other examples of artificial intelligence (AI) in society are more obscure such as smart traffic lights or systems being used to identify emotions through facial recognition (Kaplan & Haenlein, 2019). Nevertheless, with the introduction of modern generative AI (GenAI) tools, this topic has regained interest in both public discourse and in academia.

In science fiction, stories about AI often include dystopian narratives about its impact on humanity. Moreover, the speed at which AI is currently becoming integrated into society is already causing anxiety, with fears about potential job losses and the dehumanization of jobs or a general fear of AI (Khogali & Mekid, 2023). Additional concerns include AI-produced movie and TV scripts (Merchant, 2023), increased surveillance, excessive micromanagement, and the monitoring of employee performance through AI-enabled systems (Mantello et al., 2023). However, since the Industrial Revolution, there have been significant technological changes which have transformed society and AI can be argued to be just one of the latest developments.

On the other hand, GenAI is markedly different from other types of AI. Clearer definitions are provided in the following chapter, but all GenAI is AI and not the other way around. Crucially, the distinction is not trivial because the way in which people engage with these technologies differs considerably as GenAI is designed for direct interaction with people. Unlike some more traditional types of AI that require technical knowledge, most GenAI tools are either publicly available free of charge or only require a paid license to access them. This can create uneven levels of understanding, confidence and usage as people from vastly different backgrounds engage with these systems.

Furthermore, Dwivedi et al. (2023) stress that guidelines and regulations often struggle to accommodate GenAI as there are open questions about its risks related to privacy, transparency and accountability. Companies need to consider governance as an important part of their AI strategy. Papagiannidis et al. (2025) point out that, despite there being many governance frameworks available, there is a limited amount of information on how they can be applied in practice as the field of responsible AI use remains fragmented. Combined, these problems create a critical challenge for businesses as there can be vast differences in users' capabilities at the same time as the rules of engagement with GenAI remain inconsistent.

Consequently, this highlights the importance of AI and GenAI literacy because not only do users have varying degrees of competence, but their job requirements are equally varied. Compared with literacy in educational contexts, the amount of research about workplaces and organizational frameworks is much smaller (Almatrafi et al., 2024). Therefore, the purpose of this thesis is to further examine perceptions of GenAI literacy across organizational roles.

1.2 Motivation

The idea for this thesis initially came from observing the ongoing “hype versus doom” debate about GenAI that spanning news and social media. Additionally, conversations with company management and colleagues indicated a lack of awareness of how the technology could be meaningfully integrated into their workflows or used to make business processes more productive aside from comments such as “increasing efficiency”. Elsewhere, others had fully embraced these tools and quickly learned to automate complex tasks. However, in most cases, it seemed that companies only provided access to these tools but did not provide any follow-up support, training or guidance on their use.

Finding research about this phenomenon proved challenging as studies about employees’ GenAI literacy overlapped with several fields of study including AI literacy, AI adoption and AI governance. In practice, multiple articles discussed GenAI adoption while referring to digital literacy (see for example Moravec et al., 2024) or GenAI literacy but not in the workplace (see for example Park, 2025). There are technology acceptance models which have been shown to be successful with AI adoption (see for example Kelly et al., 2023), but specific examples with GenAI are minimal. Lastly, there is an urgent need for more AI literacy training as studies point to how organizations are falling short in their educational efforts (Pinski & Benlian, 2025).

Furthermore, literacy itself is not a focus point in AI or technology acceptance literature, so its role in this process is relatively unexplored. Instead, contemporary research focuses more on skills, capabilities and trust. Here, literacy should not be considered solely as the ability to read and write but to encompass a variety of competencies such as critical thinking, responsible engagement and advanced prompting.

Essentially, it is not just about knowing how to use AI tools but also about when and why to use them, recognizing their limitations, and considering their broader impact on society. Importantly, this applies to every employee and does not exclude experts or management. AI is increasingly becoming a present reality for many organizations, but many are still struggling to understand how it can be effectively leveraged and practically applied (Jafarzadeh et al., 2024). As there is a limited amount of research into employees' AI and GenAI literacy and as every role engages and interacts with it differently, understanding their perspectives provides the motivation for the study.

1.3 Research Questions

The main research question is:

RQ1: *How is GenAI literacy perceived across organizational roles?*

The supporting question examines this further through existing research:

RQ2: *How do these perceptions compare to existing literacy frameworks?*

The study uses qualitative interviews to explore these questions. Their results are then compared to existing frameworks on how well they reflect the reality in the workplace, and these are introduced in the literature review section. The interviews themselves were semi-structured around specific themes to foster a more open discussion. Collectively, they produced a variety of perspectives from individuals with different backgrounds, positions and industries.

The overall aim is to contribute to the surrounding literature by providing empirical evidence on how GenAI literacy is understood in organizations. Furthermore, the contributions of this text may also be applicable in the fields of AI adoption and AI governance as well as shedding light on the differences between roles and how they can shape the outcomes of AI initiatives.

1.4 Scope & Structure

This research was conducted in Finland, and the empirical data was gathered in the spring of 2026. While AI literacy has a longer history, GenAI is still relatively new and evolving and the concept of GenAI literacy has only recently emerged as a separate idea.

The purpose is to explore the perspectives of experts, managers and employees in a number of organizations on their understanding of GenAI literacy while synthesizing relevant interdisciplinary research. Additionally, measuring the literacy levels or capabilities of employees and GenAI systems is not within the scope of this thesis. Moreover, while areas such as AI governance and AI adoption are mentioned, they are not the main focus.

The thesis is structured so that it begins with defining key terms that provide a foundation for the rest of the study and allow for better analysis and discussion of the interviews. The literature review in chapter three offers more insight into AI and GenAI literacy, examining the development and status of these topics. Next, the section on methodology explains the research design, data collection, analytical processes and ethics of the study. This is followed by the findings chapter which presents the results of the interviews. These are then further discussed, compared to existing frameworks and determined as to what their potential implications are. Finally, the limitations and opportunities for future research are outlined and the study concludes by summarizing its main discoveries ending with a list of references and appendices.

2 Definitions

2.1 Artificial Intelligence

This chapter lays the groundwork for the thesis by defining a few key concepts. As stated by both Long & Magerko (2020) and Ng et al. (2021) an important aspect of AI literacy is to understand AI systems and consequently be better able to perceive its potential risks and benefits. Therefore, before discussing the differences in literacy perceptions between users, it is necessary to clarify what is meant by AI and GenAI.

At the time of writing, scholars do not have a consensus on how to define AI. Moreover, explanations can vary depending on the target audience of the text as well as the context of the research with for example a regulatory (see for example the EU AI Act, 2024) or an academic (see for example Russell & Norvig, 2021) focus. In fact, Kaplan & Haenlein (2019) emphasize how, despite its prominence in society and culture, the idea of what AI is still rather hazy and there are many open questions about its use. Their description reads:

> "A system's ability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation" (Kaplan & Haenlein, 2019, p. 1).

The history of AI goes back more than 70 years. During the 1980s machine learning (ML) emerged as a subset which further led to deep learning (DL) as a prominent field in the 2010s. The latter in particular has enabled computer systems to recognize images, process speech, and interpret complex patterns. Today, AI is present in our daily lives in several ways, including personalized content on Netflix or Spotify, Google Maps optimizing travel routes or spam filters in emails flagging potential viruses and scams (Dada et al., 2019; Kaplan & Haenlein, 2019). However, they are not all the same type of AI.

Instead, AI should be seen as an umbrella term that encompasses many types of systems. In fact, there is a significant amount of research that goes into further detail on AI's background, ML and DL as well as the numerous applications and ways in which it has changed sciences, technology and industry (see for example LeCun et al., 2015; Xu et al., 2021), but these are outside of the scope of this study. Accordingly, AI is defined here as stated by Kaplan & Haenlein (2019) and includes multiple systems, methods, and disciplines.

2.2 Generative Artificial Intelligence

Similarly, Ray (2023) points out that understanding the origins of ChatGPT (an example of GenAI) is necessary in order to develop the application further. As the name suggests, GenAI refers to a subset of AI technologies that can "generate" content. Similar to other types of AI, there is no shortage of papers that go into detail regarding the technical aspects (see for example Feuerriegel et al., 2024), potential implications or provide multidisciplinary perspectives of GenAI (see for example Dwivedi et al., 2023). Overall, while there is some degree of variance in terminology and phrasing, most overlap in their general understanding of the subject. According to a systematic review by Sengar et al. (2024, p.3):

> "Generative Artificial Intelligence refers to artificial intelligence systems with the capability to create text, images, or other forms of media through the utilization of generative models."

Their study goes on to point out how in a relatively short period of time, they have shown advanced capabilities in a number of fields, most notably in medicine, natural language processing and image translation among others (Sengar et al., 2024). Additionally, Al-Kfairy (2025) states that GenAI has transformed the way in which companies operate with numerous documented applications ranging from content creation to fraud detection. However, despite its recent prominence and hype, it should not be understood as a more advanced form of AI. Rather, it is a particular sub-class specialized in generative tasks while other types of AI can outperform GenAI models in certain analytical or predictive applications.

The differences between GenAI models and how they can be applied are illustrated in the figure below (see figure 1). The model level explains that outputs are generated from existing data using DL methods to process information and respond in a manner similar to humans. Moreover, these models can be either unimodal (accepting text to generate text) or multimodal (accepting multiple types such as text + image → text or image). The system level demonstrates how computer infrastructure consists of various elements, but for GenAI specifically these include the AI model, underlying infrastructure, user interfaces and the way in which prompts are processed. Finally, the application level contains the potential real-world cases and ways in which GenAI outputs can be used to produce value in organizations.

From a literacy perspective, this suggests that, across all levels of GenAI systems, users may need differing levels of knowledge depending on their organizational role, responsibilities, technical expertise, and interaction with these technologies. As a practical example, company management making decisions concerning the direction of the company requires a different set of knowledge, whereas employees are more likely to be trained in prompting and analyzing their output.

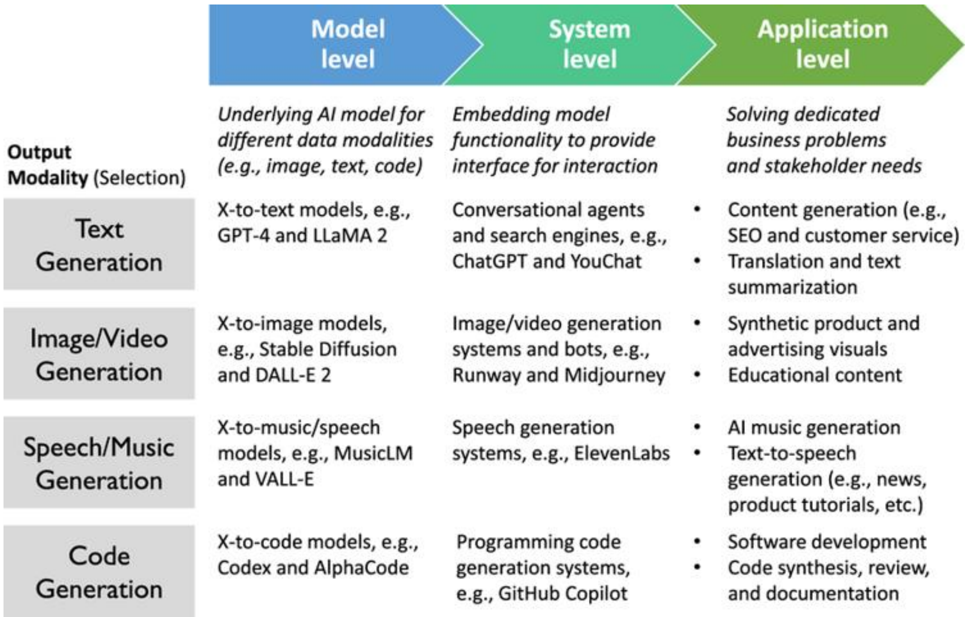

Figure 1. A model-, system-, and application-level view on generative AI

Source: Feuerriegel et al. (2024, p. 113)

Other well-known models (not shown in the figure) include Generative Adversarial Networks (GANs) which are used for image and video generation, Variational Autoencoders (VAEs) for synthetic data creation, and multimodal foundation models which can process and generate multiple input/output types simultaneously (Sengar et al., 2024). These models have already shown promise in a variety of industries ranging from education to medicine.

However, some of the most recognizable applications are large language models (LLMs) that are designed to process and generate text-based outputs. On the application level this means responding to user prompts in a conversational manner. These models gained widespread public attention through systems such as Claude, Google Gemini and ChatGPT (Dwivedi et al., 2023; Feuerriegel et al., 2024). Comparatively, the AI found in search engines and Customer Relationship Management (CRM) copilots such as HubSpot or Microsoft can be a combination of LLMs and broader multimodal foundation models.

This illustrates that there is plenty of variety when it comes to choosing which tools to utilize in organizational processes. Comprehending these differences enables the user to make an informed decision about which systems are best suited for a given task. Moreover, Azzabi & Bouchnak (2026) note that higher levels of AI literacy also mean prioritizing AI quality attributes instead of interaction-related features. Drawing on Sengar et al. (2024), GenAI is understood here to be a subset of AI capable of generating content such as text, images, and sounds through generative models.

2.3 Limits & Potential of GenAI

GenAI has significantly changed the way individuals and companies engage with AI technologies. Feuerriegel et al. (2024) argue that before, AI capabilities were mainly considered to be analytical, but now it has agency as it can create and interact with people, which has shifted the dynamic of how people engage with it. Furthermore, it means that older definitions need to be updated or refined as the adoption dynamics, literacy requirements and challenges depend greatly on context. According to Benk et al. (2025) trust in AI can be seen as a "moving target", which becomes especially challenging with GenAI as scientific research as well as organizations struggle to keep up with the latest developments. Jia et al. (2025) argue this very point by stating that contemporary reviews have largely focused on published articles before 2023 and therefore do not adequately capture the most recent developments in AI research. On the other hand, trying to stay up to date can also lead to matters being superficially covered instead of providing deeper analysis from a particular perspective.

Additionally, it is necessary to be aware of the current limits of GenAI. Feuerriegel et al. (2024) highlight that there are 4 major concerns: incorrect outputs, bias and fairness, copyright issues and environmental impact. Similar concerns have been raised in several studies (see for example Ray, 2023) and each of these are most likely to persist for the foreseeable future.

Likewise, Chong et al. (2021) discovered that if companies do not foster collaboration between AI chatbots and staff, it can lead to employees viewing AI as a threat instead of as an opportunity, which in turn triggers resistance to change. Although this was not an example of GenAI, it suggests that an employee's level of AI literacy may play an important role in shaping these perceptions and whether it is viewed as a supportive tool or a potential threat. As a final comparison though, Moravec et al. (2024) studied the role of digital literacy in the adoption and use of ChatGPT. They found that higher levels of literacy can lead to diverse applications, but there was also no significant correlation between digital literacy and using ChatGPT for work or education. The concept of literacy will be examined more closely in the next chapter.

3 Literature Review

3.1 Mapping out AI & GenAI literature

This section reviews existing research on GenAI literacy to understand and compare it to how it is currently perceived in organizations. After initial consideration, the process began by extensively surveying articles with a focus on Information Systems (IS) journals and conferences. The aim was to find appropriate search terms and keywords for the review. However, it quickly became apparent that, for example AI and GenAI were often used interchangeably, which made narrowing down the articles difficult. More overlapping terminology included AI literacy, digital literacy, data literacy, generative AI literacy and AI skills to name a few. This was discovered by testing out various searches on Volter (the electronic library service used at the University of Turku), Scopus and Google Scholar.

Overall, these demonstrated how similar terms, abbreviations and keywords could have very different results. Synthesizing a field this complex would have required a systematic literature review, which was not the chosen methodology. Nevertheless, a similarly detailed approach was included to explain the complexity of gathering material for the present study.

Furthermore, the number of studies on this topic has grown significantly in recent years. A Scopus search for "AI literacy" (Search within Article title, Abstract, Keywords) conducted in April of 2026, resulted in 7,995 documents found with a sharp increase in publications after 2019 (see Figure 2). Moreover, searches for "Generative AI literacy" (2,200 results) and "GenAI literacy" (739 results) showed a similar pattern though smaller in scale with the latter emerging for the first time in 2023. It is worth noting that OpenAI released ChatGPT in November 2022 and after two months had already gained over 100 million users (Busch et al. 2025) which may have accelerated both public and scientific interest.

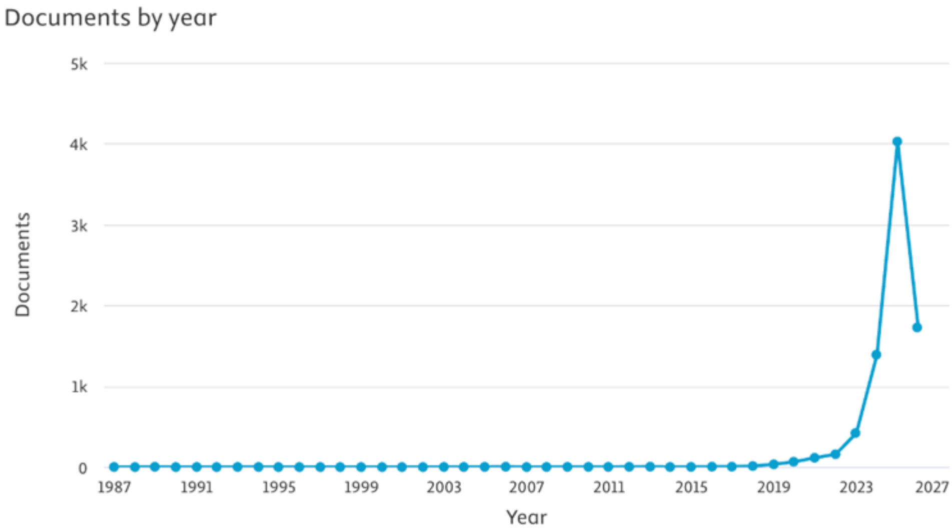

Figure 2. Search results for “AI literacy” documents by year

Source: Scopus (2026)

Therefore, the first challenge was choosing the correct set of queries and keywords to use. Ultimately, the author decided to execute this review in several stages. Scopus was used as the primary database with Google Scholar and Volter being used as a complementary source. Next, a search was conducted with the following query:

> "(TITLE (AI literacy) OR TITLE (Generative AI literacy) OR TITLE (GenAI literacy) OR TITLE (Data literacy))"

By focusing on document titles, the goal here was to find relevant texts while reducing the amount of literature. This resulted in 2530 documents, but once "data literacy" was removed from the query, the number dropped to 1383. An additional search was done with AI literacy removed which resulted in only 215 papers. After further experimentation and testing, the third resulted in 105 documents:

> "(TITLE (AI literacy) OR TITLE (Generative AI literacy) AND TITLE-ABS-KEY (Organization) OR TITLE-ABS-KEY (workforce) OR TITLE-ABS-KEY (employee) OR TITLE-ABS-KEY (workplace)) AND (LIMIT-TO (LANGUAGE , "English")) AND (LIMIT-TO (PUBSTAGE , "final"))"

However, the two searches shown here left out some foundational documents which were considered important, even after adding AI literacy back to the query. The latter also showed how, even with a more specific search, much of the surrounding research was still focused on education while at the same time leaving out studies from the workplace that were present in the first. Therefore, all three had to be considered separately. To do this, the results were filtered by "Cited by (highest)" to find foundational documents and then with "Newest" and "Relevance" to compare findings and ensure a thorough approach. Additional filters included limiting the language to English and excluding subject areas such as medicine or mathematics which were not considered relevant, because these types of studies appeared to the author as highly technical and not business oriented. Comparatively, Google Scholar, searches included the following queries "allintitle: generative ai literacy review", "allintitle: GenAI literacy literature review" and "allintitle: AI literacy review workplace -student -students -school -"K 12" -education " with multiple variations.

Final documents included in the review were based on first their screened titles followed by their abstracts with an emphasis on business workplace contexts and on literature reviews and bibliometric studies to gain a comprehensive understanding. Lastly, all articles and texts were moved into the reference management software Mendeley. It is entirely possible that some relevant studies may have been left out due to variations in searches, terms or certain queries. Nevertheless, the methods used here were considered to be sufficient by the author.

3.2 Conceptualizing AI literacy

To begin with, literacy is generally understood as having the ability to read and write, but according to UNESCO (2026) it should be considered more as a "continuum of learning" that includes a number of various skills that are particularly relevant in the digital age. Regarding AI literacy, a study from Long & Magerko (2020), which has been cited frequently by academics, pointed out how closely it is linked to digital and data literacy. This was further supported by an equally seminal exploratory review from Ng et al. (2021) who found 17 out of 30 peer-reviewed articles anchored their explanations of AI literacy to ideas of ‘literacy' more broadly while citing how the field is still relatively new and growing.

Polomoshnov et al. (2026) also underlined how the history of digital literacy goes back to the late 1990s whereas data literacy has been actively used in academia for over a decade. An illustration from the AILit Framework (OECD, 2025) shows how these different terms and literacies connect to AI literacy (see Figure 3).

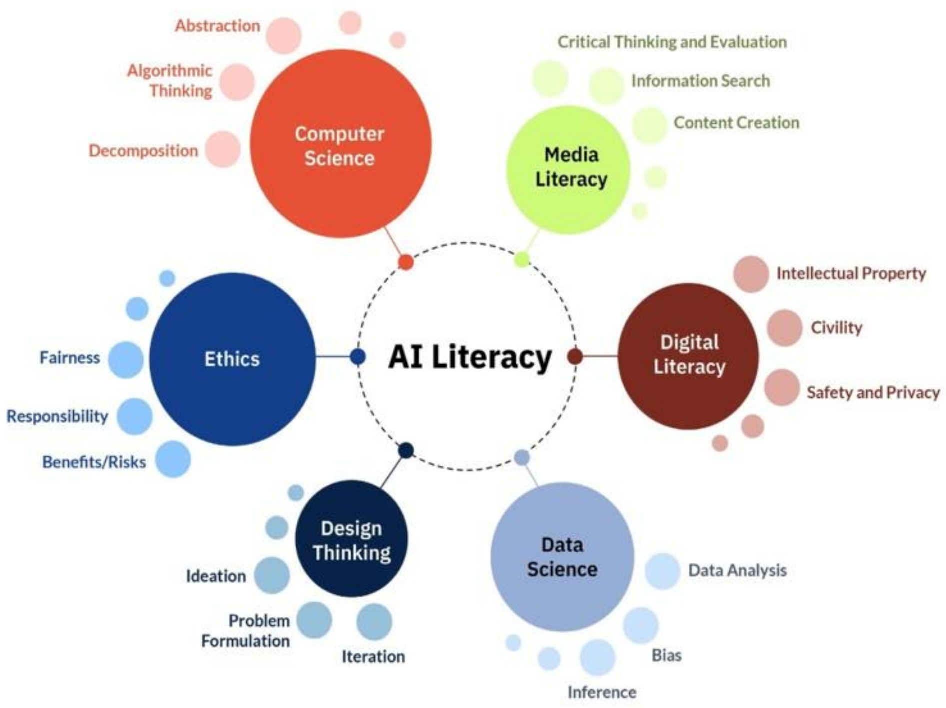

Figure 3. The AILit Framework: Relationship to Other Topics and Disciplines
Source: Empowering Learners for the Age of AI - Review Draft (OECD, 2025, p.17)

A later systematic review by Almatrafi et al. (2024) stresses that it is still difficult to conceptualize AI literacy given the number of definitions vary depending on the purpose, target population and field of study, while noting many similarities across articles. Conversely, Chiu et al. (2024) argue that, while there may be connections to other forms of literacy and competency, these concepts remain distinct even though the surrounding literature often fails to clearly differentiate between them. Their document also made a further distinction between AI literacy and AI competencies. Given the wide range of definitions, Pinski & Benlian (2024) went on to explain how they depend on context and that literacy emphasizes different things with different users. Their research extensively categorized them as either expert or non-expert users, with teachers and managers often being considered as experts (see table 1).

Table 1. AI Literacy Definitions (in alphabetical order)
Source: Pinski & Benlian (2024, p. 4).

Source	AI User Domain	Definition
Carolus et al. (2023, p. 1)	Non-expert	"AI literacy covers “competencies needed to interact with AI technology in a self-determined and rational manner.”
Cetindamar et al. (2024, p. 11)	Expert	"Employees' AI literacy is “a collection of technology, work,

Source	AI User Domain	Definition
		human-machine, and learning capabilities. These capabilities could allow employees to actively join in on designing and utilizing AI at their workplaces.”
Dai et al. (2020, p. 3)	Non-expert	"Student's AI literacy is the “ability to access and use AI-related knowledge and skills.”
Deuze and Beckett (2022, p. 1)	Expert	"AI literacy is “the knowledge and beliefs about artificial intelligence which aid their recognition, management, and application.”
Hermann (2022, p. 1270)	Non-expert	"AI literacy is an “individuals' basic understanding of (a) how and which data are gathered; (b) the way data are combined or compared to draw inferences, create, and disseminate content; c) the own capacity to decide, act, and object; (d) AI's susceptibility to biases and selectivity; and (e) AI's potential impact in the aggregate.”
Laupichler et al. (2022, p. 1)	Non-expert	"AI literacy is “the ability to understand, use, monitor, and critically reflect on AI applications without necessarily being able to develop AI models themselves.”
Kong et al. (2021, p. 2)	Non-expert	"AI literacy “includes three components: AI concepts, using AI concepts for evaluation, and using AI concepts for understanding the real world through problem solving.”
Long and Magerko (2020, p. 2)	Expert & Non-expert	"AI literacy is “a set of competencies that enables individuals to critically evaluate AI technologies, communicate and collaborate effectively with AI, and use AI as a tool online, at home, and in the workplace.”
Ng et al. (2021, p. 1)	Non-expert	"AI literacy is “a new set of technological attitudes, abilities and competencies that people use AI effectively and ethically in everyday life.”
Pinski and Benlian (2023, p. 169)	Expert & Non-expert	“General AI literacy is humans' socio-technical competence consisting of knowledge regarding human and AI actors in human-AI interaction, knowledge of the AI process steps, that is input, processing, and output, and experience in AI interaction.”

Even though the number of AI literacy publications is growing, Pinski & Benlian (2024) stress that the field remains fragmented with Almatrafi et al. (2024) also noting future research should clarify related terms to avoid overlap. Several studies and documents approach AI-related competencies not through AI or GenAI literacy, but digital literacy (see for example Moravec et al. 2024) or media, scientific and digital literacy (see for example Ray, 2023). Although there are documents studying the interconnectivity of these literacies (see for example Polomoshnov et al., (2026).

3.3 Generative AI Literacy

Research from O'Dea (2026) stresses that AI and GenAI literacies are not the same, with the former usually requiring a range of interdisciplinary skills and the latter focusing more on critical thinking and responsible use. However, their study goes on to discuss that it is not clear what capabilities are necessary for GenAI. Furthermore, Wang et al. (2025) distinguish GenAI literacy from digital literacy as being about understanding and critically engaging with the technology.

Annapureddy et al. (2025) argues that the rapid rise and adoption of GenAI tools also requires a unique and specific set of skills which go beyond the traditional competencies associated with data, digital literacy, or AI literacy. This is echoed by Chiu et al. (2024) and Park (2025) who underline that the conceptualization of AI literacy must be expanded to accommodate GenAI features.

Beninger et al. (2025) suggests that GenAI literacy is a way to help maintain the interpretive flexibility of these systems by allowing understandings to evolve and different applications to emerge naturally. Likewise, Bozkurt (2024) calls for a cautious approach when defining GenAI literacy because of the speed of technological development. He goes on to state that contemporary definitions should be flexible to accommodate future changes, and a basic knowledge of AI is not enough. Additionally, Lin et al. (2026) highlight that the disruptive nature of GenAI makes the development of literacy both essential and challenging.

Overall, while there is no consensus on GenAI literacy, it is commonly associated with the practical and responsible application of GenAI tools as well as an ability to remain flexible and adapt to changes. Currently, the status of the surrounding literature implies a lack of cohesion with a growing understanding of the importance of context for defining what literacy means. Despite differences in terminology, much of the research emphasizes awareness, skills and the impact AI will have on society.

3.4 AI Literacy Frameworks

Frameworks are used to help organize ideas and to effectively communicate them. There is a considerable amount of groundwork already done into mapping out the components of AI literacy. However, Almatrafi et al. (2024) point out that the majority of them are also geared towards educational settings with some aimed at kindergarten through 12th grade (K–12) (see for example Lee et al., 2021; Casal-Otero et al., 2023; Chiu et al., 2024; Zhong et al., 2025) and others towards students in higher education (see for example Wang et al., 2023; Southworth et al., 2023; O'Dea et al., 2026; Hackl et al., 2026). Among these, the framework from Ng et al. (2021) remains one of the most influential and commonly used. Their description condensed AI literacy into four dimensions: knowledge and understanding of AI, use and application of AI, evaluating and creating AI and finally AI ethics. Nevertheless, as this study is interested in the literacy levels of employees in organizational settings, educational approaches will not be considered further.

3.4.1 General AI literacy frameworks

Earlier, Long & Magerko (2020) had directed their framework at a larger audience with seventeen AI competencies grouped into five main questions: 1. "What is AI?", 2. "What can AI do?", 3. "How does AI work?", 4. "How should AI be used?", 5. "How do people perceive AI?". Comparatively, Kong & Zhang (2021) constructed theirs for educated citizens more generally with three dimensions: cognitive, affective, and sociocultural. Faruqe et al. (2022) drafted an educational framework on the premise that implementing AI literacy in education would lay the foundation for using AI in the workplace. Finally, others attempted to create cohesive structures such as with Schüller (2022) combining data literacy with AI literacy into a single framework for both students and teachers or Kambhampati & Patel (2025) aiming to bridge the gap between academia and the workplace through AI and digital literacy. Together, these show how conceptualizations of literacy can change depending on the target audience or context as well as what they prioritize. On the other hand, they can also be too general and not necessarily suitable for workplace environments.

3.4.2 Organizational frameworks

Notably, Chee et al. (2025) designed a framework to accommodate different learner groups including employees, but they were mostly limited to medicine and engineering and did not fully address how literacy manifests in business organizations. Similarly, Knoth et al. (2024) proposed a holistic approach, because they identified an urgent need for domain-specific assessment methods. Both studies highlighted how the current literature surrounding AI literacy is incomplete and that future research should explore workplace needs as well as validating these theoretical ideas in practice. They also indicate that literacy is not only contextual, but role specific.

In contrast, frameworks aimed at employees are structured with more of a focus on skills, capabilities or competencies. Cetindamar et al. (2024) conducted a bibliometric review of 270 articles to examine employees' understanding of AI literacy. They established that employees' AI literacy consists of four core capabilities: technology-related, human-related, work-related and learning-related (see Figure 4). Their study underlines how difficult it is to define AI literacy capabilities and calls for future research to examine the interactions between employees and AI technologies.

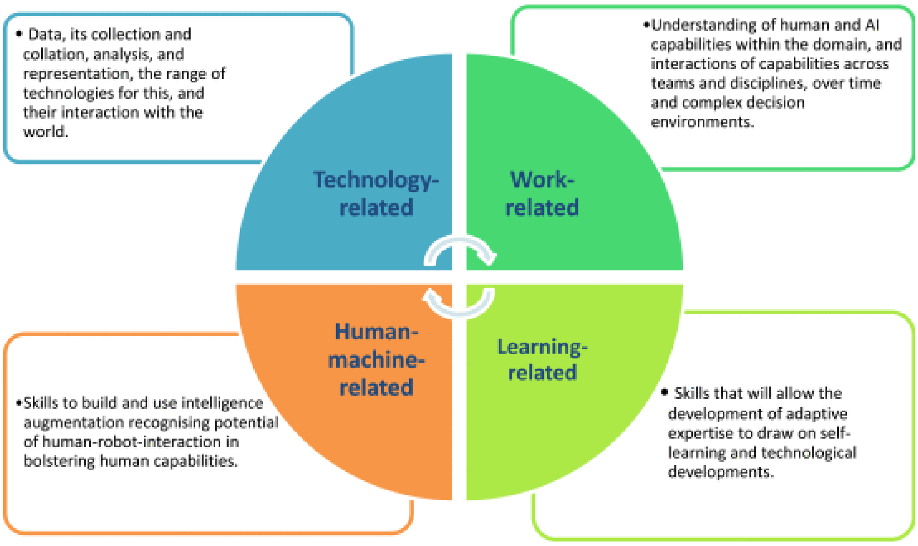

Figure 4. Capabilities for AI literacy

Source: Cetindamar et al. (2024)

An earlier framework from Heyder & Posegga (2021) had only three aspects: functional, critical, and sociocultural. The latter was particularly relevant to this study as they analyzed AI literacy in organizational settings through semi-structured interviews, which they argue extended earlier conceptualizations. They further highlight how the sociocultural dimension plays an active role in enabling employees to engage with AI systems. Additionally, the AI Literacy Assessment Matrix by Pinski & Benlian (2025) was designed for companies and recognized there to be distinct needs between user groups: executives, middle managers, and non-IT employees. It has three dimensions: 1. Conceptual AI literacy (Cognition/Knowledge), 2. Ethical AI literacy (Attitudes), 3. Practical AI literacy (Behavior/Skills). This specifically underlines how the assessment of AI literacy cannot be applied across different roles or departments in an organization. Instead, literacy requirements vary based on an employee's job, responsibilities and intended use of the technology.

3.4.3 GenAI literacy frameworks

Likewise, Annapureddy et al. (2025) proposed that existing frameworks tend to be quite generic and not able to accommodate GenAI tools. Moreover, their study pointed out that GenAI poses a unique set of challenges and requires specific competencies to manage them. They identified 12 competencies which define GenAI literacy that were derived from surrounding literature into AI, digital and GenAI literacy among others. Importantly, this framework underlines the relevance of establishing clear guidelines and policies on GenAI use for public institutions.

On the other hand, a more recent systematic review from Park (2025) presented only five competencies (see Figure 5). While this framework primarily focuses on educational settings and fostering students' GenAI literacy, it emphasizes the significance of attitudes towards GenAI and self-efficacy as central factors enabling engagement with these technologies.

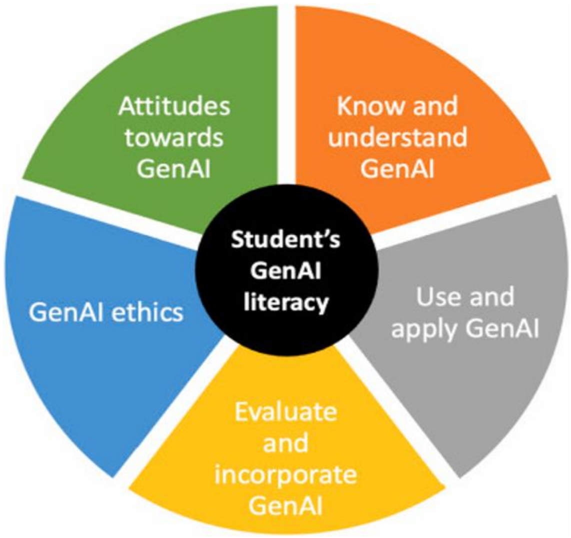

Figure 5. GenAI literacy framework

Source: Park, J. (2025)

Furthermore, Beninger et al. (2025) propose that different types of AI may require distinct approaches to literacy, with GenAI being no exception. Their research goes on to emphasize that compared with earlier frameworks, the socio-ethical component should be integrated into every aspect of GenAI literacy instead of being considered separately. Another important aspect of GenAI frameworks is that they are structured with a growing emphasis on being able to adapt to changes and stay up to date with future developments. For example, Bozkurt (2024) presents the 3wAI Framework which is designed for GenAI and intended to remain flexible. It has three main dimensions: Know What, Know

How, and Know Why (see Figure 6). This was constructed as a comprehensive approach combining theoretical knowledge, practical skills, and critical reflection.

Collectively, the GenAI frameworks which have been mentioned here place less emphasis on understanding the technical aspects of AI systems and more on effective interaction and evolving in tandem with technology. While they acknowledge the importance of attitudes, flexibility and clear guidelines, they have not been fully tested or applied in the workplace.

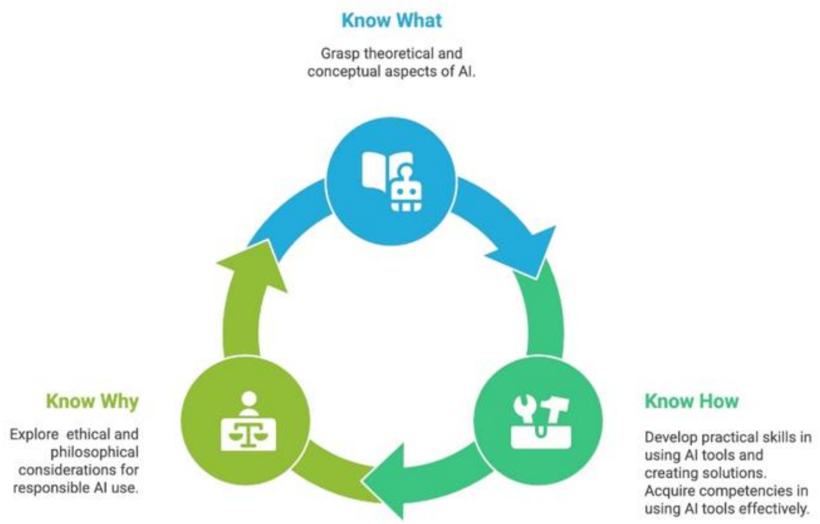

Figure 6. 3wAI Framework
Source: Bozkurt, A. (2024)

3.4.4 Synthesized frameworks

Lastly, there have been additional studies aimed at synthesizing existing frameworks. Almatrafi et al. (2024) reviewed forty-seven articles and synthesized their findings into a further six core constructs: Recognize (Be aware), Know & understand, Use & apply, Evaluate, Create, navigate ethically (Understand ethical and societal implications). Their research makes only a single reference to GenAI, but they also highlight calls for more contextual studies examining how users actually use these systems. Moreover, Almatrafi et al. (2024) only examined documents published prior to 2023 which may not capture the most recent developments in both technology and in academia.

On the international stage, the AILit framework is a joint initiative created by the European Commission and the Organization for Economic Cooperation and Development (OECD, 2025), which builds on several existing frameworks such as the AI4K12 5 Big Ideas and the UNESCO AI competency framework for students. It primarily focuses on educators and learners and has four domains that encompass twenty-two competencies (see Figure 7).

Both of these examples highlight different things and vary on their scope and applying them within the scope of this thesis can be considered too broad as they do not specifically focus on GenAI and the workplace.

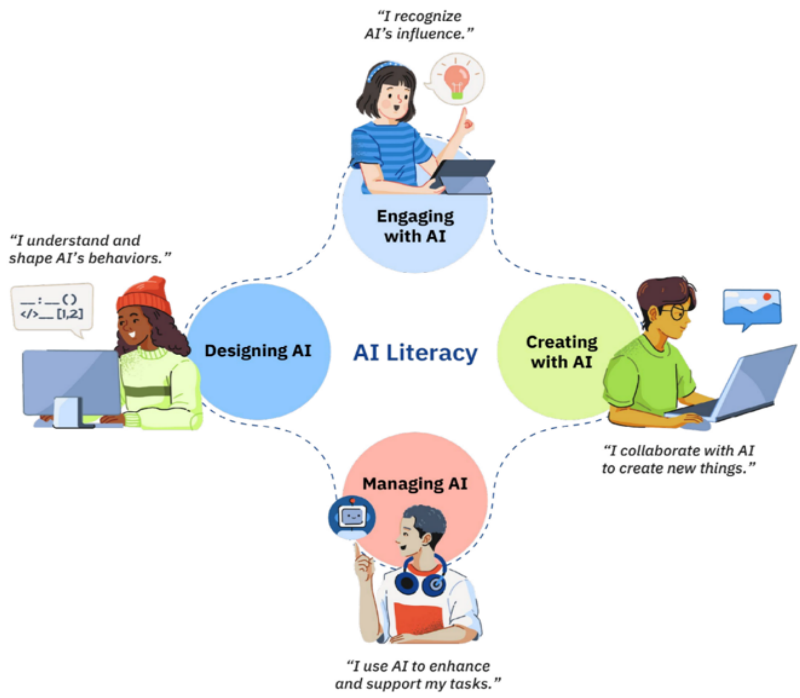

Figure 7. The AILit Framework: Four domains of AI

Source: Empowering Learners for the Age of AI - Review Draft (May 2025, p.24)

3.5 AI Literacy in Organizations

As this study focuses on organizational contexts, it is important to examine the literature from this perspective as well. Currently, a substantial amount of contemporary research into AI literacy is geared towards educational contexts from K–12 to higher education with a focus on either students or teachers (see for example Ng et al., 2021; Laupichler et al., 2022; Pahi et al., 2024; Korte et al., 2024; Stolpe & Hallström, 2024; Ayanwale et al., 2024; Zhong et al., 2025), with far fewer focused on workplace environments.

Comparatively, other studies use alternative terminology with for example Akash et al. (2024) chapter on digital literacy and attitudes with human resources (HR) employees. Others such as Faruqe et al. (2022) and Kaspersen et al. (2024) note how AI literacy in education will positively impact the transition into the workplace. Nevertheless, the findings from Cetindamar et al. (2024) reinforced the notion that most of the scientific literature centers around education and that definitions depend on context, with skills and capabilities being a central focus area when it concerns employees' levels of literacy. Their research also underlined the importance of AI literacy for non-AI professionals. Additionally, a recent study from Reichardt et al. (2025) explored the role of AI literacy in workplace AI implementation and how it can affect the perception of what skills are necessary. Notably, they found that higher levels of literacy do not predict what individuals consider as relevant skills in the future.

According to Jia et al. (2025), AI is already present in the workplace, highlighting how many large companies either have or are in the process of adopting it. Romeo & Lacko (2025) found four main drivers for AI adoption: 1. Crucial Role of Leadership and Organizational Support, 2. AI-skilled workforce, Training and Skills Development, 3. Availability of Financial and Technological Resources and 4. Favorable Policies and Regulations. Their review also underlined how company leadership is the starting point in any undertaking. Even though the article does not explicitly mention AI literacy, the drivers share similarities with existing frameworks.

For example, the first driver is aligned with the core area of *Humans, Organizations, and Society* from Pinski & Benlian (2024) and the second with *Know & Understand* as well as *Use and Apply* dimensions from both Ng et al. (2021) and Almatrafi et al. (2024). Similarly, Deepa et al. (2024) identified managerial capabilities and organizational competencies as important enabling aspects in the adoption process. While their study did not mention AI literacy and made only a single reference to digital literacy, their analysis did call for future research to investigate the impact of competency mapping and AI implementation at different levels.

Furthermore, Kaplan & Haenlein (2019) suggested that businesses can manage the changes AI will bring through having managers foster trust and transparency as they develop the capacity to accurately assess their employees' skills. Meanwhile, employees are required to adapt to changes in their workflow which are being integrated with AI. Notably, their study also does not directly refer to AI literacy, but their analysis does imply varying literacy demands across organizational roles.

User acceptance is central to the success of AI initiatives within companies. Collectively, there is a substantial amount of studies (see for example Kelly et al., 2023; Moravec et al., 2024; Romeo & Lacko, 2025) emphasizing the success of various technology acceptance models with AI including the Technology Acceptance Model (TAM; Davis, 1989), the Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh et al., 2003) and The Technology-Organization-Environment framework (TOE; Tornatzky & Fleischer, 1990).

Combined, they demonstrate how a variety of factors such as the perceived usefulness, organizational support and ease of use influence an individual's readiness in adopting new technologies. In fact, Ray (2023) points out how this is particularly relevant with GenAI systems as they are easy to use, but there are valid concerns over their reliability, bias and questions about data protection.

Importantly, these challenges may be experienced differently by individuals as well as roles. A key finding is that many technology acceptance models have an underlying assumption of literacy within the workforce. This was further supported by Kelly et al. (2023) who highlighted how several users participating in AI adoption studies did not have a clear understanding of AI technology and that the lack of a systematic synthesis limits the exploration of user acceptance. They further recommend that future research should focus on how AI is perceived, which is what the present study aims to achieve.

As stated by Jia et al. (2025), it is essential to comprehend the significance of the perspectives from both management and employees in AI adoption. Company management, experts and users all have separate job descriptions and requirements meaning that their levels of AI literacy will be equally varied, but that the approach must also be tailored to their position. Based on this, it appears that the success of AI initiatives depends, among others, on the alignment of AI literacy throughout organizational levels.

3.6 User's AI Literacy

With the central focus of the present study on how individuals perceive GenAI literacy, it is also necessary to examine the differences in AI literacy between user groups. Borrowing from AI adoption literature, many publications discuss organizational readiness and technical factors but also assume that employees are homogeneous in their characteristics and needs (Khanfar et al., 2025). While this does not fully cover the concept of literacy, in their review Laupichler et al. (2022, p.2) state that:

> "To the best of our knowledge, a closer look at the AI literacy of individual target groups through literature analysis is still lacking."

In recent years, the number of studies has grown. However, there is still a limited amount of research into employees' levels of AI literacy with some notable exceptions, namely Cetindamar et al. (2024), Pinski & Benlian (2024), and Pinski & Benlian (2025). The latter established how scholars had focused on distinct target audiences with their definitions. More broadly, Chee et al. (2025) highlight that research on the AI literacy of different learner groups is still in its infancy and that existing guidelines for learning are largely inconsistent. Almatrafi et al. (2024) also point to research that children from different socioeconomic backgrounds held different attitudes towards AI, particularly with a more positive view of collaboration with AI, but skepticism and trust issues with AI generated content.

Nevertheless, in the absence of further organizational studies, educational environments can serve as a reference point. Among them, O'Dea et al. (2026) conducted a survey that demonstrated how the student’s country, education, and prior knowledge greatly affected an individual's level of AI literacy, whereas for example age did not. Other studies have found similar results with differences between countries' school systems (see for example Rožman et al., 2025) and gender (see for example Cheng et al., 2025). Together, these highlight how important it is to implement comprehensive AI literacy programs for everyone.

However, studies from outside of academia appear to show that AI literacy may develop unevenly throughout competencies or age groups. For example, a report by consulting firm Ernst & Young (EY) and TechAI Inc. examines how Generation Z (Gen Z) perceived and used artificial intelligence. Their survey displayed that nearly half of respondents scored poorly on measures related to “evaluating and identifying critical shortfalls with AI technology” (Merriman & Sanz Sáiz, 2024, p. 18). At the same time, respondents performed better with listing common applications of AI. This implies that familiarity with AI does not necessarily translate into critical thinking skills or other AI literacy-related competencies when interacting with these systems. Notably, the study did not investigate workplace contexts, so the results may not necessarily be applicable in organizational settings.

Finally, there have been studies done in the workplace that are worth exploring. Research from Kaspersen et al. (2024) involving union workers generated comparable findings that while workshops improve their understanding of AI, they did not seem to increase their self-efficacy or confidence in using AI. Furthermore, Reichardt et al. (2025) discovered that AI literacy is an indicator for workforce readiness for engaging with AI systems. Their research goes on to point out that AI literacy should be reinforced by role-specific upskilling tailored to organizational needs.

On the other hand, Benk et al. (2025) conducted a bibliometric analysis of trust in AI, spanning over two decades that emphasized the importance of tailored, context specific approaches to AI systems as a one size fits all solution is not achievable. Chee et al. (2025) demonstrated this by underlining the nuanced requirements of different users. Collectively, these findings indicate that AI literacy and consequently, GenAI literacy develop unevenly across individuals and contexts, further strengthening the need for this study.

3.7 The Need for AI & GenAI Literacy

In order to explore why there is a need for AI literacy, it is necessary to know the reasons behind it. One significant factor is the increasing speed at which AI is being integrated into almost every facet of society. According to Sengar et al. (2024) AI literacy should be considered as an essential technological skill in the 21st century. Moreover, Casal-Otero et al. (2023) state that advancements in computing power, data, and ML algorithms led to significant improvements in AI technologies, which further accelerated their adoption throughout society. This in turn called for a major push to implement AI literacy in schools both for students as well as educators (see for example Laupichler et al., 2022; Sperling et al., 2024). O'Dea et al. (2026) cite additional reports from Statista (2023) and IBM (2022) that indicate an accelerating upward trend in AI adoption while the AI market size is expected to grow exponentially in the next few years. Further studies demonstrate how GenAI can improve organizational business processes and boost innovation (Al-Kfairy, 2025).

Additionally, Pinski & Benlian (2024) argue that AI (referring to GenAI) is uniquely different to previous technologies as it can learn and act on its own and this is why for example media, data or digital literacy are not enough for people to meaningfully and effectively engage with it. Similar studies also highlight the need for GenAI literacy (see for example Bozkurt, 2024; Beninger et al., 2025). Furthermore, O'Dea et al. (2026) bring up a UNESCO report which found that only 16 out of 27 member countries had even started to introduce AI into school curricula, while others such as the University of Hong Kong had temporarily banned the use of AI tools all together.

Research from Walter (2024) makes a comparable point about how a lack of training and guidelines for GenAI tools can lead to potential misuse by students. At the same time, it is harder for educators to detect the use of AI as technology becomes more sophisticated. This may point to a sense of uncertainty and concern both educators and students feel about using GenAI. This point is further underlined by Park (2025), who stresses that the potential for hallucinations, errors and bias calls for robust measures aimed at developing students' knowledge and capabilities with these systems. Similarly, concerns have been raised over insufficient AI literacy in healthcare-related studies (see for example Naamati-Schneider & Alt, 2025; Rodger et al., 2025) but these were outside of the scope of this thesis. Lastly, as stated by Lin et al. (2026), GenAI literacy can positively affect students' levels of confidence and address the feelings of discomfort and uncertainty associated with this technology. While this does not refer to employees or the workforce, the finding may still be applicable.

In summary, there is no clear consensus on definitions, terminology or required competencies for AI or GenAI literacy. However, common themes and competencies did emerge throughout the multiple studies. These included ethics, training and support, company policies and guidelines, engaging with GenAI and personal experiences. Together, they formed the basis for gathering empirical data from the interviews. As the number of publications increases and technology develops further, this will remain a challenge in the future. Narrowing the scope was equally challenging, with deciding on the appropriate frameworks for the second research question.

Based on Bozkurt's (2024) point about flexibility, GenAI literacy refers here to the skills and knowledge needed to meaningfully engage with AI systems. In other words, knowing how these systems work, what they are capable of and what their limitations are, while being aware of their ethical implications.

Collectively, the literature review found that despite a substantial increase in publications regarding AI and GenAI literacy, there is very little empirical data on how it is understood and applied in organizational settings. At the same time, GenAI adoption in society is not slowing down, which underlines the growing need for GenAI literacy. The present study aims to fill this gap by exploring how employees, managers, and experts understand and apply GenAI literacy in practice. The goal is to produce valuable insights and contribute to the field of GenAI literacy.

4 Methodology

4.1 Selection

Compared to the subject of AI more broadly, AI literacy is a much younger field of study with a growing body of literature. Moreover, the introduction of modern GenAI applications underlines the need for flexible methodologies in contemporary and future research. This thesis adopts a qualitative approach, which allows for a critical and reflective way to explore social dynamics. Eriksson & Kovalainen (2008, p.6) describe the process as follows:

> "Qualitative business research gives a researcher an opportunity to focus on the complexity of business-related phenomena in their contexts."

For the present study, individual perspectives in a business environment match these criteria. Several options were considered including grounded theory and the Gioia method. Since the goal is not theory construction but exploring a variety of perspectives on how GenAI literacy is understood in the workplace, reflexive thematic analysis (RTA) was ultimately chosen as the most appropriate method. RTA, as conceptualized by Braun & Clarke (2019, 2021), is based on the broader Thematic Analysis (TA) approach also by Braun & Clarke (2006). The background being that TA developed over the years from a singular methodology to include a variety of techniques that have different assumptions and practices (Braun & Clarke, 2019).

RTA follows the same six-phase process as stated by Braun & Clarke (2006) for TA: familiarization with the data, generating initial codes, searching for themes, reviewing themes, defining and naming themes, and producing the final report. RTA specifically highlights the researcher's role in engaging with, interpreting and reflecting on data. A common misconception is that this approach is a rigid structure and coding can either be done inductively or deductively instead of a continuum (Braun & Clarke, 2021).

However, it is essential to avoid letting prior research or contemporary literacy dimensions predetermine the results from the interviews. Instead, the codes and themes are allowed to develop inductively through immersion with the data and careful analysis of answers. During the discussion, the findings will be analyzed deductively in order to compare them to existing frameworks. Coding and theme development are central to RTA, and they require continuous reflection throughout the analysis.

4.2 Data collection

Interviews have been widely used in qualitative research in a number of topics within IS (Schultze & Avital, 2011). This thesis utilizes semi-structured interviews with different organizational roles, namely experts, managers and users with the last two being easily identifiable. However, defining an AI or GenAI expert is tricky primarily, because there is no fixed definition for either found among scholars. Drawing from the field of cognitive psychology, Bourne et al. (2014, p.1) states that:

> "Expertise is consensually defined as elite, peak, or exceptionally high levels of performance on a particular task or within a given domain."

Based on this definition, an expert is someone who demonstrates advanced capabilities in their understanding of AI systems, has practical experience in using them and the ability to critically evaluate outputs while being aware of its risks and limitations. To clarify, experts were chosen for interviews based on their reputation and the recommendations of colleagues as well as their overall experience with GenAI.

There are inherent complexities when engaging with GenAI systems, depending on an individual's background, experience, attitudes and job requirements as well as on the continued support, guidelines, leadership and industry of their organizations. Experts can provide specialized knowledge or insight, particularly with more traditional forms of AI, but GenAI has become widely accessible to non-expert users and does not require expertise to be able to use it. Therefore, other roles had to be considered as well. Managers were included because they play a key role in organizational decision-making and are responsible for the planning and implementation of company strategies. Their perspectives can explain how GenAI should be implemented, supported and governed. Users represent the primary group targeted by GenAI initiatives, and their experiences help explain the practical challenges and opportunities associated with integrating these technologies into daily work routines.

All three roles were chosen because they present a broader range of perspectives than a single role and as companies are in the process of implementing it into their business processes, it is necessary to have a broader perspective on this process.

In total, ten interviews were conducted in late April and early May of 2026, most of which were conducted remotely via Zoom, scheduled via email and recorded with the participants' permission and only one was conducted in person. The discussions lasted between 30 to 50 minutes. All participants worked at four large corporations in Finland, two of which are owned and operated internationally. The companies themselves operate in different industries and participants came from a variety of professional domains (see table 2).

Table 2. Interview details

Interviewee	Job profile	Industry	Duration
C1 Expert	Sales	E-Commerce	35 min
C1 Manager	Business leadership	E-Commerce	46 min
C1 User	Human resources	E-Commerce	35 min
C2 Expert	Technology leadership	IT consulting	52 min
C2 Manager	Management consulting	IT consulting	56 min
C2 User	Business consulting	IT consulting	41 min
C3 Expert	Logistics	Retail	44 min
C3 Manager	Project management	Retail	53 min
C3 User	Account management	Retail	40 min
C4 Expert	Finance & accounting	Marine industry	51 min

Lastly, Myers & Newman (2007) identified several potential pitfalls related to the qualitative interview and among them artificiality, lack of trust and time. Therefore, in order to avoid these, each participant was informed of the possibility of refusing to answer any question in both the interview invite and at the beginning of the recording. Additionally, instead of a full script, the interviews only had a handful of open-ended questions, designed to foster an open dialogue to explore views related to GenAI use across organizational roles.

The questions themselves were constructed around the themes identified at the end of the literature review. In fact, each one had their own set of follow-up questions that emerged from the discussions so that those being interviewed had the freedom to express their thoughts openly. They provided the structure for the discussions and can be found in the appendices. While some of the themes were familiar to the participants, GenAI literacy was less familiar. This encouraged dialogue as they also wanted to know more about the subject. Finally, everyone was given a participation sheet and a consent form which explicitly described what would be done with the recordings afterwards and how no personal or company details would be used. This was done to ensure transparency and confidentiality.

4.3 Data analysis

In their later reflection Braun & Clarke (2019) emphasize how the six phases are not a rigid construct but a set of guidelines and in RTA it usually means moving back and forth between phases. It can be argued that data analysis began already with the literature review as it provided the author with the necessary background information. This was followed up by identifying common themes in existing research which were then incorporated into the interview script.

Once finished, the interviews were transcribed using an AI tool developed by the University of Turku. The texts were stored in Seafile, the University cloud service, which runs on their own network and later combined into a single file that the author began to read through. The raw transcripts were edited to separate the interviewer and the participant, making the reading and analysis much easier. Afterwards, the texts were further edited to remove filler words, greetings, stutters and other non-related information. These were then added to a table to better track their development (see Figure 8). Simultaneously, this officially started the first phase of RTA (familiarization with the data) which meant going through the interview material and making preliminary notes. Here the first and second phases (familiarization and generating initial codes) already began to blend as notes and codes changed and were modified over time with repeated read throughs. Braun & Clarke (2019; 2021) specifically highlight the role of the researcher and how coding is a creative process. Therefore, the challenge was to avoid letting the literature review affect or predetermine the codes.

INTERVIEW 6

Theme	Data item	Notes	Iteration 1	Iteration 2
Describing GenAI literacy	I think the official version is that Gen AI literacy is just an angle on AI literacy and for me, AI literacy is the ability to utilize the Gen AI tooling and understanding their backgrounds.	Clear understanding between the two.	Clear awareness of differences Background and job affects own understanding?	The importance of role and context based literacy Personal attitudes and external influences (including organizational, peers and societal) shape engagement and learning with GenAI systems.
Differences with AI literacy	I think for me, it started from data literacy, which is the root of understanding how to use data. Then on top of that, AI is an umbrella term for a lot of different things. Then also in discussions with clients I usually try to understand	Tools are more focused on the end user and creating value, whereas AI is more complex.	AI understood as a broad umbrella. Related to many terms and literacies. Continuous development Clear distinction between terms Client languages indicates level	The importance of role and context based literacy GenAI literacy and skills a moving target, because of rapid development Limited theoretical understanding, but strong

Figure 8. Screenshot of RTA and code tracking.

Source: Author's screenshot

All ten interviews generated a lot of data, and any one quote could have been useful for the thesis. Deciding on the most relevant ones was based on the author's own perspectives. Allowing subjectivity instead of objectivity to make this determination is part of the RTA process. The second round of iterations (starting from the first interview) meant combining codes into larger subthemes. Similarly, as these progressed new notes were added and later modified to better encompass all the interviews.

Afterwards, twenty-one subthemes emerged in total, and they were moved to another table. These can be found in the appendices. Even though Braun & Clarke (2019) caution against reporting on theme frequency, the author did this to provide an additional reference point on what topics were discussed most often. Based on these commonalities, the subthemes were then combined into larger themes. However, as the writing on the findings chapter progressed these themes were once again reflected on and refined. Indeed, the entire six-phase process blended in a non-linear fashion. Lastly, during the discussion chapter, the final six themes were compared to existing literacy frameworks.

Importantly, all interviews were conducted in English except for one which was held in Finnish. Therefore, it is possible that some of their views or statements have not been expressed accurately. This can be due to limited language skills of the interviewee or the author unintentionally mistranslating something.

4.4 Research ethics

The author requested permission for the informed consent from all those being interviewed so that they could be recorded. This meant that the purpose and objectives of this study were clearly stated in the email sent to participants. Additionally, it included the participation information sheet and the consent form found in the appendices as well as what themes would be covered to give them time to prepare. The consent form was required to be returned with a signature and a timestamp (an email with the consent form attached as a pdf was acceptable).

Moreover, at the beginning of each interview, they were asked once more for their consent orally and informed that they could refuse to answer any question or end the interview at any time. No personal or company details were used and they were purposefully avoided during the conversations. Any identifiable features or unintended mentions were removed from interview citations and data, preserving the anonymity of the participants.

Choosing the participants involved using the author's connections, acquaintances and third parties to find those who would be willing and were interested in being interviewed. Another aspect worth considering is that the author previously knew some of the participants, which may have affected their answers. Furthermore, there was an attempt to maintain a gender balance, but due to scheduling conflicts not everyone who was asked to participate was available. In the end, the sample consisted of seven men and three women.

All data related to this thesis were stored on Seafile. Interview recordings were deleted after they were transcribed, and the transcripts were deleted from the AI tool after they had been saved. The use of AI tools is detailed and found in the appendices.

5 Findings (RQ1)

5.1 Perceptions of GenAI literacy across organizational roles

This chapter presents the sixth phase (writing the report) of RTA and synthesizes the discoveries from the interviews into themes. The writing itself played a central role as themes were developed through careful analysis and were continuously being reflected on, organized and rewritten. It is important to note how the author's own choices and questions influenced the end result and an alternative perspective may well have discovered something else.

Six themes were developed around the first research question. They relate to participants' attitudes and engagement, user responsibilities, organizational culture, governance and support, practical application, as well as perceptions regarding the development and future implications of GenAI. The themes are illustrated below in table 3 and later compared to the literacy frameworks in the following chapter.

Table 3. Themes identified through Reflexive Thematic Analysis

Source: Author's own analysis of interview data (2026)

THEME
PERSONAL ATTITUDES AND ENGAGEMENT
USER RESPONSIBILITIES AND EXPERIENCE
ORGANIZATIONAL CULTURE, MANAGEMENT & GOVERNANCE
UNDERSTANDING GENAI IN PRACTICE
ORGANIZATIONAL TRAINING & SUPPORT
THE FUTURE OF GENAI

5.1.1 Personal attitudes and engagement

Throughout the interviews, attitudes towards GenAI ranged from enthusiasm and curiosity to caution and uncertainty depending on what was being discussed. Early on it became clear that these personal experiences and external influences (including organizational, peers and societal) shaped the way in which participants engaged with GenAI systems. Generally, those being interviewed expressed excitement and a curiosity to learn and test out new features in their own routines, but they also demonstrated an awareness of certain risks and concerns. Many understood the versatility and potential of GenAI tools across different tasks. As an example, the first interviewee described themselves as an early user actively trying to get the most out of this technology:

> "I would say I've been kind of a super user and very keen to learn new things and understand the technical structure behind AI since the beginning. I still remember the first AI tools that really felt almost magical when they were released." (C1 Expert.)

Conversely, another had a much more difficult time starting out, but their answer seemed to indicate how their confidence developed over time:

> "When we first got the tools, I didn't use them at all. I think I tried it a few times, but I had to correct a lot of stuff so then I just decided I'm not going to use it. I saw resistance to change in myself, and I did not see any value of it. But then the tools improved rather quickly and when we got ChatGPT Enterprise, that's when I really started using GenAI tools." (C2 Manager.)

Combined, these convey how early experiences could have a profound impact on the willingness of users to engage with these systems. Moreover, this means that their first impressions were formed based on the perceived quality and usefulness of available tools. Importantly, with the latter their attitude or "resistance" was not fixed but rather changed due to organizational support and access to specific licenses.

Nevertheless, GenAI was still present in the daily routines of each participant. ChatGPT and Microsoft Copilot tools were cited most often and overall, the interviews mentioned fewer than a dozen others.

> "I know Gemini, Claude and those I've heard about, but I have never used them, only ChatGPT and co-pilot." (C3 User).

> "We basically have a variety of tools that we use including Google Gemini, ChatGPT and others. For example, I have Granola and Cursor which I'm using to achieve different things." (C1 Expert.)

> "I have Granola for note taking or ChatGPT for sparring. I'm a beginner with tools like Claude and Cursor unfortunately." (C1 Manager).

For most, their usage revolved around practical tasks such as summarizing meetings, taking notes, and writing emails. GenAI appeared mostly as a supportive tool that assisted individuals during their daily activities and automated repetitive or routine tasks and assignments. However, the most common uses were related to brainstorming, drafting, refining, planning, and sparring for ideas with each participant having personalized their own uses. This was found to be the case for most roles meaning that, despite differences in job requirements, there were similar patterns of engagement.

> "I mostly use it for like ideation and getting out of the fear of white paper. So, I have ideas on how to structure the presentation and then after I start writing, I'll go back to it and say that I want everything to be shorter and more precise. If I have meeting notes or

> data sets from interviews, I use it to kind of keep the first draft of what the main points are." (C2 User.)

> "I use it as a sparring partner in preparing for meetings and I mirror my own views against it: Is there something I wouldn't have come up with? Is there something new here? The other thing is I have agents that are prompted to generate stuff for me, so when someone sends me an email that this needs to be done just copy paste the text for the agent and it spits out the right csv file in the exact format it needs to be to be uploaded and then I just skim it through and validate." (C3 Expert.)

> "It's part of my daily routine. I start and end my day with GenAI and it's not about giving it more responsibility or making decisions for me, but instead I am giving it the most boring and not that fun tasks that I should be doing that are constantly taking time for my day. I also am letting it improve the quality of my work, so I can make the training sessions better and more understandable for people and so on." (C3 Manager.)

Collectively, experts from all companies had gone the furthest in mapping out their workflows to find ways in which their job could be made more efficient and to increase their productivity. In practice, this meant creating their own AI agents that performed more complex tasks. Consequently, this suggests that a higher level of GenAI literacy can lead to in-depth solutions. Although there was some restraint as well, that was expressed in the following way:

> "I use it as a research tool, summarizer, sparring partner, a fact checker and as a kind of devil's advocate. I have to digest a lot of information from many different sources, and I have my own perspectives, insights and then with the entity behind the chat being the other party, we come up with kind of a common understanding of what would be a good message to give. Be it a PowerPoint presentation or a blog post." (C2 Expert.)

This indicates a deeper collaboration with GenAI systems instead of simply automating tasks or delegating their responsibilities. Participants generally showed an eagerness to use GenAI in a manner that enhances their thinking and better structures their work, but differences between user attitudes can have implications for the rest of the organization. A manager not seeing value in GenAI can have a bigger impact on AI initiatives than an expert automating a function in their workflows, as was demonstrated earlier by the participants resistance to change. Furthermore, experimentation seemed to increase participant confidence in using GenAI which was emphasized by a user's who noted how familiarity and personal preferences with specific tools could influence their personal progression:

> "We are allowed to use ChatGPT and Gemini. I've used both, but I am more confident using ChatGPT, because I have used it for such a long time, so it's also quite trained in my way of communicating, working and so on. I'm sure that if I would have started to use Gemini from the early beginning, it would probably be as good. It's about how lazy you can be in terms of training your tools." (C1 User.)

This shows an awareness of how individuals could be just as confident with other tools if they had been exposed to those first. A clear pattern emerged with other participants with how confidence improved through daily interactions rather than theoretical or technical understanding. In summary, literacy in organizations appears to be experimental and iterative. The description of GenAI being “trained in my way of communicating” is particularly notable because it shows how familiarity and personalization shapes confidence and trust over time. In this sense, literacy was not simply knowledge about AI, but a practical capability developed through repeated use and experimentation.

Managers and users often described similar everyday use cases, but experts tended to integrate GenAI more deeply into their workflows with creating agents and experimenting with advanced forms of customization. Consequently, these differences did not necessarily appear in how often the participants used GenAI, but rather in the complexity and depth of their engagement. This is particularly significant because it complicates existing frameworks that broadly categorize managers or decision-makers as experts.

Finally, everyone maintained boundaries regarding responsibility and oversight. Even highly engaged users emphasized that they did not want GenAI systems to make decisions on their behalf. Instead, they delegated repetitive, administrative and low-risk jobs while retaining responsibility for final outputs and judgments. This implies that trust in GenAI was conditional rather than absolute. Everyone appeared comfortable integrating these tools into their workflows only when they felt capable of reviewing, validating, and controlling the outputs.

Taken together, personal experiences, opinions and first impressions can have major impacts on user attitudes towards GenAI and delay AI initiatives. Further, generally people want to work with these systems instead of allowing them to operate without oversight. Lastly, experimentation and personalization develop steadily, but also unevenly in organizations.

In summary, the key findings regarding the theme Personal Attitudes and Engagement are:

- GenAI engagement was shaped by the participants’ attitudes, experiences and external influences such as friends, colleagues or the news.
- Confidence developed through repeated use and experimentation.
- GenAI was primarily used as a collaborative tool for brainstorming, planning, summarization and refinement of their daily tasks.

- Differences between users were reflected mainly in the complexity of their engagement rather than how often they used GenAI tools.
- Trust in GenAI was conditional and dependent on human oversight and validation of outputs.

5.1.2 Users, Responsibilities & Validation

Notably, every interviewee stressed how essential it is to understand that the user is always responsible and accountable for GenAI output. Their view was that people need to ensure quality and verify the generated content before it is used with all types of tasks, although some stated that they only perform a "quick check" with their own work.

> "The starting point must be that AI is not responsible for anything and instead a human is always held accountable for the outcome. In other words, we cannot end up in a situation where AI simply makes the decision, and we just go with it. The final responsibility always lies with the individual and in my opinion, especially from the perspective of someone working in finance, this is perhaps one of the most important things to comprehend." (C4 Expert.)

Others had similar opinions highlighting the significance of having a "human in the loop". They acknowledged that these tools could save time and boost the performance of certain business processes, but that they should still exercise caution and critical thinking.

> "It's super important to have humans in the loop to kind of be the last stop before we release anything. I believe that there are other skills that will become more relevant because of this shift in the technological field." (C1 Expert.)

> "I have to be the one holding the wheel. There are some tasks, mechanical or manual, that GenAI will help with, but I must be the one in charge and I think that has to do with literacy. To be able to evaluate the output, you must have experience and knowledge about the subject matter." (C2 Manager.)

These further support the earlier point of a collaborative approach to using GenAI systems, where these tools are used to refine and structure ideas, but people always maintain the decision-making power and stay in the driver's seat. Another interviewee had conflicting views on the need for GenAI oversight, because early in the conversation they claimed that they had not seen anything that would suggest that there is a need to have a human operating and checking AI. Later however, the same person stated that:

> "I would say 70% of the work that I do today can be automated, but I would still believe that I am in a better position to decide because there must be somebody accountable." (C1 Manager).

These quotes illustrate tensions between specific roles, but also potential ambivalence within the same individuals. On the other hand, managers have separate priorities from experts and other employees. They may have to balance responsibilities with driving organizational change. This manager in particular was very enthusiastic and confident about GenAI, encouraging and at times even demanding its use from team members. Therefore, this may indication an attempt to balance between a push for transformation and the need for regulation and oversight.

Most realized that their own areas of expertise and professional experience allowed them to critically evaluate GenAI performance even though they acknowledged that defining and measuring the idea of experience is not simple. Moreover, the interviews described this in abstract terms such as “You just need to be good enough” or “I think it just develops over time” implying that these skills do not evolve in a similar fashion for everyone. In contrast, one manager claimed that being critical of GenAI is no different than questioning anything you read or see online, while others emphasized how they always verified and if necessary, edited the content so that it does not appear generic or “AI generated”.

> “I think I mostly see the difference when I know what I want to get out. If I’m researching something or doing a market analysis, I'm not sure if I would, but if I'm doing presentation materials that's when I mostly see it. Maybe it's easier to see when I know what I'm looking for and I have the feeling of that's how I would like to say it, but I’ve been using them for quite some time, and I think it just develops over time when you have that experience.” (C2 User.)

> “I would say that it varies a lot between the different topics. You need to be able to check if the answer is true and to see if it makes sense before you release it or use the material. The more you use AI, the more allergic you become to these sloppy AI things. Nowadays I can easily see if messages or content has been created with AI and with, like, zero effort. I don't want to waste my time reading those things.” (C1 Expert.)

> “I belong to the group of people who can use this technology alongside my professional experience, and I think it gives me an advantage over those who have grown up with this technology.” (C4 Expert.)

Additionally, participants demonstrated an awareness of the fact that the quality of generated content depended heavily on accurate prompting, context, previous data, and the model in question. Across roles, individuals noted that effective prompting could markedly improve or weaken outputs. This in turn connects to the earlier points regarding user experience and confidence. Based on the discussions, prompting developed as a direct result of daily use and experimentation. This meant knowing how to provide constraints as well as testing out and learning how GenAI responds under different circumstances.

> “One of the ways in which I've been developing myself is by getting better at prompting and that's how you get better outputs. But this is a problem when we have too many tools. I might use the same prompt for two tools and then kind of compare which answer is better. You just learn from experience.” (C2 User.)

> “Basically, I might have projects where I dump all the data related to those and after I have given the tools enough context, we can draft pretty good strategies and playbooks on how to do things. With day-to-day activities you can do prospecting, contacting, follow-ups and drafting proposals. If we're modelling a business case on profitability, this can now be super-efficient with GenAI. However, it's very important to give the context in a format that these tools can truly comprehend and that's the key.” (C1 Expert.)

> “I would say the biggest difference are the prompts that you write and the constraints that you have in that prompt or the information that you give as a context etc. This has a bigger impact than switching tools.” (C2 Expert.)

Generally, those being interviewed had not experienced major differences in quality between various tools, but they did agree on the value of choosing the right tools for the right tasks. This was widely considered to be a sign of literacy, which meant having the ability to understand the strengths, weaknesses, and applications of GenAI systems.

> “Regarding the output, I don't see any differences, but I do think that it's important to use the right tool for the right job and if you are GenAI literate then you should be aware of all this. New tools come every two weeks, and the pace of change is unprecedented. It's nothing that we've seen before even as professionals we haven't seen this.” (C2 Manager.)

> “I should know better because I'm a consultant and I should be using specific tools for specific cases. That's something that I know I need to get into when I don't have this much work. That's also kind of the responsibility side of it because larger models obviously take much more energy and whatnot.” (C2 User.)

Comparatively, some participants knew that there could be significant variations between the actual models behind the tools. Over time, they had noticed how GenAI tools were improving and began providing more personalized responses. Moreover, while many noticed a massive improvement in both the quality and accuracy over the previous year, mostly experts could articulate the differences between models. They also argued that not knowing or being aware of this could result in literacy misalignment and substantial disparities in the productivity of teams.

> “I would say that the biggest difference is in the levels of the same tool. How they train the models on how to behave and how to react to the user input is key. I'm not really that keen on comparing Google, OpenAI or Claude. I feel that I just grab whichever is closest and then if I don't really feel that the answer is something that I'm looking for, I might try another. Or then usually I just use the tools that are available or handy to use.” (C2 Expert.)

> “With co-pilot, you can choose from instant and think deeper with the selector that goes up to GPT 5.5. The issue is that people need to choose that manually. We are in a very difficult position as organizations because you can have night or day differences with answers if you use the GPT 5.0 to 5.5. We might see groups who know everything about the tool and then colleagues who are doing the exact same things, but don't even know that there is a model selector. I think this is the first time in IT history when we give so much power to the user to choose how to use the solution itself.” (C3 Manager.)

> “One thing I have noticed is that it always shows the model that it uses and updates are frequent so for example this agent I mentioned that creates the upload files, the models have progressed and during that time its performance has increased considerably. At first, it had some misses and interpreted the input wrong but now it's quite precise.” (C3 Expert.)

As a final point, one expert explained that the context in which GenAI responds is built while people work and engage with these systems and in some cases, providing fewer prompts can be better. Therefore, context might be a good or a bad thing, which ultimately depends on a user’s understanding of the topic at hand. Starting small, doing iterations and gradually improving might achieve better results than trying to work with a massive amount of data with equally specific constraints.

In contrast, other interviews underlined how overreliance on GenAI can have risks. These are related to signing off on reports that have been either summarized or aggressively oversimplified by AI. More conventional examples included using it to write simple Slack messages to colleagues or using unedited outputs in messages, social media posts or job applications. The concern was that people are becoming incapable of functioning without GenAI tools.

> “I think there's always the risk that you shouldn't trust everything that AI might tell you because it doesn't always have this logical thinking. If you blindly trust information, then you can be in trouble so you should always keep in mind to use it as a supportive tool. Additionally, there could be a risk in the future, like when you use a calculator you also get worse with counting figures in your head. So can it make us dumber?” (C3 User.)

> “Something that I've noticed with the junior ones is that they don't have substantive knowledge. They trust the LLMs and the GenAI tools too much. We see a lot of mistakes. When you blindly trust GenAI, that's a very dangerous thing. So, it's my job to guide them, ensure they check and verify everything and have the discussion about what can be done and cannot be done AI-assisted.” (C2 Manager.)

This phenomenon has been popularized by the term “AI slop” and it was mentioned a few times in interviews. The participants agreed that being able to operate without AI provides the foundation for its use and allows users to more accurately assess generated content. The implication here is that allowing GenAI tools to do the work for people is significantly riskier than working collaboratively with them. Finally, one expert cautioned that automating too much can have broader consequences leading to burnout or the loss of achievement.

In summary, the key findings regarding the theme Users, Responsibilities and Validation are:

- Participants emphasized that user responsibility and accountability regarding GenAI use were essential.
- Professional experience and intuition were closely linked to being able to critically evaluate their output.
- Effective prompting and contextualization were seen as important skills for improving their quality.
- GenAI literacy was associated with selecting the right tools for the right tasks while understanding their strengths, limitations, and applications.
- Simultaneously, awareness of the differences between models and their capabilities may contribute to literacy misalignment and productivity gaps.
- Concerns were raised about overreliance on GenAI with risks related to loss of critical thinking, unsubstantiated trust in generated content and a general dependency on automated work.

5.1.3 Organizational Culture, Management & Governance

The importance of management and organizational approach to GenAI consistently emerged as a central theme regardless of role or industry. Several interviewees stressed that guidelines provide employees with a roadmap and structure within which they can operate and learn responsible GenAI use. In short, everyone wanted governance, but for different reasons. For example, managers pointed to the EU AI act as a framework that companies could base their policies on. They saw AI governance as a prerequisite for AI adoption and believed that, if the tools and how they are taught follow the law, then AI adoption has been done the right way minimizing potential risks.

On the other hand, there were concerns about too many restrictions slowing down progress. One manager argued that the only thing that companies should be worried about would be falling behind in AI adoption and not being able to compete in the marketplace. They went on to state that regulations should be worked out on a societal level before problems occur. Overall, there was widespread agreement that the purpose of guidelines should not be to discourage the use of GenAI tools.

> "I think the most important thing is about guiding people and, in some cases restricting them from using third party solutions that are not approved by your company. The newest toys might be based on US or Chinese companies who don't have any interest in fulfilling the GDPR, but we also don't want to be the gatekeepers of the technology and say that we are only using Copilot." (C3 Manager.)

> "We have a GenAI handbook in the company that guides people on what they can build, and it's based on the EU AI act, so it explains what a high risk is and a low-risk system. That is mandatory for people to read. Then we have AI literacy training for the whole organization in eight separate countries that started this May. It provides the basic level of understanding of these tools, of prompting, what are the correct tools, what you can use, what you cannot use. I think we are on the frontier considering the size of our organization." (C3 Manager.)

During the interviews, employees and users believed guidelines should be clear and practical. Users expressed uncertainty and noted the lack of use cases and clear restrictions on what is and is not allowed. Some general dos and don'ts existed in most circumstances, but users highlighted the amount of gray area in daily operations. Moreover, one interviewee claimed that they did not know who to turn to with questions or support.

> "I appreciate that the policies are short, clear, and easy to understand instead of being some huge 50-page governance document that nobody reads. But I still think there are gaps that need clarification. For example, there are very practical questions that remain unanswered such as, do I need permission from a client before using certain kinds of client data in AI tools." (C2 User.)

> "I think it was unclear in the beginning because we had lists of what we could do and what we couldn't do and then only a few case studies which didn't cover everything that we do. Initially, you could not feed any sensitive information, then it was like okay you can but then there were no examples of what counts as sensitive information. I don't know who to ask, who can confirm or what is the source of truth." (C1 User.)

Additionally, experts were more aware of guidelines and their implications. They recognized the need for clarity with GenAI guidelines as they reduce the feeling of uncertainty and provide boundaries for responsible use. One expert claimed that Finnish culture was further associated with being hesitant of doing anything unless it is in black and white. However, experts went on to state that it is unlikely for there to ever be a fully complete set of principles for all possible cases, which can also stay up to date with new developments in a fast-moving industry. Here, literacy can be viewed through the ability to comprehend the rules and regulations surrounding GenAI use, with different focus points for different roles. The nuance appears to be that, while literacy is not mentioned outright, it emerges through the repeated importance of understanding AI governance and company guidelines.

> "There is probably no perfect set of guidelines anywhere yet, but whether the guidance is currently clear enough is another question. A massive standalone document full of

> technical jargon is something that nobody will have the energy to read. Instead, it should be broken down into smaller parts that include information security, data protection policies, and ethical principles. The purpose of the guidelines should not be to prevent the use of AI, but to encourage more responsible use." (C4 Expert.)

A closer look revealed that organizational culture and management were a significant factor in shaping GenAI use and the attitudes of their personnel. Specifically, this meant how they approached the implementation of company guidelines. For example, two interviews from the same workplace pointed out that management and senior leadership appear to be disconnected from day-to-day operations:

> "I guess that's the biggest problem with management, because CEOs and the senior leadership teams are pretty far away from the day-to-day operational stuff. So, they will just say use AI, but if I would truly want to see something happening, I would try to emphasize more on curiosity, teaching and showing concrete stuff. That's the key because if you don't show the value, if you can't make people feel like hey whoa that's like magic then then it's basic leadership and people don't want to change the ways they work which is super typical." (C1 Expert.)

> "In the beginning, it felt a little bit unclear what we were able to do. We've always had enterprise licenses, but it was still questionable in terms of personal data and people's salaries and so on. I think we are now able to feed almost everything, but to be honest that insecure feeling has stuck to me so I always add the info directly into our equipment system, because I would not be comfortable feeding personal information into these tools." (C1 User.)

This suggests that governance and access are not enough when it comes to GenAI adoption. Employees need to understand their value and be encouraged to use them. In contrast, the manager from the same company had an approach which even forbade not using GenAI and argued that the company had recently taken a massive leap in their adoption process. Collectively, these responses demonstrate that approaches as well as perspectives can vary substantially within the same company.

Other interviews had somewhat different experiences. This was underlined by a respondent who stated that organizational approaches depend largely on industry and context. As an example, the public sector may be cautious due to environmental risks or societal responsibilities, and an SMB will have a separate approach to that of a larger company. According to the participants, some governance measures were implemented more systematically than others, either with a top-down or company-wide approach. These showcased the value of structure and planning in the implementation and enforcement of their guidelines, that notably engaged their workers. It implies that organizational culture is just as relevant to GenAI use as individual attitudes and perceptions are.

> "Every time I open my laptop, the first screen that comes up before I log in is a picture or an infographic reminding what you can input to an external GenAI tool. This is being pushed and I think it's necessary because people need guidance." (C3 Expert.)

> "We had an internal competition where there were people from all different parts of the organization and were offered a prize, for who invents the best copilot agent. I could see that everybody who participated and went to the finals had to have a presentation: I created this co-pilot agent. It does this type of work for me just by clicking a button. It was inspiring to see that people use it like that in different teams." (C3 User.)

> "Initially, when these GenAI tools became available, organizations purchased only a few licenses, then tens and later maybe hundreds so it was kind of a bottom-up approach and there is a need for more structure. It's not just about use cases or leading or having a vision, but it's also to do with stuff like AI governance and having a clearer direction and ambition levels." (C2 Manager.)

Combined, earlier findings pointed to the importance of managerial GenAI literacy. Across the interviews, respondents agreed that company leadership shapes the direction of GenAI use. While governance was seen as providing structure and rules, management was considered as the starting point. They set priorities and the pace of change. A common user perspective was that their team leads and managers could lead by example, but at the same time, if they did not require AI use, then it was much harder to begin using these tools. Typically, users first turn to their managers for support. Consequently, if there are gaps in managerial literacy, it can slow down the process of GenAI adoption.

> "At least within our business unit, I feel that management is very engaged with AI and understands its potential well. They seem genuinely interested in using AI both internally and within the solutions we provide to clients. Of course, there are always legal and ethical restrictions that need to be considered, but within those boundaries I think management is eager to explore possibilities and innovations." (C2 User.)

> "I think change comes from the managers. If my manager doesn't use AI or never requires or asks me to use it or doesn't show an example, then I think it's harder for me to take on the AI myself. The change starts from there. The managers at the end of the day are the ones who determine the pace of change and action in a company whether you're a team lead or a c level manager." (C3 User.)

In contrast, experts viewed managerial literacy levels more strategically and through their ability to understand the "big picture". They noted how the age difference between c-level management and the rest of the workforce can create challenges as the former may not be able to see the value that GenAI can bring to the table. However, they did emphasize that it is not necessary for leadership to know everything about this technology, only that they are the enablers of change.

> "I think in large organizations top-level decision makers who maybe are older and against change but also can have a ton of other things to consider. A CEO of a tech

> company might behave differently than a massive retail company where physical stuff needs to move and where AI is more of a support tool than a complete game changer. So, it depends on the company, but in many organizations the c-level lacks understanding." (C3 Expert.)

> "Of course, there are companies where everyone understands everything, but then there is the other side where they don't. For example, management might be very old, and the rest of the employees are very young, meaning that a middle layer is completely missing. Especially in companies like these, situations can become very challenging. The guidelines should be defined clearly enough so that every level of the organization can see the bigger picture. Management does not necessarily need to understand every detail, but they are the driving force that gets things moving." (C4 Expert.)

Finally, managers viewed the organizational capabilities as a key factor in GenAI adoption. While context and industry were mentioned as relevant factors, managers argued that a bigger challenge is the uneven levels of maturity across companies. Some will be further along than others, but more essential is whether there is a project leader or roadmap in place. The findings suggest that in many companies, GenAI adoption projects are still in their early stages and largely dependent on a handful of individuals who are enthusiastic about the technology.

> "I always start with the organization's own capability, because before you make a roadmap for change you have to know where the organization is. They are not in the same position on their journey, some are quite far ahead, others haven't even started. According to our own research we did last year, 90% of businesses had started experimenting with AI, but only 50% had a systematic strategy or plan on how to adopt AI." (C2 Manager.)

> "I was running this project in another company before I switched and what I've heard is that the project has pretty much stopped when I left. We need to have the right people pushing this and we need to have management and bottom-up support for those who want to teach and learn so it all comes down to the people. Why aren't other companies doing this? I think it all comes down to the people who are in charge and if the company doesn't have a person who is pushing forward this agenda, then it's not going to happen." (C3 Manager.)

Therefore, the evidence directly points to literacy misalignment across roles. This was discussed during the interviews from a variety of perspectives. Those who worked in consulting found there to be distinct differences in managerial levels of understanding depending on who they talk to. Access to the right tools had a lot to do with internal company dynamics, including who grants licenses, which employees receive them and who receives training.

> "Last year, we started a top-down approach where we started defining more role-based and unit-based guidelines and for kind of GenAI usage. At a corporate level we realized that this affects everyone, so we've had mandatory GenAI training and all our people have to go through that training program. That was a big investment for our company, but there is still some lack of clarity with, for example, who gets what and why. We've

> also been establishing supporting structures where we have AI champions or AI ambassadors, kind of change agent networks, supporting GenAI usage in teams and we have these virtual communities, where we share use cases and problems et cetera." (C2 Manager.)

Together the interviews showcased how literacy is viewed differently, with users emphasizing practicality, experts focusing on strategy and guidance, and managers on organizational capabilities and change-management. Importantly, some of the companies were revealed to have begun addressing literacy gaps with role-specific training programs and using AI champions to manage change on the grassroots level.

In summary, the key findings regarding the theme Organizational Culture, Management and Governance are:

- Governance and company guidelines were consistently viewed as necessary for enabling responsible GenAI use.
- Different roles emphasized different aspects, and many highlighted the need for practical and understandable rules.
- Organizational culture and approach have a significant impact on GenAI adoption with for example encouragement mattering more than access alone.
- Participants noted significant variations in organizational maturity and capabilities.
- Management was widely seen as the starting point for these initiatives through setting the direction, priorities and leading by example.
- Literacy misalignment emerged across roles with managerial understanding being identified as a potential barrier for GenAI adoption.

5.1.4 Understanding GenAI in practice

The fourth theme revolved around an awareness of GenAI capabilities and potential in varying contexts. The conversations revealed how and why people chose specific GenAI tools for their tasks. Throughout the interviews individuals largely understood the differences, strengths, and limitations of various applications. This in turn demonstrated practical literacy, which was noted earlier with the second theme.

Participants were aware of how the current speed of development was producing new applications at an accelerated rate. Some considered this exciting, but it also created uncertainty as it becomes harder to stay up to date with changes, while the larger implication for the future of work remains unclear. Many considered that GenAI tools are mostly designed for a particular purpose which already explains what they should be used for, but with newer systems this may be harder to determine given their advanced capabilities.

> "We have Google, OpenAI and Claude and they are all kind of racing; week after week, they're releasing these new models that are even better. Now we are at that level of staff engineers with advanced coding and next, we are going to have all the other capabilities. It's a wild time to be alive and you don't know what's going to be waiting for you around the corner." (C1 Expert.)

Additionally, there was further uncertainty about what happens to the data stored in these systems. Typically, users readily accepted low-risk applications such as text refinement, but anything that required complex work and sensitive data, people were more cautious.

> "I mostly use it with text refinement because I am still concerned that it will take over the human decision. Within recruitment you have quite a lot of written material, all kinds of reports, job ads, assignments, and so on which we do with GenAI. We always need to be very diligent and basically make sure that the candidates do not see them as AI produced. So basically, we use it as a tool behind the scenes but then always add the human flavor to it." (C1 User.)

Notably, this reinforces the notion of collaboration with GenAI systems and maintaining oversight and being aware of data protection risks. In other words, the value is not in the system itself, but in how it is being used and applied in practice.

> "Currently the biggest benefits are in reporting and drafting materials. It is also useful for explaining narratives around what the numbers mean. In addition, it can assist with various types of analyses, forecasting, budget-versus-actual analyses, what-if scenarios, sensitivity analyses, identifying deviations, and saving time. The value is not in the program itself, but in the ability to interpret the figures. Now, AI acts as a supporter and enhancer of financial thinking in my work." (C4 Expert.)

The interviews identified a wide array of options in which GenAI could be applied. However, they were simultaneously clear about their limitations. Generally, they were able to recognize between tasks that could be supported by GenAI and those that required more personal focus. One expert questioned whether people should be allowed to use an AI generated analysis, unless they themselves see the logic behind it. Many pointed out how the training data may not be neutral, and this could misrepresent facts in several ways. Lastly, there were some tasks that AI tools could not manage and still required human interaction.

> "In my line of work, they are hard facts, which cannot be solved analytically, and most decisions need people and interpersonal relationships. For example, if we are discussing

> the availability of inventory to cover our customers' needs then I would have to engage in conversation with the customers, like, okay, what do you mean by availability? The whole problem is usually so rooted in the physical and non-physical world of us humans that GenAI tools cannot drink coffee with a customer so it's not always facts." (C3 Expert.)

When asked to define GenAI literacy, most had a limited vocabulary and could not distinguish between AI and GenAI. Everyone had a different perspective on the matter, but there were similarities in their descriptions, which were aligned with the numerous definitions for AI and GenAI literacy highlighted in the literature review. Moreover, a few were also aware of how certain terms were interchangeable or overlapped with each other.

> "My view is that these are being used interchangeably and if I had to draw a line with this, I'd say that GenAI is related to generating images or text, but AI in general might be baked into any kinds of tools or products and that of course is a semantic swamp. What does AI mean? Is machine learning AI? Are neural networks AI?" (C3 Expert.)

Furthermore, while some struggled to explain literacy, they simultaneously identified a number of competencies which are commonly associated with AI and GenAI literacy such as responsible use, awareness of risks and limitations, validation of outputs and user responsibility. This suggests that employee literacy levels may, in fact, be high even though many are not familiar with the terminology. Paradoxically, being able to define GenAI literacy does not appear to be necessary for being literate.

Generally, definitions centered around practical matters and user responsibilities with managers highlighting organizational, governance and ethical perspectives, and the majority of participants emphasizing the importance of critical thinking and being able to differentiate between high-risk and low-risk circumstances. This can have implications for literacy frameworks, which primarily focus on the individual and not the company.

> "I see it as a combination of practical skills, responsible use, data protection and legal awareness. We see GenAI as a democratizing force because traditional AI is still very much out of reach for regular people. GenAI brings those capabilities to people. The issue is that GenAI is completely based on probabilities, it will never answer the same way, and it will make mistakes." (C3 Manager.)

> "I think it has to do both with how capable the organization and the individuals are, both in using GenAI tools, but also in understanding the broader context such as privacy, security values and ethical matters. When I think about GenAI literacy I don't think about how literate or capable a single individual is in using a tool or certain tools, but about the whole GenAI capability and technology." (C2 Manager.)

Lastly, the interviews displayed how the participants had a clear awareness of the risks related to information and data security. Several stressed how companies should reinforce their guidelines by continuously reminding their workers of the dangers of sharing private or confidential data.

> "I think that it's ultimately a leadership issue. This is not just some technical detail within organizations and ethical challenges should be identified and understood from different personnel-level perspectives before making any rushed decisions. For example, when discussing the blurring of responsibility, the very first question should be who is responsible if AI-generated content turns out to be incorrect." (C4 Expert.)

> "We do not yet know all the ways that it can be used. I think the important thing is understanding the use case, because that is really where the risk comes from. If I use it for polishing a text, then the risk is fairly low, but if I use it to screen candidate CVs, then suddenly it becomes a much higher-risk use case. So, the risk levels can vary significantly depending on the situation and what you are doing with it. There are limitations, and I think organizations should communicate those more clearly." (C2 User.)

There were additional concerns raised during an interview about recent global events which had led to discussions about sovereign AI. In practice, this meant that companies were gradually diversifying their GenAI solutions. The reasoning was simple: what would happen if some day Microsoft decided that European companies can no longer use their tools? Essentially, mitigating the risks associated with losing access or being dependent on any particular system. Overall, this section showcased how theoretical knowledge is not a prerequisite to demonstrate proficiency in other key competencies and that literacy includes knowing when, how and why to use GenAI.

In summary, the key findings regarding the theme Understanding GenAI in Practice are:

- Participants demonstrated strong practical understanding of GenAI capabilities, limitations and potential use cases, while lacking more formal knowledge of AI-related terminology.
- Many were able to identify competencies commonly associated with AI and GenAI literacy.
- Different organizational roles emphasized different competencies.
- Awareness of risks such as data security, bias and hallucinations was consistently highlighted during the interviews.
- Participants noted that the risks can vary significantly depending on the context and use case.

- GenAI literacy was associated with knowing when, how and why to use these systems appropriately.

5.1.5 Organizational Support & Training

The need for training and specific case studies was mentioned in every interview. Moreover, support from colleagues, peers, and the company was consistently brought up as an important factor, especially for users, but experts also highlighted this as a major focus point. Additionally, the use of AI champions and leading by example was consistently seen as potential methods to encourage learning in teams throughout organizations. Many argued that not providing support and training could substantially slow down progress for any GenAI initiative. On that note, some participants felt they were not getting the support they needed.

> “We probably have some company-wide AI training, but they are usually given globally at times which are not suitable for Nordic employees. We also have an AI community and quarterly training but again we’re talking about quite a lot of people and topics to cover for one hour and if I would have a case or want to do something with AI, I don't know who I would ask. Probably send a ticket to the help desk and then get an answer in four to six weeks.” (C1 User.)

Comparatively, a manager from the same company argued the responsibility of training lies mainly with the individual. However, during the same interview they went on to state that companies should grant access and organize beginner sessions for employees to get started, which can already go a long way in enabling GenAI use.

> “It would be easy for me to say that companies are not doing enough and there’s probably truth to that, but it’s not like we're not doing anything either. My point is that people invest a lot of their personal free time in these tools and to be good you also need to have personal interest and skin in the game. Ultimately, it's up to the people themselves.” (C1 Manager.)

On the other hand, respondents from different companies were much more optimistic, because they had their own GenAI transformation team, which oversees the project and supports employees across the company. Their answers reflected the overarching approach their organization had taken with clear guidelines, regularly enforced, mandatory training and company-wide competitions for most innovative use cases of GenAI.

> “People on social media are saying that AI is useless and it's only making people dumber are coming out of organizations that have not supported them. We have a GenAI change ambassador network inside of the company where we teach the latest features with use cases and then they are teaching the units that they have. We have these tailored sessions where we can completely focus on legal, marketing or store

> owners use cases. So, we are putting a lot of effort on giving people the training and support that they need." (C3 Manager.)

> "We have made a great effort to embrace this in our team, and we have two champions who support us. We have workshops and collectively figure out how we could use GenAI and this is a company-wide effort. The head of GenAI transformation for the whole corporation is always available and we even had an internal company competition about copilot agents." (C3 Expert.)

Based on this, it appears that organizations can have vastly different approaches to support and training programs and they can depend on a variety of factors ranging from culture to leadership. As an example, one user stated that working in consultation, there is an expectation to be technologically savvy, which further indicates how an industry can also affect employee attitudes towards learning. Nevertheless, the interviews largely favored tailored training and case examples over generic sessions. The challenge is staying up to date with developments, new capabilities and applying these in practice.

> "While this technology develops, guidelines need to be updated as well so it makes more sense to provide continuous support rather than a single training session." (C4 Expert).

Further, multiple participants stressed the importance of role-specific training for the workforce. Especially, users considered it very important to be able to receive case studies tailored towards their roles, but experts generally agreed as users as well as organizations have different needs. Moreover, managers argued that technology initiatives rarely progress according to plan and this is an issue especially with GenAI as available acceptance models or frameworks can be too rigid.

> "The same training is not sufficient for everyone, but at the same time not everything can be tailored to specific needs. In the long run, investing in training early on would also pay itself back very quickly. At the moment, these technologies are still in such a developmental stage, and training remains quite limited." (C4 Expert.)

> "There are a lot of frameworks that presume that the AI journey goes in a certain manner or as a step-by-step process, but in real life it's not that linear. You have to assess different components and then build individual roadmaps." (C2 Manager.)

Essentially, company support begins by providing access and licenses to GenAI. However, it is not enough as employees require training to be able to use it efficiently. The training itself depends on the tool in question as well as the target audience. Lastly, the training cannot be limited to a few times, but it should be continuous with follow-ups to monitor employee progress.

Literacy is present at every level of the cycle. It should not be interpreted merely as, "employees need training", but as a multifaceted and ongoing project. Although not explicitly mentioned aside from one company, it was considered important to have a project manager or someone that employees could turn to with questions. Therefore, this implies that GenAI adoption benefits from clear planning and having an individual who is responsible for its implementation. From this perspective, GenAI is the same as any other organizational initiative or project.

Choosing which tools to acquire and who gets them are managerial decisions that require literacy. This introduces a strategic and managerial aspect to GenAI literacy. Finally, the method through which employees can learn appeared to have two distinct perspectives. On the one hand, company training is necessary and they need to include practical use cases as well as being tailored to suit the diverse needs of different users. However, a few pointed out individuals have a responsibility to learn and further their skills, but with GenAI this presents a challenge because in many cases, using these tools is not mandatory, which makes training and self-learning optional.

There is a difference between something being voluntary or mandatory and this ultimately affects user attitudes. Consequently, organizations can provide support and training, but they cannot force employees to take them. In contrast, many expressed an interest in learning more about GenAI and improving their skills, but the issue was that they felt that they never had the time, which means that employees' literacy development depends on their motivation or willingness to invest their personal time.

The key findings regarding the theme Organizational Support and Training are:

- Every participant stressed the importance of training and support and the absence of these can be seen as a significant barrier to GenAI initiatives in organizations.
- There were substantial differences between organizations in the availability and quality of their support structures and training programs.
- Access to GenAI tools and licenses was considered an important starting point but insufficient without accompanying training and guidance.
- Training was seen as a continuous process that should not be limited to occasional sessions.
- Participants argued for role-specific training and practical use cases to reflect their daily tasks.
- Literacy development and learning were ultimately seen as a shared responsibility between organizations and individuals.

5.1.6 The Future of GenAI

The final theme revolved around participants' perceptions of the future of GenAI. During these discussions, numerous perspectives were presented, with GenAI being a cause for both optimism and anxiety. On the negative side, all interviewees were aware of the associated risks such as bias, data security, potential job losses and environmental challenges. This could mean concern over Gemini recording conversations and not being able to delete them afterwards or being extra careful about what information to upload into GenAI tools.

> "AI tools can be biased when writing scorecards even if I always prompt it to stay neutral, don't make any assumptions etc. I don't know how it's trained and it probably knows what kind of person I am which is creepy. The uncertainty of not knowing causes a little bit of anxiety, like is AI manipulating me or am I manipulating AI?" (C1 User.)

Moreover, external sources such as the news and social media were seen as factors influencing the attitudes towards GenAI. In this way, user attitudes are not only influenced by their personal experiences and backgrounds, but by their peers, media narratives and public discourse.

> "It changes depending on what I hear and read. Sometimes I feel like the media exaggerates the issue, but then I hear about certain solutions or use cases and start thinking that maybe the concerns are not completely unrealistic. There are professions where AI can handle a lot of tasks, but I still believe there will always be a need for people." (C2 User.)

Nevertheless, GenAI was mostly considered to be a net benefit to society and something that people should "play with" rather than sit around in meetings all day. Furthermore, experts and managers pushed back on fears of an AI takeover as organizational and technological change takes time, but they also did not think that it is currently advanced enough for that. As an example, GenAI has occasionally been used as an excuse to downsize even though the real reason could be something else entirely.

> "The other responsible things like, is it going to take jobs? I don't see that we are there yet. AI is used as a scapegoat to make the thing a little bit more positive for the stock owners or the shareholders." (C3 Manager.)

One manager described how GenAI is not markedly different to any other technological transformation companies have previously dealt with. Therefore, GenAI adoption is just the latest addition to a larger trend of technology acceptance.

> "Fear is a natural reaction, and we already see that in the market that people are being laid off, but I would say people don't worry about AI taking their jobs, yet at least. For us, it's kind of business as usual. AI transformation is one transformation among others. In five years, when I look at organization strategies, there's going to be something else.

> Two years ago, three years ago, it was sustainability in every company strategy.” (C2 Manager.)

However, multiple participants still assumed that GenAI would remain a part of both private and public life. Likewise, one manager noted that for many organizations GenAI adoption is viewed as something that is unavoidable, even when they express concerns over environmental or ethical risks. Another user even pointed out that going back to work without these tools could be very difficult as people have already gotten used to it being able to automate their daily tasks.

> “Going back to work without AI would be very hard. We are a bit lazy, because we know that AI can help us. In general, I think AI is a good thing even though it can replace some of the workforce, which is a big problem, but it is probably also going to help a lot of problems that we have in the world.” (C1 User.)

Environmental risks generated discussion as well with shared concerns over water and electricity consumption. At the same time, others suggested that GenAI has the capacity to lessen emissions in other cases.

> “Then there are other risks such as how much these tools use water or electricity which we are mitigating by saying that we use these tools only with a purpose, but then we also don't lean into the doom argument. For example, if we generate a picture with AI for an advertisement, can you imagine how much less CO2s that would be compared to sending a 10-person group of people with cars to shoot that advertisement or location?” (C3 Manager.)

Combined, the interviews suggested that while larger or macro level fears were acknowledged, they seemed out of reach for most. In fact, opinions appeared grounded in practical matters, which mirrored similar viewpoints in previous themes with most believing that the benefits of GenAI outweigh its risks.

With regard to unemployment and layoffs, there were arguments that instead of being afraid of AI replacing workers, people should be more concerned about someone who knows how to use it taking their jobs. On the other hand, respondents argued that companies that have laid off their employees because of AI might have done so prematurely as the technology is not yet capable of complex tasks.

> “We've seen organizations that you know fire their customer support teams and then after two months they realize that maybe AI can't do everything and then they hire them back.” (C2 Manager.)

Additionally, GenAI literacy and skills were considered to be a moving target because of its rapid development. Several interviewees noted that this speed created ongoing demands for both employees and leaders to continually adapt to changes. During their conversation, a manager pointed to a similar challenge facing GenAI research. Participants also argued that it is not realistic to keep up with the latest advancements.

> "After ChatGPT came out I tried to be really on the pulse of everything, and I lost sleep because there was too much happening. Later, I understood that I can't really be on top of all the new cool things that are happening but maybe take more of a managerial level understanding: these things I must know about, and these things are good to know." (C2 Expert.)

> "Also, a big challenge for research on AI is that when the research will be published it will be already old because it's moving so fast." (C2 Manager).

> "One final thought I have is that the speed of development is incredibly fast. It constantly feels like you are trying to catch up with the newest tools and you always feel slightly behind, while trying to understand what is new, what is allowed, and how everything should be used properly." (C2 User.)

The first quote highlights another important point about how literacy was perceived. It is not only about learning or staying up to date, but about the user deciding what to focus on. This means being able to identify the most relevant knowledge for each specific role. Current models were seen as requiring oversight, but future versions might be advanced enough so that they can be fully autonomous. Many argued that the AI being used today will quickly become outdated because of the pace of change.

> "I feel like the current technology will not be the final iteration. I believe that someday people can trust these systems pretty much blindly, but we are not there yet. With GPTs, it's baked into the system that they can hallucinate because it doesn't have the knowledge humans have, but it will get better. A year ago, we had to be very careful with numbers when using these tools, even with frontier models. But now, since last August I haven't seen a single error related to numbers because they are no longer using LLMs to do calculations, they are using Python." (C3 Manager.)

Finally, the discussions reflected on the future of GenAI and what they considered to be most important. The interviewees called for a baseline level of AI literacy to be implemented throughout society and agreed that people should be aware of when they are engaging with AI systems. A lack of understanding can leave people exposed to fraud or misinformation.

> "I think on the EU level they want to have this kind of overall AI literacy for all member countries. There should be some kind of base level of understanding, because the risks are very high. If people don't really know or see the difference between real or AI generated or what is currently possible, then they're at high risk of fraud." (C2 Expert.)

> "It all comes down to the person itself. We can train people, offer incentives but if the person itself is not willing to change their way of working, our hands are tied. I've been banging my head on the wall multiple times about why these people cannot understand

> that you need to think outside of the box with how to use these tools. That is the most difficult thing that I'm trying to solve here but I'm not sure if we can change the human itself." (C3 Manager.)

Organizations, governance and company management all have their part, but ultimately everything depends on the individual. Each user has their own perspective, background and knowledge which impacts their attitudes towards engaging with GenAI and in the workplace this is further shaped by job requirements.

In summary, the key findings regarding the theme The Future of GenAI are:

- GenAI was a cause for both optimism and anxiety and these perceptions were heavily influenced by the media, public discourse, and colleagues.
- Participants generally agreed that GenAI will remain an integral part of societal life in the future, but human oversight will still be required.
- GenAI literacy and its research were seen as moving targets due to the speed of technological development.
- The participants emphasized the ability to identify and focus on the most relevant knowledge, tools, and developments for their specific role and context.
- Finally, individual attitudes, motivation, and willingness to learn were considered as the primary drivers of GenAI literacy development.

5.2 Summary of findings (RQ1)

The purpose of this thesis was to explore how GenAI literacy is perceived across organizational roles in workplace settings. Various tools were present in most workflows, and they were mainly seen as an opportunity to improve or enhance individual performance. During the conversations literacy was viewed through having practical and applicable skills rather than theoretical or technical knowledge.

At the same time, clear differences emerged between roles, particularly regarding how participants understood, applied, and discussed GenAI in their work, which further supported the existence of literacy misalignment. Only a few managed to distinguish between AI and GenAI, but many simultaneously demonstrated competencies commonly associated with AI and GenAI literacy.

GenAI was mostly seen as an opportunity, but many experienced uncertainties regarding its risks and limitations. Organizational guidelines and the role of management were consistently seen as essential factors that can enable or encourage GenAI use throughout the company. Finally, learning and skills development were seen as a continuous process and a shared responsibility between employees and their companies.

Table 4. summarizes the key findings from each theme, the differences between roles and their implications for organizations.

Table 4. Summary of themes & Key findings

Theme	Key findings	Role differences	Organizational implications
Personal Attitudes and Engagement	Confidence developed through repeated use and experimentation; GenAI was primarily used as a collaborative tool; Trust in GenAI was conditional	Experts had more advanced workflows; managers and users focused on automating practical tasks	Organizations should encourage experimentation and learning opportunities
Users, Responsibilities and Validation	User responsibility and accountability; professional experience and intuition linked to evaluation; prompting and contextualization	Experts underlined critical evaluation, managers accountability and users' responsibility	Organizations need clear responsibility structures and to maintain awareness over model variations between teams.
Organizational Culture, Management and Governance	Governance and company guidelines are necessary for enabling responsible GenAI use; different organizational roles emphasized different aspects; Management was widely seen as the starting point	Managers focused on governance, users on practicality and experts on their balance	Clear policies, guidelines, direction and leadership are essential
Understanding GenAI in Practice	Strong practical understanding and limited formal knowledge; different organizational roles emphasized different competencies; risk awareness	Experts distinguished between models and capabilities, managers emphasized strategic and organizational perspectives, and users focused on practical applications and risks	Literacy development should focus on the applications of GenAI in different circumstances
Organizational Support and Training	Continuous support; role-specific training; organizational support structures and maturity were viewed as critical for GenAI adoption	Managers argued for self-learning, users needed practical support and experts understood both sides	Organizations should provide tailored training, access to licenses and continued support structures
Future of GenAI	GenAI was a cause for both optimism and anxiety; literacy requires continuous development and the ability to identify relevant knowledge	Experts focused on relevant developments; managers viewed it as another transformation among many, and users had an emphasis on their daily routines	Organizations are required to regularly update their policies, guidelines and training programs

6 Discussion

6.1 Reflecting on the findings (RQ1)

The findings both support and extend existing research on AI and GenAI literacy. Notably, the overlapping terminology and definitions discovered during the literature review appeared to reflect the practical realities of organizational use. Instead of constructing a common understanding, the results of this analysis indicate that there is no one-size-fits-all solution to engaging with GenAI systems. Collectively, experiences were mixed but leaned more positively as participants generally seemed interested in learning about how to use GenAI tools. These convey how early experiences could have a profound impact on the willingness of users to engage with these systems, which is aligned with what technology acceptance research says about perceived usefulness, trust, and risks as important factors in AI adoption (see for example Moravec et al., 2024; Khanfar et al., 2025).

Approaching potential candidates became the first valuable observation because a very common response was, "I don’t know much about GenAI. You should instead go talk to...". This was particularly noteworthy among company management. Likewise, Kelly et al. (2023) found that participants in AI adoption studies typically had a limited understanding of the technology. Experts can provide valuable insight, but they are not necessarily the ones making decisions on company policies, governance or the adoption of technological systems. Furthermore, employees also require a specific level of knowledge to effectively use GenAI in their daily work. This was reinforced by the interview findings, and together they suggest the existence of literacy misalignment within organizations as expertise, responsibility, and decision-making regarding GenAI are distributed unevenly between different roles.

Additionally, several themes were aligned with the main drivers and blockers for AI adoption outlined by Romeo & Lacko (2025). Particularly, their first (Crucial Role of Leadership and Organizational Support) and fourth driver (Favorable Policies and Regulations) are directly aligned with the theme of organizational culture, management and governance from this study. Likewise, the importance of an AI-skilled workforce, training and skills development, and the availability of financial and technological resources were reflected in the participants’ answers. While the primary challenges from Romeo & Lacko (2025) emphasize resistance to change and lack of skills, the interviews complement this by highlighting how personal experience and encouragement can either strengthen or weaken GenAI adoption attitudes among employees.

The final theme was also related to research from Benk et al. (2025) on trust in AI. Their argument about trust in AI as a moving target was similar to how the participants considered it difficult to stay up to date with the latest updates in GenAI due to the rapid pace of change. Overall, these demonstrate how there are connections to other fields of study that extend beyond AI literacy and GenAI literacy.

6.2 Comparisons with frameworks (RQ2)

Starting with the first theme, Personal Attitudes is explicitly mentioned by only a few frameworks. Park (2025) includes *Attitudes towards GenAI* as a main component of its framework. Additionally, Heyder & Posegga (2021) directly reference trust, attitudes, and habits towards AI as key characteristics of the sociocultural dimension. With these cases, the connection between themes and research is relatively direct, but with others it is less evident. The AILit framework (OECD, 2025) argues that attitudes provide a foundation for AI literacy development and Chee et al. (2024) point out that attitudes shape the way individuals engage with AI. This was strongly reflected in the interview findings. Lastly, Pinski & Benlian (2024) and Almatrafi et al. (2024) note that the relationship between AI literacy and attitudes towards AI remains unclear and requires further research. Notably, attitudes and confidence are discussed frequently in educational frameworks, indicating that these factors have not been fully explored in workplace studies.

Comparatively, Collaboration as a term appeared more often, but usually embedded into the concepts and competencies such as *Human-machine-related* from Cetindamar et al. (2024) or the *Human Role in AI* from Long & Magerko (2020). Meanwhile, Annapureddy et al. (2025) argue that human-AI collaboration should be at the centre of future frameworks. Confidence was much less present with the notable exception of Chee et al. (2024) who identified it as one of eight AI literacy competencies. Nevertheless, it emerged quite often during the interviews. The participants underlined many times how confidence increased their experimentation and improved through repeated use.

Collectively, the first theme was partially supported by existing frameworks. Therefore, it expands the conceptualizations of AI and GenAI literacy by suggesting that the attitudes and confidence of individuals may have a more significant role in workplace GenAI literacy than is currently reflected in the literature. In contrast, the second theme of Users, Responsibilities and Validation had much stronger alignment. Across frameworks, capabilities related to the practical and responsible use of AI as well as the critical evaluation of outputs were consistently considered as competencies (see for example Long & Magerko, 2020; Almatrafi et al., 2024; Annapureddy et al., 2025; Bozkurt, 2024; Park, 2025; OECD, 2025). These were similarly reflected in how the participants repeatedly emphasized the importance of maintaining human oversight in GenAI use and decision-making. This indicates that the second theme, or variations of it, represents one of the most consistently recognized dimensions of AI literacy including in workplace settings.

Moreover, there are notable differences that are relevant to the second theme. Specifically, GenAI literacy frameworks (see for example Annapureddy et al., 2025; Bozkurt, 2024; Park, 2025; OECD, 2025) were the only ones that identified prompting as a competency, which is unsurprising given their focus on GenAI systems. The interviews frequently discussed prompting through contextualization and refinement and how this can have a substantial impact on the overall quality of generated outputs.

Regarding Organizational culture, Management, and Governance, the support was more mixed. The clearest connection came from workplace-oriented frameworks such as Pinski & Benlian (2024) who had *Humans, Organizations, and Society* as a core area. Furthermore, Heyder & Posegga (2021) reported comparable findings with *Corporate culture* and *Leadership*, being identified as important components of AI literacy. Chee et al. (2024) had partial connections to this theme through their emphasis on career related competencies and problem solving, but they did not further address what role organizations or management have in literacy development.

At the same time, frameworks from Park (2025), Almatrafi et al. (2024), Bozkurt (2024) and Long & Magerko (2020) primarily focus on individual competencies and do not spend much effort addressing the influence of workplace structures, culture and governance. Comparatively, the interviewees considered these factors to be central in guiding responsible use and encouraging workers to integrate GenAI into their workflows. The contrast demonstrates that, despite its apparent significance to employees, the organizational dimension remains relatively underrepresented in AI and GenAI literacy.

A majority of frameworks demonstrated strong support for the fourth theme of Understanding GenAI in Practice. Throughout the literature, multiple skills, capabilities, and competencies related to the use of AI and GenAI systems have been identified (see for example, Long & Magerko, 2020; Pinski & Benlian, 2024; Almatrafi et al., 2024; Annapureddy et al., 2025; Bozkurt, 2024; OECD, 2025; Park, 2025). Likewise, awareness of risks, data security, bias and potential for hallucinations are consistently recognized as key areas within AI and GenAI literacy. While participants highlighted their importance during the interviews, they also noted that the risks often depend on the context and intended use. Additionally, literacy was associated with knowing when, why and how to use GenAI.

In fact, here is where the findings began to diverge from current frameworks, because scholars often underline the relevance of foundational AI knowledge and literacy (Long & Magerko, 2020; Heyder

& Posegga, 2021; Almatrafi et al., 2024; Annapureddy et al., 2025; Bozkurt, 2024; Park, 2025), whereas the interviews revealed a different pattern. Participants overwhelmingly demonstrated practical capabilities while acknowledging their own limitations with specific terminology and in understanding the technical aspects of AI and GenAI systems.

From an organizational perspective, this indicates that GenAI literacy is heavily geared towards practical competencies. Furthermore, the findings indicate that the literacy requirements may vary according to an employee's role, background, and responsibilities. Consequently, competencies that are essential for one group of users may be less relevant for another. Therefore, the present study suggests that role-based literacy frameworks may be more suitable especially for the workplace instead of common sets of GenAI competencies for all users. Notably, Heyder & Posegga (2021), Chee et al. (2024), Cetindamar et al. (2024), Pinski & Benlian (2024) and Pinski & Benlian (2025), have already begun to address this with each acknowledging that there are differences between user groups and that literacy is affected by a variety of factors including workplace contexts and job requirements.

Most of the frameworks which have been covered so far in the study stress the significance of continuous learning and skill development such as the *Ability to continuously learn* from Annapureddy et al. (2025) or *Learning-related* capabilities from Cetindamar et al. (2024). However, many do not discuss organizational support and training, which received substantial support from the participants. On the other hand, some of the responses did highlight that the individual has an obligation to train and improve their abilities. There was broad agreement that the process of learning and support should be continuous especially due to the speed of GenAI development.

A key observation was that the process of learning and support was viewed as a shared responsibility between employees and their organization, but this perspective is less evident in literature. There were exceptions to this with for example Heyder & Posegga (2021), Pinski & Benlian (2024, 2025) noting that organizations have a role in supporting AI literacy. A particularly strong connection to this theme came from AI adoption research with Romeo & Lacko (2025), demonstrating how *Leadership and Organizational support* is a main driver of successful AI initiatives in organizations. Nevertheless, the implication is that, while individuals are expected to grow their AI-related competencies, organizations must also provide the support and opportunities necessary for employees to do so.

Finally, The Future of GenAI appears directly in several frameworks. For example, Long & Magerko (2020) include the competency *Imagine Future AI*, Bozkurt (2024) highlights *Imagine Alternative Speculative Future Scenarios* and Pinski & Benlian (2024) identify *Future literacy* as a cross area.

Others indirectly encourage future-oriented thinking through competencies related to adaptability (Cetindamar et al., 2024) or career development (Chee et al., 2024). Moreover, this was reflected in the participants' answers where they discussed different scenarios on the future of work, their personal prospects or how GenAI will impact society. Additionally, while many were aware of ethical risks, they were generally more concerned with practical challenges such as data security or bias. Furthermore, when it came to keeping up with the pace of change, interviewees were able to distinguish what they considered to be important to know and what was simply useful. Consequently, the findings suggest that workplace GenAI literacy involves the ability to identify and prioritize the most relevant skills related to a particular role.

Across the frameworks covered in this study, several themes repeatedly aligned with competencies related to the practical, evaluative, ethical, and future-oriented use of AI and GenAI systems. However, attitudes, confidence, organizational influences, and role-specific literacy requirements received considerably less attention. Collectively, this implies that despite the prominence of many of these frameworks in academia, they do not fully capture the complexities of GenAI literacy in workplace settings. These comparisons are summarized and presented in Table 5.

Table 5. Framework comparisons

Theme	Alignment	Notable Frameworks	Key findings
Personal attitudes and engagement	Partial	Heyder & Posegga (2021) Chee et al. (2024), Park (2025), OECD (2025)	Attitudes and confidence in organizations not fully explored
Users, responsibilities and validation	Strong	Most frameworks	Strong alignment across frameworks
Organizational culture, management and governance	Mixed	Heyder & Posegga (2021), Pinski & Benlian (2024, 2025)	Organizational dimensions not fully explored
Understanding GenAI in practice	Strong/partial	Most frameworks	Competencies related to GenAI use supported. Practical competence preferred over theoretical or technical knowledge
Organizational support and training	Partial/Mixed	Cetindamar et al. (2024), Annapureddy et al. (2025), Pinski & Benlian (2025)	Continuous learning and adaptability supported, but organizational responsibility not fully explored
Future of GenAI	Strong/partial	Long & Magerko (2020), Bozkurt (2024), Pinski & Benlian (2024)	Future and ethical considerations supported. Role relevant knowledge emerged

6.3 Limitations

There are several limitations to this thesis that should be addressed. To begin with, during the literature review there were multiple studies that may have been relevant: the first was a GenAI literacy framework by Fleischmann et al. (2024) and based on the abstract it is specifically designed for higher education and those who are about to enter the workplace. The second, by Lee et al. (2026), investigated how AI literacy impacted employee performance in South Korea and the impact that different personalities and company support can have. These texts were not accessible for the study, but their descriptions indicate that they could have been beneficial. Additionally, Li & Kim (2024) published an article stating the importance of Human Resource Development (HRD) in developing AI literacy within organizations, but this was also unavailable.

Furthermore, GenAI literacy intersects with many related disciplines. As established, the field of AI literacy is fragmented, with more research centred around education and with organizations the language tends to shift towards skills, capabilities and outcomes. Studies from AI adoption, technology acceptance or AI governance are closely related, but not necessarily in an obvious way where a number of papers can discuss the significance of ethical guidelines or worker skills and capabilities related to AI without mentioning literacy. However, this would have required a much wider literature review, which was not possible.

Lastly, the scope, queries, and search terms which were used may have inadvertently excluded valuable data and insights from a number of different sources, including non-English papers published in other databases.

In regard to the chosen methodology, Braun & Clarke (2021) argue that the process of RTA takes time and dedication. Therefore, the approximate one to two months given to this part of the study may not have been sufficient and could have produced alternative results given more time. Typically, researchers that use RTA rely on data analysis software such as ATLAS.ti or MAXQDA (Ahmed et al., 2025) which were not available. Further theme refinement could have also combined specific findings such as Organizational Culture, Management and Governance with Organizational support and training.

The interviews themselves were initially planned to be for twelve people, but unfortunately the manager and user from the fourth company were unavailable. Their perspectives may have brought useful information, as could have a larger sample size. Finally, it is necessary to point out that another set of interview questions could have yielded different results.

6.4 Future research

Following the limitations identified in this thesis, there are several potential avenues for future projects. First, the interplay between AI adoption, governance and literacy calls for more in-depth analysis. Participants consistently highlighted the importance of organizational dimensions in their answers. Synthesizing research from these fields of study could produce valuable insights into how they connect to each other as well as understanding the workplace dynamics and complexities of implementing GenAI in various workflows.

Moreover, the findings indicate that there is a lack of research addressing role-specific literacy requirements and needs across organizational roles. Studying how educational background, confidence, experience, and job responsibilities influence literacy development may help explain literacy misalignment within organizations. These dimensions are also covered in educational frameworks as well as in AI adoption, which provides another opportunity for future research.

The speed of GenAI development was found to be a challenge in both contemporary literature as well as in the workplace. However, the findings suggest that the ability to identify and prioritize which updates to focus on may be more important than maintaining a comprehensive understanding. Therefore, longitudinal studies could explore how literacy requirements for specific systems evolve over time as individuals and companies become more capable and mature. Further, examining how organizations can support GenAI literacy through a variety of training programs or governance initiatives provides an additional avenue for future research.

Lastly, the present study focused on larger enterprise-level companies. Addressing this limitation could be done by analysing small and medium-sized businesses, increasing the sample size or conducting context-specific investigations to determine whether similar patterns emerge across industries. Overall, these directions highlight the need for AI and GenAI literacy to move beyond individual competencies and include organizational and role-specific dimensions in order to better understand how they shape GenAI literacy in the workplace.

7 Conclusion

The purpose of this thesis was to explore how GenAI literacy was perceived across organizational roles. Additionally, it studied how these perceptions compared to existing literacy frameworks. As the adoption of GenAI technologies continues, literacy provides the foundation for the necessary skills and competencies required to use these systems effectively. However, there are clear differences between individual levels of literacy, highlighting the importance of examining the factors that influence an employee's literacy development in the workplace.

In response to RQ1, ten interviews were conducted with participants from a variety of backgrounds and organizational roles. Collectively, they demonstrated that GenAI literacy was primarily viewed through practical capabilities rather than theoretical or technical knowledge. The respondents generally considered GenAI development to be a shared responsibility between employees and their organizations. The differences between roles appeared to be influenced by the backgrounds, experiences, attitudes, and job requirements of the participants. Moreover, factors such as culture, management, governance and support structures heavily influenced individual engagement and skills development. The findings suggest that role-based literacy frameworks that synthesize research from AI adoption and governance literature can help in the implementation of GenAI initiatives.

In response to RQ2, comparing the findings to AI and GenAI literacy frameworks revealed substantial alignment in some areas, but notable gaps in others. Competencies related to practical use, evaluation, learning and ethics showed the strongest connections, while attitudes, confidence, organizational and role-specific dimensions received comparatively less attention. Consequently, this indicates that existing frameworks only partially capture how GenAI literacy manifests itself in the workplace.

In conclusion, this thesis contributes to the surrounding research by showcasing how organizational GenAI literacy extends beyond individual competencies. Furthermore, it is shaped as much by the role as it is by the individual and their organization. Therefore, future researchers may benefit from incorporating personal, contextual and role-specific dimensions into their frameworks.

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Appendices

Appendix 1 Development of Codes

This appendix provides an overview of the twenty-one second-order codes that were revisited, refined and combined into the final six themes.

1. Personal attitudes and external influences (including organizational, peers and societal) shape engagement and learning with GenAI systems.
2. Awareness of GenAI capabilities and potential in different contexts.
3. Integration into workflows with personalized and specialized use depending on context.
4. Collaborating, engaging and Creating with GenAI.
5. The user is responsible for engaging with and accountable for GenAI output and decision making.
6. Professional experience, exposure and expertise help evaluate GenAI performance.
7. User confidence, engagement and experimentation develop over time.
8. The rapid development of AI, depending on personal attitudes and experiences, is cause for optimism and anxiety.
9. Overreliance on GenAI has risks.
10. The importance of organizational and peer support with practical case examples for training.
11. The importance of management and organizational approach to GenAI policies and guidelines.
12. The importance of role specific training and requirements.
13. The importance of management GenAI literacy.
14. GenAI literacy means confidence in practical application and awareness of risks and information data security.
15. Time constraint in learning and personal development.
16. The importance of role and context-based literacy.

17. The importance of GenAI models and data training over time.

18. GenAI literacy and skills are a moving target, because of rapid development.

19. Literacy misalignment across organizational roles.

20. Organizational culture and management shapes GenAI use and attitudes.

21. Limited theoretical understanding, but strong practical knowledge.

Appendix 2 Interview questions

The interviews broadly covered the following themes:

- Ethics

- Training & support

- Company policies and guidelines

- Engaging and experiences with GenAI

QUESTIONS:

- Can you describe how you use AI/GenAI during your daily activities?
- How familiar are you with GenAI tools?
- How comfortable are you in your understanding of GenAI?
- How do you evaluate the output?
- What happens if the output has produced wrong/biased/inaccurate information?
- How do you interact with AI?
- How well do you understand company policies and guidelines regarding GenAI use?
- How does your company offer guidance and support to help you grow in your abilities with GenAI?
- How would you describe your general attitude towards AI?
- What kind of experiences have you had with AI?

Appendix 3 Explanation of the use of AI

During the course of this thesis, AI tools were used in the following ways:

Scopus AI was used to gather information about various subjects, identify foundational works and potential keywords. Mendeley AI was used to summarize articles. ChatGPT was used for proof reading, language refinement, finding and correcting duplicate words, grammar checking as well as scientific formulation.

After each time, the author reviewed and edited the content in order to take full accountability and responsibility of the publication. AI was not used to generate findings or analyze interview data.

Final decisions regarding wording, structure, and content remained the responsibility of the researcher. All coding, theme development, interpretation, and conclusions were conducted by the researcher.

Appendix 4 Interview consent form

Consent for participation in scientific research

<u>Studying role-based differences of GenAI literacy in business organizations</u>

University of Turku, master's thesis of Nikolas Rawlins.

I have been invited to participate in the above-mentioned research.

I have read and understood the participant information sheet. I understand that participating in the research is voluntary and that I can at any point withdraw from participating in the research without giving any reason or cancel my consent without any negative consequences. The information collected of me until the withdrawal and cancellation of consent cannot be used as part of the research data.

I have received sufficient information about the research and how my personal data is processed. I have had the opportunity to ask questions from the researchers. With my signature, I give consent for participating in the research.

I consent that my interview can be recorded for research purposes, but it has to be modified in the research results and publications so that I cannot be recognized from it.

Yes ☐ No ☐

I consent that the anonymized research data can be archived and opened to the use of other researchers.

Yes ☐ No ☐

Verification

I have given oral consent, and the researcher has documented it at the beginning of the interview recording.

I have given my consent by returning this form to the researcher with my signature and date.

Contact information

Nikolas Rawlins

Turku School of Economics

(Phone number hidden in the thesis for privacy concerns)

(Email hidden in the thesis for privacy concerns)

Appendix 5 Participation information sheet

Studying role-based differences of GenAI literacy in business organizations

Invitation to participate in research

You are invited to participate in research that studies how is GenAI literacy is perceived across different organizational roles in practice, specifically with managers, experts and users.

You are requested to participate in this research because you belong to one of these three categories. I am interviewing 12 people from 4 different companies (1 x manager, expert and user per company). Moreover, this study aims to compare results on existing literacy frameworks.

Voluntary participation

It is voluntary to participate in the research. You can refuse to participate in the research, withdraw from the research or cancel your consent to participate in the research at any point without any negative consequences. If you withdraw from the research or cancel your consent, the recorded interview will not be used as part of the research data.

Responsible persons and funder of the research

This research is conducted by Nikolas Rawlins as a master's student at Turku School of Economics. No funding was received for this study.

Research process

The interview will last approximately 30 – 45 minutes and be conducted remotely via zoom and recorded.

Possible benefits and risks

The research contributes to the surrounding scientific literature by examining how GenAI literacy is understood across different organizational roles and if literacy frameworks hold up in practice.

Incentives for participation

No fee is paid for participating in the research.

Processing personal data

The information obtained in the research is confidential, no personal or company details are necessary and all answers will be anonymized. Any corresponding emails containing personal details or requests for the study can also be deleted after the thesis has been completed. The emails are stored on the university email server.

Storage of research data and reporting the research results

The data collected during the research will be stored in Seafile.utu.fi where only the student conducting the research will have access to it. Moreover, the recordings will be deleted right after they have been transcribed using Transcribe.utu.fi approved by University of Turku. The transcriptions will also be stored on Seafile.utu.fi and stored until the thesis is completed.

The research results are reported in the master's thesis.

Contact person for further enquiries

If you have questions about the research, you can contact Nikolas Rawlins, the student in charge of this research.

Nikolas Rawlins

Master's student

Turku School of Economics, Information Systems Sciences

(Email hidden in the thesis for privacy concerns)

(Phone number hidden in the thesis for privacy concerns)

Jani Koskinen (Supervisor)

Senior Researcher, Information Systems Science FT, Dosentti Future Ethics Research Group

University of Turku

(Email hidden in the thesis for privacy concerns)

(Phone number hidden in the thesis for privacy concerns)

Salla Westerstrand (Supervisor)

Doctoral researcher

Turku School of Economics, Information Systems Science

(Email hidden in the thesis for privacy concerns)

Appendix 6 Research data management plan

Research data

Research data refers to all the material with which the analysis and results of the research can be verified and reproduced. It may be, for example, various measurement results, data from surveys or interviews, recordings or videos, notes, software, source codes, biological samples, text samples, or collection data.

Research data type	Contains personal details/information*	I will gather/produce the data myself	Someone else has gathered/produced the data	Other notes
Data type 1: Recorded interviews		x		

Processing personal data in research

I will prepare a Data Protection Notice and give it to the research participants before collecting data ☐

The controller for the personal details is the student themself ☐ the university ☐

My data does not contain any personal data ☒

Permissions and rights related to the use of data

Data type 1: Interview recordings

All participants are contacted via email explaining the purpose of the interview and how that data will be used. This will include asking for their permission to use the interviews for the purpose of the study as well as their participation.

Storing the data during the research process

Where will you store your data during the research process?

In the university's network drive ☐
In the university-provided Seafile Cloud Service ☒
Other location, please specify: ☐

Data documentation

To document the data, I will use:

A field/research journal ☐
A separate document where I will record the main points of the data, such as changes made, phases of analysis, and significance of variables ☒
A readme file linked to the data that describes the main points of the data ☐
Other, please specify: ☐

Data arrangement and integrity

How will you keep your data in order and intact, as well as prevent any accidental changes to it?

I will keep the original data files separate from the data I am using in the research process, so that I can always revert to the original, if need be. ☒

Version control: I will plan before starting the research how I will name the different data versions and I will adhere to the plan consistently. ☒

I recognize the life span of the data from the beginning of the research and am already prepared for situations where the data can alter unnoticed, for example while recording, transcribing, downloading, or in data conversions from one file format to another, etc. ☒

Metadata

Metadata is a description of you research data. Based on metadata someone unfamiliar with your data will understand what it consists of. Metadata should include, among others, the file name, location, file size, and information about the producer of the data. Will you require metadata?

I will save my data into an archive or a repository that will take care of the metadata for me. ☐

I will have to create the metadata myself, because the archive/repository where I am uploading the data requires it. ☐

I will not store my data into a public archive/repository, and therefore I will not need to create any metadata. ☒

Data after completing the research

What happens to your research data when the research is completed?

I will destroy all data immediately after completion, because: because: there is no need for it outside of the thesis