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2024

AI Integration in the IT Professional Workplace: A Scoping Review and Interview Study with Implications for Education and Professional Competencies

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Abstract

As Artificial Intelligence (AI) continues transforming workplaces globally, particularly within the Information Technology (IT) industry, understanding its impact on IT professionals and computing curricula is crucial. This research builds on joint work from two countries, addressing concerns about AI's increasing influence in IT sector workplaces and its implications for tertiary education. The study focuses on AI technologies such as generative AI (GenAI) and large language models (LLMs). It examines how they are perceived and adopted and their effects on workplace dynamics, task allocation, and human-system interaction.

IT professionals, noted as early adopters of AI, offer valuable insights into the interplay between AI and work engagement, highlighting the significant competencies required for digital workplaces. This study employs a dual-method approach, combining a systematic and multi-vocal literature review and qualitative research methods. These included a thematic analysis of a set of 47 interviews conducted between March and May of 2024 with IT

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ITiCSE-WGR 2024, July 8–10, 2024, Milan, Italy

ACM ISBN 979-8-4007-1208-1/24/07
https://doi.org/10.1145/3689187.3709607

professionals in two countries (New Zealand and Sweden). The research aimed to understand the implications for computing students, education curricula, and the assessment of emerging professional competencies.

The literature review found insufficient evidence addressing comprehensive AI practice methodologies, highlighting the need to both develop and regulate professional competencies for effective AI integration. Key interview findings revealed diverse levels of GenAI adoption, ranging from individual experimentation to institutional integration. Participants generally expressed positive attitudes toward the technology and were actively pursuing self-learning despite some concerns. The themes emerging from the interviews included AI's role in augmenting human tasks, privacy and security concerns, productivity enhancements, legal and ethical challenges, and the evolving need for new competencies in the workplace.

The study underscores the critical role of competency frameworks in guiding professional development and ensuring preparedness for an AI-driven environment. Additionally, it highlights the need for educational institutions to adapt curricula to address these emerging demands effectively.

CCS Concepts

• Social and professional topics → Professional topics; **Computing education**; **Computing education programs**; **Computer science education**;

Keywords

Artificial intelligence, generative AI, large language models, IT Profession, computing competencies, computing curricula

ACM Reference Format:
Tony Clear, Åsa Cajander, Alison Clear, Roger McDermott, Mats Daniels, Monica Divitini, Matthew Forshaw, Niklas Humble, Maria Kasinidou, Styliani Kleanthous, Can Kultur, Ghazaleh Parvini, Mohammad Polash, and Tingting Zhu . 2024. AI Integration in the IT Professional Workplace: A Scoping Review and Interview Study with Implications for Education and Professional Competencies. In *2024 Working Group Reports on Innovation and Technology in Computer Science Education (ITiCSE-WGR 2024), July 8–10, 2024, Milan, Italy.* ACM, New York, NY, USA, 34 pages. https://doi.org/10.1145/3689187.3709607

1 Introduction

Artificial intelligence (AI) is rapidly advancing and becoming increasingly integrated into various industries, including education. Despite its growing presence, there is limited understanding of how AI has impacted work practices, professional development, and educational processes, particularly within the *Information Technology (IT) industry*[32], or IT sector [12, 80, 84]. As we have seen from our interviews, this uncertainty is especially pronounced among IT professionals and students at the forefront of implementing and interacting with AI technologies. Investigating these impacts is crucial to provide valuable insights for industry stakeholders and educational institutions, preparing future professionals for co-existing in an AI-embedded work environment.

Studying IT professionals is particularly interesting since they are often early adopters of new technologies, including AI. As a result, IT professionals are most likely the group that has used AI the longest in their work practice and in the most diverse ways. This makes them an ideal population for examining the broader implications of AI integration on work dynamics and professional competencies. Understanding their experiences can provide valuable lessons and insights applicable across various sectors and educational contexts.

While AI integration in the IT industry is growing, there remains a critical gap in the literature regarding the competencies required for professionals to engage with AI technologies effectively. Existing research on AI competencies in the IT sector is fragmented, with varying definitions and perspectives on what constitutes essential skills for professional practice. We have chosen to use the competency model defined in CC2020 [19] as the basis of our work. By exploring academic and grey literature, this study seeks to identify whether current AI competencies adequately capture and reflect the evolving demands of professional practice in the Computing and IT industry.

The primary objectives of this research are to examine the effects of AI on work practices and job roles within the IT sector and to identify changes in professional competencies required due to AI integration. By addressing these objectives, the study aims to inform the broader area of computing education on the implications for education, focusing on current and prospective IT professionals. In addition, it will contribute towards filling a critical gap in the current understanding of AI's broader implications.

A mixed-methods approach addressed the research questions presented below, combining a systematic academic and grey literature review with qualitative interviews. The literature review established the foundation for understanding current practices, challenges, and competencies associated with AI integration in IT workplaces. The qualitative interviews with IT professionals in New Zealand and Sweden provided in-depth insights into their experiences and perspectives. The interview study was structured around three key topic groups: 1) understanding AI, 2) socio-technical work dynamics, and 3) professional development and competencies. These groups guided the data collection and analysis, ensuring that both technical and human dimensions of AI adoption were explored comprehensively. By integrating these methods, the study aims to provide a well-rounded understanding of AI's impact on IT workplaces and its implications for professional competencies and education.

Therefore, this study seeks to address the following research questions (RQ):

RQ1. What is the evidence from the academic and grey literature that current AI competencies capture and reflect the needs of professional practice in the Computing and IT industry?

RQ2. How is AI currently used by IT professionals, including the use of specific tools, motivations and challenges to adoption?

RQ3. How does the integration of AI influence workplace dynamics, task division, and human-system interaction among IT professionals?

RQ4. What are the implications for education and IT professionals of integrating AI on their needs for professional development and developing new professional competencies?

2 Literature Review and Competency Framework Analysis

This literature review and analysis section has been designed primarily to answer RQ1, to establish what evidence exists within the academic and grey (e.g. non peer-reviewed, practitioner and professional society or governmental sources) literature that current AI competencies capture and reflect the needs of professional practice in the Computing and IT industry. To do this, two separate reviews were carried out. The first was a literature review on academic papers found through ACM and IEEE databases. This literature review mainly highlights AI tool capabilities, necessary for understanding AI-related competencies. The second was a literature review focusing on available white and grey literature relevant for professional AI competencies in the Computing and IT industry, professional competence frameworks, and occupational standards.

2.1 Academic Literature Review

The decision to limit the first literature review for this study to academic peer-reviewed sources, was to secure some measure of the credibility of the chosen sources, while acknowledging potential limitations in ignoring the proliferation of grey literature in repositories such as arxiv.org. But, given the current hype and early adopter enthusiasm for new technology, the team recognised that a large positivity bias exists in the grey literature on AI and genAI. However, the analysis and discussion in the paper did reference several recent arxiv.org sources. In addition, the overall design of this study inherently included the practitioner voices through interviews to counterbalance the academic sources.

2.1.1 Academic Literature Review Methodology. The protocol for the academic literature aspect of this exercise draws on the work of Razzak et al. [96] at Lero, looking at Global Software Development process models. It consisted of the identification and grouping of search terms, which were arranged disjunctively inside broader categories and conjunctively across those categories. Two databases were chosen for inquiry, the ACM Digital Library and the IEEE Xplore database. The decision to use these was motivated partly by pragmatic concerns based upon access to the full-text of the papers by members of the reviewing team, and partly by concerns that the output of the search of academic literature had some element of peer review.

Search Terms. An initial scoping study was performed to identify key relevant search terms. Generation of search term candidates resulted in sixty terms, divided into two broad search categories, together with a third modifier category. The candidate search terms underpinning the Lero Literature Review approach are detailed in Table 1.

The initial category contained technological terms such as *artificial intelligence*, *generative AI* while the second category contained terms from professional practice such as *IT*, *software development*, and *software engineering*. The final category contained terms that were either derived from, or modified, the professional practice terms such as *industry*, *employers*, and *practitioners*.

Several preliminary scoping studies were carried out on individual search terms within the chosen databases to investigate the magnitude of the number of returns. For example, as of June 2024, the query *artificial intelligence OR AI* applied to all metadata for the broadest date range, returned 251,093 papers from IEEE Xplore and 217,883 papers from the ACM Digital Library. These numbers were reduced to 62,759 and 13,278, respectively, for search within the abstract and 20,397 and 5,843 within the title. Including disjunctive terms within the categories led to the rejection of some terms because of their imprecise scope (e.g. *Computing*, *Engineering*) and others because of their minimal contribution inside the categorical search terms to the number of returns (e.g. *tester*, *system*, *workforce*). After steaming, the resulting search terms became:

- **TECHNOLOGY:** "artificial intelligence" OR AI OR "generative AI" OR "large language models" OR LLMs OR "machine learning" OR "deep learning" OR "artificial general intelligence" OR "expert systems" OR "foundational models"
- **PROFESSION:** "information technology" OR "software develop*" OR "software engineer*"
- **MODIFIER:** industr* OR employ* OR practition* OR profession* OR programm*

This gives rise to the search string (TECHNOLOGY) AND (PROFESSION) AND (MODIFIER). This string resulted in 39,540 returns and 105,702 returns from all sections of the IEEE Xplore and ACM databases, respectively. It was, therefore, decided to place further restrictions on both the date range for publication and the database sections queried. The widespread introduction of generative AI (GenAI) into academic and professional discourse, prompted by the development of ChatGPT in late 2022, has meant that most relevant publications have occurred since this period. Database searches were therefore restricted to the period 2022 to 2024.

Furthermore, for pragmatic reasons, the queries were restricted to subsections of the two databases. For PROFESSION and MODIFIER, returns were sought from the abstract section. For TECHNOLOGY, it was found that the majority of papers that mentioned the technology did so in the context of both the document title and the abstract metadata. Consequently, it was decided to restrict queries on TECHNOLOGY to the document title.

The resulting, final, search string could be represented figuratively as: `(Title:TECHNOLOGY) AND (Abstract: PROFESSION) AND (Abstract: MODIFIER) AND Filter(2022-2024)`.

Summary. Following the Lero protocol [96], the relevant parameters of the literature review can be stated as:

Electronic Bibliographic Databases

- IEEE Digital Library (IEEEXplore)
- ACM Digital Library

Inclusion Criteria

- Publication year: 2022-2024
- Language: English
- Full text available and accessible
- Peer reviewed work
- Experience reports
- Answers research question
- Empirical studies and theoretical studies were included.

Exclusion Criteria

- Exclude duplicated studies (where authors report similar results in two or more publications – e.g. a journal paper that extends a conference paper).

Table 1: Candidate Search Terms underpinning Lero Literature Review approach.

Technological terms	Industry	Industry Modifier
Artificial intelligence	Information Technology	Industry
Generative AI	Software development	Employers
Large language models	Software engineering	Practitioners
Machine learning		Profession/Professionals
Deep learning	Engineering	Programmer
Artificial general intelligence	Computing	Testing
Expert systems		System
Foundational models		Workforce

- Exclude sources which did not discuss the concept of AI in professional IT practice
- books, presentations, blogs

Results. A total of 552 documents were returned from the IEEE Xplore database and 115 documents from the ACM Digital Library. These results were further analysed by the review team, with each document stratified across two independent reviewers. After further analysis by the review team, using the inclusion and exclusion criteria, the number of documents was reduced to 152.

In the following section, findings from the academic literature review are presented.

2.1.2 Findings from the academic literature review. AI and machine learning models helped software engineers develop applications and software for almost a decade. For example, Software reusability has proven to be a very effective way to increase software quality. Yeow MY [110] designed tools that can predict software reusability using machine learning models. Over the past few years, GenAI (including *"Generative artificial intelligence (AI) tools, such as Bard, ChatGPT, and CoPilot"* [30]), came to help with designing more accurate and powerful software. This results in more robust software being developed in a short time. The relationship between generative AI and software engineering is not one-way. GenAI has recently helped developers construct software and applications faster and more conveniently, but there are also many software applications designed to make generative AI more powerful. These include software that helps GenAI generate more relevant answers and software that helps humans communicate with GenAI through clearer and more precise prompts to get what they need and want more easily [97].

Many tools and software have recently utilized GenAI and LLM-based models to meet specific needs. For example, Mitchell [82] used GenAI to generate test cases. Software testing is an important component of software development for quality assurance. Test case generation (TCG) can assist developers by speeding up this process. It accomplishes this by evolving an initial set of randomly generated test cases over time to optimize for predefined coverage criteria. Using generative AI and LLMs in designing software that can translate code from one programming language to another has also proven to be a useful tool [79]. In organizations where developers use different languages to develop an application, they can save a lot of time by using AI-based code translator tools to achieve a better-organized and unified codebase.

Table 2: Example papers of AI-based tooling embedded within software development practices.

Area of Activity	Example Papers
Code Classification	[46, 111]
Code Summarisation	[26, 46, 76, 87]
Code Clone Detection	[46, 74, 111]
Code Quality Assessment	[26]
Code Translation and Multi-lingual Code Evolution	[79]
Detecting Vulnerabilities	[60, 107, 111]
Testing (fuzz testing, test case generation)	[50, 82, 109]
Documentation Generation	[29]

AI-based assistive tools are proposed to support various duties of IT professionals and software developers (Table 2). For example, AI solutions have been proposed to support automatic code generation, test case generation, code fuzzing and vulnerability detection. These approaches vary in the extent to which the AI features are communicated to the professional. In several cases, AI-based solutions underpin functionality otherwise available in a more simplistic form within the IDE. In other scenarios, an AI-based VR avatar is developed to support pair programming activity.

In the remainder of this section, we unpack the issue of explainability, the implications of low- and no-code solutions, and the challenges of AI agents as members of software development teams, as these issues were frequently highlighted or noted in the reviewed papers. Finally, we reflect on the positioning of artificial intelligence with respect to software development lifecycles and process models that govern the development and deployment of software systems.

Explainability of AI Assistants. In related contexts, explainability is critical in developing trust between human-AI teaming [69]. Papers identified through this search highlighted these practical challenges. For example, Li et al. [74] highlight the issue in the context of code summarisation and show that post-hoc methods such as SHAP (SHapley Additive exPlanations) [78] are ineffective in explaining LLMs' behaviours in this task. We found an overwhelming lack of coverage of explainability approaches within the papers surveyed. Furthermore, we saw very limited discussion of the expected competencies of the users of AI assistants. Very few papers introducing AI assistants for software developers were evaluated by users.

Low- and No-Code Solutions. The availability of assistive tools, including low-and-no-code tools democratize access to increasingly complex models and predictive approaches [13]. With this reduced barrier of entry comes an increased need to ensure that assistive tools place appropriate guardrails to prevent inadvertent misuse of inappropriate models. For example, a tool may facilitate a user to apply a predictive model to a dataset without being aware that it violated an underpinning assumption of the model. This trend has further implications for expanding training on ethical practice and responsible innovation to non-technical audiences.

AI Agents as Members of the Team. Several approaches from the literature position AI agents as team members, rather than just as assistive tools [69]. For example, Elvira et al. [31] explores the opportunity for conversational AI within extreme programming methodologies. Similarly, Spinellis [103] explores the dynamics of pair programming using generative AI. Finally, Okuda and Amarasinghe [87] explores the implications of more deeply embedded LLM technology within the software development workflow. This topic should be further investigated in future research since AI agents as team members could have consequences, not only for the relationships within teams but also, for the composition of teams and what competencies are needed.

Methodologies and Process Models. A second group of papers discussed the implications of AI on the software engineering process and the process models used to underpin AI system development. Process models most frequently appearing within our literature search include traditional data mining process models applied in an ML/AI context, such as CRISP-DM, SEMMA, and KDD. CRISP-DM (Cross-Industry Standard Process for Data Mining) provides a structured, six-phase process comprising business understanding, data understanding, data preparation, modeling, evaluation, and deployment phases. It articulates the need for business understanding and the technical aspects of system development. More recently, Analytics Solutions Unified Method (ASUM-DM) [51] by IBM has adapted CRISP-DM with increased focus on predictive applications.

More recently, frameworks have highlighted the multidisciplinary aspects of the AI lifecycle and the importance of collaboration. The link to the CC2020 competency model [19] is apparent here for example, with the increasing importance of the disposition **being collaborative** apparent, as a disposition incorporating, "engaging appropriate involvement of other persons and organizations helpful to the task". [38] Similarly, MLOps is said to be underpinned by *"an ML engineering culture and practice that aims at unifying ML system development (Dev) and ML system operation (Ops)"* [42]. The recent proliferation of low- and no-code solutions has also brought domain experts closer to developing AI-based solutions [13]. Oakes *et al* [85] introduce a conceptual framework for the challenges domain experts face as part of domain-specific machine learning workflows. Finally, Berman *et al* [7] focuses on software engineering practices with respect to establishing an evaluation approach to assess the extent to which AI development practices support responsible AI (RAI) values. Again, here the importance of dispositions is emphasised, such as **being responsible** e.g. *"Making responsible assessments and taking actions using professional knowledge, experience, understanding and common sense".* [38] So, the evolution of AI methodologies and development processes brings new demands for competency to AI practitioners.

2.1.3 Summary of Findings from the Academic Literature Review. As mentioned above, the main objective of the academic literature review was to try to establish what evidence there was that current competencies surrounding the use of AI capture and reflect the needs of professional practice in the Computing and IT industry. The analysis of the published literature found in the ACM and IEEE databases suggests that the professional community is adopting a growing number of AI tools with greater frequency for a wider range of development and management purposes. While many of the analysed papers on tool usage provided some element of justification for the reliability of the technology using standard data analytics metrics, there was, however, a lack of clear evidence that the deeper issues regarding practice methodologies for robust use of the technology were being addressed. Many of the papers dealt with one or, perhaps, two parts of the production pipeline, and there was less discussion on how AI could be used across tasks to provide a more consistent and thorough approach to development. Given the opaque nature of much of the output of GenAI technology, this has direct implications for the need to develop professional and meta-competencies which focus on the integration and consolidation of constituent tasks and the regulation and evaluation of the resulting deliverable.

2.2 Analysis of Competency Frameworks

We further sought to understand the rapid proliferation of competency frameworks related to data science and Artificial Intelligence from the literature. Specifically, we seek to understand the extent to which existing competency frameworks capture the needs of the current and future IT profession in relation to the use of AI.

2.2.1 Competency Framework Literature Search Methodology. To achieve this we performed a distinct literature review exercise using Scopus and a search of grey literature. For the survey using Scopus we used the following search terms across Titles and Abstracts; `("Artificial Intelligence" OR "Data Science") AND ("competenc*")`. The search was conducted on 6th July 2024 and resulted in 2,623 papers. By setting January 2019 as the start date of the literature search to maximise the chances to retrieve relevant sources, we were left with 1,586 papers. We further filtered using Scopus "Subject area" metadata to "Computer Science" and "Engineering", resulting in 124 papers. From 124 papers, 110 were excluded after the first pass on the title and abstract. Those excluded did not relate to the IT profession or artificial intelligence, or referred to existing frameworks. Table 3 highlights the proportion of sources considered at each step of the evaluation and also grouped by year of publication.

We applied an approach similar to that of [6] to complement our literature review with Grey Literature (GL) [41, 90] providing non-peer-reviewed but relevant insights from industry and governmental bodies. We leverage the same search term used in Scopus, which is now running using Google Search. A private browsing session was used to mitigate potential geographic bias or bias of the author's search profile already featuring competency framework searches. A total of 112 results were returned, and once duplicates

Table 3: Breakdown of competency framework literature sources by year, across first and second review phases.

Year	# Results	Filtered by subject	1st pass (title + abstract)
Before 2010	366	–	–
2010 – 2019	627	–	–
2019	167	11 (6.6%)	2
2020	222	17 (7.7%)	2
2021	237	17 (7.2%)	2
2022	305	20 (6.9%)	3
2023	445	38 (8.5%)	3
2024	210	21 (10%)	2
All	1586	124 (7.8%)	14

from the literature search and irrelevant results were removed, 15 additional sources remained. These sources underwent two passes of review; within the first pass, the titles and abstracts were each considered to gauge relevance for further consideration. Articles which were disregarded included application of AI technologies within a particular domain, or which were otherwise out of scope for the review. The second pass of the review considered the full paper and removed from further consideration papers whose contents did not match the title and abstract and papers which considered the application of competency frameworks without providing further reflection on the competency frameworks themselves.

2.2.2 Summary of Competency Frameworks. The EU EDISON project and its EDISON Data Science Framework (EDSF, Version 1.3) [33], released in 2017, provides a comprehensive body of knowledge in relation to data science activity. The UK Data Service Data Skills Framework [49] has originated from the social sciences data training community. It *"emphasises continued development of traditional data skills for contemporary research needs, [...] as well as promising opportunities presented by AI and machine learning for enhancing analysis"*. This highlights that many competencies required to make safe and ethical use of emerging technologies, including AI, are a cross-cutting concern and can persist over time at an appropriate level of abstraction. Throughout the remainder of the competency framework, it emphasises valuable skills underpinning data-driven analysis (in this context, concerned with large-scale survey data), highlighting machine learning among quantitative approaches. Whilst it recognises the potential of LLMs applied to qualitative research, there are no specific competency statements relating to these.

BHEF DSA Competency Map (V1, November 2016) [44] introduces a competency map which describes the skills, knowledge, abilities and attributes for data science and analytics (DSA) at the graduate level. The framework comprises four 'tiers'; Tier 1 describes "Personal Effective Competencies", where we see significant complementarity with CC2020 dispositions. Tiers 2 and 3 are Academic Competencies and Workplace Competencies respectively, and show close alignment to related works such as the *"AI Skills for Business Competency Framework"* [59]. Tier 4 intends to capture sector-specific competencies representing the "knowledge and skills common across sectors within a broader industry. These technical competencies build on, but are more specific than, competencies represented on lower tiers". Exemplar Tier 4 competencies are not presented within the Competency Map, nor are any publicly available uses of the framework at Tier 4 available in the literature.

The Digital, Data, and Technology (DDaT) framework [45] is a strategic model implemented by the UK government to help grow its digital capabilities and modernise public services to use data when making informed decisions. It introduces consistent job titles, job descriptions, and career paths for technology professionals across the government to identify talent with experience in key digital capabilities like data science, cybersecurity, and software engineering. The framework is designed to help the public sector work faster and be more innovative and adaptive by delivering recruitment, training and development of digital skills across the board; ensuring that technology is used correctly to facilitate change throughout citizen need. The framework provides skills required for a variety of data roles within government, with each skill defined through substatements at the following levels; Awareness, Working, Practitioner and Expert levels. DDaT is distinct among the frameworks considered in this work, in that it provides granular descriptions of 12 IT operations roles which do not receive equal treatment in comparator frameworks. Furthermore, DDaT includes eight user-centred design roles which a) will require strong collaboration with IT professionals across job families and b) whose work may face disruption risk due to generative AI (e.g. through AI assistance within wireframing tools such as Figma and generative AI for graphic design and technical writing tasks).

Psyche et al. explore the competencies required of project managers working on AI projects [94]. A competency framework is developed through surveys, systematic literature reviews, interviews and focus groups. The framework is divided into five domains; project management, AI-related job expertise, AI-related technologies, governance of an AI project, and human relations. The framework highlights the importance of project managers possessing sufficient awareness of the risks and opportunities of AI technologies to support their project governance roles. There is a strong emphasis on collaboration, including the ability to *"translate exchanges into common AI language"* which highlights the importance of shared terminology. This accords with the remarks of Davies et al; *"At the basic level developing a shared common language to enable interdisciplinary teams to effectively co-create digital health technology solutions centered around areas such as machine learning will be key to implementation into practice"* [25].

Data to Decisions CRC present a framework which follows the AI software development lifecycle phases, and describes the competencies required at "Awareness", "Practitioner", "Senior" and "Lead" levels. This framework maps job roles, specifically data scientist, data engineer and data analyst. The extent to which such a mapping is actionable is questionable given a) the changing nature of responsibilities within particular families of roles and b) the inconsistent application of role descriptors within organisations. The framework helpfully defines an "Awareness" level akin to the "AI Worker" persona within [59]. Still, there is limited coverage of the competencies required of a non-technical leader with governance responsibilities for introducing AI technologies.

In the remainder of this subsection, we outline key themes from an in-depth study of the resulting papers, including challenges with reconciling AI competencies across differing models and pointing towards new directions for professionalism and competency frameworks.

2.2.3 Findings - General Themes and Issues with Competency Frameworks. As we conducted our analysis, a range of issues emerged, with the more general themes presented below.

Long-term Sustainability and Stable Custodians. We have seen inconsistent adoption of open-source practices to support the long-term preservation and reliable versioning of competency framework assets. Historically, frameworks such as EU EDISON [33] were unavailable due to funding cessation, highlighting the importance of stable custodians of framework documents. There are examples where platforms such as Zenodo support long-term availability of framework assets (e.g. [49, 59]).

Adoption and adaptation of existing competency frameworks. We observe limited adoption and adaptation of existing competency frameworks. In many cases, competency frameworks are made available in PDF forms, which limits the ability to synthesise and draw connections between disparate frameworks. Inconsistent use of terminology across these frameworks further hinders efforts to develop a unified view of competency in the field.

Furthermore, the need for industry-specific competencies is recognised. For example, SFIA states; *"Different industries adopt and apply AI in various ways. Employers may need to localise the SFIA skills to their specific tools, platforms, and methodologies, which are constantly emerging"* [37]. There are also challenges present in *"Ensuring that the framework remains practical and useful for current SFIA users, while also being adaptable for future advancements in AI"* [37].

Progression Through Competency. A limitation of many competency frameworks surveyed is that they do not capture any prerequisite structure - or even typical progression - between competence. Frameworks are either broken down at role or seniority level, but for a professional seeking to understand their current level of competence and prioritise their development steps, this is a significant gap limiting the usefulness of these frameworks. This effect would be particularly pronounced for professionals who are identifying short course training or using online resources to learn, where there is a lack of curation and sequencing, which a longer-form training course (e.g. postgraduate diploma or degree) would provide.

Localisation of Frameworks. Challenges around the legal and governance requirements of particular jurisdictions challenge one's ability to localise frameworks. *"As AI technologies raise significant ethical and legal issues, the framework must address these aspects comprehensively"* [37]. It is, therefore, necessary to highlight these considerations at an appropriate level of generality that any competency statement or professional duty description is portable across contexts. For example, *"Possessing a strong awareness of how legal, ethical, regulatory and compliance considerations apply to their roles and activities. "* [59]

Impact of GenAI for Code Development. We have seen within Section 2.1.2 the proliferation of AI tooling augments the software development lifecycle. There are examples where professionals are required to understand the opportunities as well as the risks within their role (e.g. "They will be aware of the risks of AI technology, and will know the steps required to mitigate these within their role" [59]). However, further emphasis must be placed on the specific competencies to manage the use of AI within the development process and avoid overreliance.

Equipping Professionals for Future Upskilling and Reskilling. The World Economic Forum (WEF) highlights that the average half-life of professional skills is only five years [108]. Several frameworks highlight the importance of a commitment to professional development and self-direct learning. However, our analysis of occupational standards suggests these elements must be further emphasised - particularly at lower qualification levels - to ensure professionals are equipped with the competencies to adapt to future role disruption.

Level of Abstraction. We see differing approaches in the level of abstraction to which frameworks describe competencies. In some cases we observe tool- and vendor-specific aspects within competency frameworks, which limit their generalisability (for example, by specifying competence of a particular programming language) and limit their future-proofing should tool choices evolve. SFIA identify the pace of change as a significant challenge in competency framework development; *"AI technologies are advancing rapidly, making it difficult to create a static framework that remains relevant over time. New tools, platforms, and methodologies are constantly emerging"* [37]. This was most evident in initiatives responding closely to industry needs. SFIA reflect on this theme as follows; *"Different industries adopt and apply AI in various ways. Employers may need to localise the SFIA skills to their specific tools, platforms, and methodologies are constantly emerging"* and *"Balancing the depth of coverage without becoming overly specific is a challenge"* [37].

2.3 Reconciling Differences Between Competency Models and Frameworks

Throughout this paper, we are adopting the competency model of CC2020, including its articulation of dispositions relating to professional values and practices [38].

2.3.1 Differing Models underpinning Competency Frameworks. At the same time, there are some differences between competing frameworks and how these fundamental concepts of competency are found. Several grey literature sources we considered were underpinned by a *T-shaped* competency profile; which involves possessing *"depth of knowledge in a particular expertise as well as having the ability to work and communicate across disciplines"* [15]. Such models have been categorised as four dimensions of competence; [106]

(1) *"Knowledge/cognitive competence: the possession of appropriate work-related knowledge and the ability to put it into effective use, e.g. theoretical/technical knowledge, tacit knowledge, procedural knowledge, and contextual knowledge"*.
(2) *"Functional competence: the ability to perform a range of work-based tasks effectively to produce specific outcomes, e.g. occupation specific skills like report writing, IT literacy, budgeting, project management, etc"*.
(3) *"Personal or behavioural competence: the ability to adopt appropriate behaviours in work-related situations, e.g. self-confidence,*

control of emotions, listening, objectivity, collegiality, sensitivity to peers, conformity to professional norms, etc".

(4) *"Values/ethical competence: the possession of appropriate professional values and the ability to make sound judgements, e.g. adherence to laws, social/moral sensitivity, confidentiality, etc".*

The CC2020 competency model [19] shows some clear commonalities with these *T-shaped* competency profiles, with its *"computing knowledge area"* mapping to the *"knowledge/competence"* aspect; the *"professional and foundational knowledge area"* (in combination with *"skill"*) mapping to the *"functional competence"* aspect; and the set of aspects encompassed by the *"Personal or behavioural competence"* and *"values/ethical competence"* being effectively contained within the CC2020 *"dispositions"*.

2.3.2 Challenges in Incorporating AI. In exploring some issues in comparing frameworks, it was observed that incorporating a cross-cutting concern such as Artificial Intelligence posed challenges for competency frameworks. The selected examples below illustrate the issues. For instance the *Software Engineering Competency Model v1.0 (SWECOM)* [102], in addition to being somewhat dated (2014) had a tight focus on discrete stages and activities in the software development lifecycle, so just how it might incorporate the added elements brought by AI technologies was hard to determine. The US Government's *Information Technology Competency Model* [32], presented a quite general industry wide, and layered model (quite analogous to the *T-Skilled Professional Profiles*) above, with a broader and more complex set of challenges than those facing SWECOM in mapping AI competencies. The *Skills for the Information Age (SFIA)* global competency model, (European in origin) has made a start on incorporating Artificial Intelligence with a BETA version of an AI Framework *SFIA 9 - a framework for AI skills - BETA*, [37]. The SFIA foundation has highlighted the typical challenges to be encountered when evolving competency frameworks [37]:

> *"Over the years, from SFIA v1 to SFIA v8, the lifecycle of new technologies and working practices has been observed. SFIA's regular updates have allowed for niche skills to evolve from specialist areas to more generic skills, eventually breaking down into more granular and focused activities within broader skill areas. This evolution underscores the importance of a structured yet adaptable framework to support industry, employers, and individuals in navigating the complexities of AI integration".*

In the BETA version of the AI Framework [37] an overview of AI skills is provided. Topics covered include:

(1) AI and data literacy
(2) AI Skills to Automate, Assist, Augment
(3) Skills focused on developing and operationalising AI/ML applications
(4) Skills focused on building the AI/ML Models
(5) Using AI to make individuals more productive
(6) Using AI to make teams more productive
(7) New AI-Related skills in SFIA
(8) Changes to SFIA Skills to Incorporate AI
(9) Organisation and job design incorporating AI

The challenges for competency frameworks of incorporating the cross-cutting nature of a technology such as AI, have been well captured here by the SFIA Foundation. But any competency framework will face similar challenges in attempting to address the cross-cutting needs arising out of Artificial Intelligence Technologies, and their impacts on professionals and their workplaces and work practices.

2.3.3 Complexities of Mapping Between Frameworks. We found several examples of mappings between competency frameworks, e.g. between CC2020 and SFIA7 [48] and between sector specific frameworks and EDISON DS-CF [91]. Several limitations of this approach should be noted. Mappings often rely on the interpretation of a single rater, or of a small number of authors. These mapping efforts rarely engage the end users of frameworks, e.g. IT professionals, so it is not clear that the end-users of each framework would interpret them similarly. Similarly, mapping efforts rarely acknowledge that there has been proactive engagement with the owners of other frameworks, so mapping efforts are somewhat speculative. Therefore, discrepancies in terminology and incorrect interpretations may perpetuate misunderstandings and threaten the validity of such mappings. More robust mapping of competencies could be supported by adopting ontological approaches to model competency [81].

2.3.4 Competencies in Handling the Implications of the Professionals' Own Practice. The frameworks we investigated provided little coverage of the competencies required for an IT professional to manage the impacts of emerging technology on their own role. While occupational standards gave examples where the individuals were expected to be an authority on emerging technology (*"Duty 14 Provide technical authority for the business regarding emerging opportunities for AI"* (IfATE, ST0763 Level 7 Artificial Intelligence (AI) data specialist, [52])). An example where this is more strongly evidenced is within the AI Skills for Business Competency Framework [59]; *"They will possess specific awareness of the implications of AI risks within their sector and job role. They will be able to identify potential new areas within their role where AI-based approaches could improve efficiency, accuracy or productivity".*

It is clear that IT professionals should be equipped to foresee the implications of emerging technology for their role. Furthermore, they should be equipped to engage meaningfully and effectively with their organisation in order to manage potential risks and maximise potential benefits.

2.4 New Directions for Professionalism and Competency Frameworks

The analysis now moves beyond these differences, and their implications in accommodating GenAi developments, to the more productive area of how further frameworks for Professionalism and Competency might develop in the rapidly evolving IT Sector.

2.4.1 the Rise of 'Persona Mapping' Approaches for Professional Competencies. One promising area for framing professional competencies is the use of 'persona mapping'. An example of its use as one strategy, recently adopted by one of the authors of this study, in developing an AI framework is depicted below.

Table 4: Analysis of UK Institute for Apprenticeships and Technical Education (IfATE) Occupational Standards to ACM CC2020 Dispositions

ID	Level	Occupational Standard Title	Adaptable	Collaborative	Inventive	Meticulous	Passionate	Proactive	Professional	Purpose-driven	Responsible	Responsive	Self-directed
ST0795	3	Data Technician [55]	○	●	○	○	○	○	●	○	○	○	◐
ST0118	4	Data Analyst [53]	●	◐	○	◐	○	◐	◐	◐	◐	◐	◐
ST1386	5	Data Engineer [58]	●	●	●	○	○	●	●	●	●	●	○
ST0585	6	Data Scientist [54]	●	●	◐	◐	●	◐	●	◐	●	●	◐
ST0795	7	Digital and Technology Solutions (Data Analyst) [56]	◐	●	◐	◐	○	○	●	●	◐	○	●
ST0884	7	Operational Research Specialist [57]	●	●	●	◐	○	◐	●	◐	○	◐	◐
ST0795	7	Artificial Intelligence Data Specialist [52]	●	●	●	●	●	◐	●	●	●	●	●

AI Skills for Business Competency Framework - UK Government and Innovate UK. To address the skills barriers limiting AI adoption in businesses, the Alan Turing Institute (the UK's National Institute for Data Science and Artificial Intelligence) has led the development of the AI Skills for Business Competency Framework [59] with the UK government's Department for Science, Innovation and Technology (DSIT) and Innovate UK BridgeAI. The framework defines high-level competencies required to enable responsible and safe AI adoption. The project sought to empower businesses to understand the competencies required to deliver value from AI and its underpinning technologies, supporting them in identifying upskilling routes for their existing workforce and developing a pipeline of higher-skilled talent.

Our search of the grey literature found the growing prevalence of persona-mapping approaches. Early examples include the *'Data Skills for Work'* personas by Scotland's The Data Lab [105]. The AI Skills for Business framework defines personas at the *Citizen*, *Worker*, *Professional* and *Leader* level. The Professional persona is of greatest relevance to the scope of this review, and most closely aligned to the roles held by our interviewees.

(1) *AI Professionals will possess competency in designing, creating, deploying and maintaining AI-based systems.*
(2) *They will possess specialist knowledge in one or more sub-discipline(s) of Data Science and Artificial Intelligence, e.g. Computer Science, Statistics, Modelling, and Robotics.*
(3) *Possessing a strong awareness of how legal, ethical, regulatory and compliance considerations apply to their roles and activities.*
(4) *They are conversant in operating in technical complexity and uncertainty settings.*
(5) *They will be aware of the risks of AI technology, and will know the steps required to mitigate these within their role. They will be able to support leadership to understand and mitigate these risks.*
(6) *They can interface effectively across the organisation to communicate the correctness of their technical solutions.*
(7) *They can effectively support leadership and the broader organisation to frame new AI-based opportunities appropriately to achieve buy-in from their organisation.*
(8) *They will demonstrate a strong commitment to continuous learning, and maintaining awareness of emerging AI technologies.*

Table 5: Dispositions from ACM CC2020

Element	# Elaboration
Adaptable	Flexible; agile, adjust in response to change
Collaborative	Team player, willing to work with others
Inventive	Exploratory. Look beyond simple solutions
Meticulous	Attentive to detail; thoroughness; accurate.
Passionate	Conviction, strong commitment, compelling
Proactive	With initiative, self-starter, independent
Professional	Professionalism, discretion, ethical, astute
Purpose-driven	Goal driven, achieve goals, business acumen
Responsible	Use judgement, discretion, act appropriately
Responsive	Respectful; react quickly and positively
Self-directed	Self-motivated, determination, independent.

2.5 Evaluation of Professional and Occupational Standards in the United Kingdom as a Case

Having examined Competency Frameworks and the evidence in the research of the impacts of artificial intelligence on the practice of IT professionals, we now review the extent to which these issues are articulated in existing professional and occupational standards. Furthermore, we undertake an evaluation of occupational standards in the United Kingdom. The UK context was selected as the home context for two authors, one as an original team member interviewing IT Professionals and another due to the specific expertise he brought to the working group. It was further chosen due to high-quality machine-readable data for all occupational standards across the UK's education system.

To better understand the UK context, it is first helpful to understand the challenges faced in the UK labour market in relation to AI professionals. In the UK, a 2021 study found that the supply of data scientists from universities was unlikely to exceed 10,000 per year, yet there were potentially at least 178,000 unfilled data and AI specialist roles. This indicates a clear supply and demand issue, with the UK experiencing a lack of AI practitioners and professionals [2]. Following the publication of this report we have experienced the rapid proliferation of GenAI (e.g. ChatGPT) so this demand will likely increase substantially. Given that 80% of 2030's predicted workforce is already employed, the existing workforce will require reskilling if the UK economy is to adequately fill data and AI jobs [1]. Given this supply-demand gap, we anticipate increased pressure for individuals in broader and AI-adjacent roles to feed into AI roles through upskilling and reskilling. Consequently, it is important that we better appreciate the alignment between competency-based approaches and professional practice.

Within the UK context, apprenticeships are a valuable route to upskilling the existing workforce. The Institute for Apprenticeships and Technical Education (IfATE) maintain "Occupational standards" which are *"a description of an occupation. It contains an occupational profile, and describes the 'knowledge, skills and behaviours' (KSBs) needed for someone to be competent in the occupation's duties"*. Occupational standards are co-developed by *'trailblazer'* groups, representative of employers experiencing demand for distinct occupations to be served by these standards. Here we present a synthesis of competency frameworks and occupational standards concerning IT professionals' use of artificial intelligence. For this review, we select a relevant subset of occupational standards that most closely reflect our interviewees' roles.

We sought to understand the extent to which the dispositions of CC2020 are encapsulated in the Knowledge, Skills and Behaviours outlined in the apprenticeship standards. These dispositions are summarised at Table 5 and serve as a solid basis for the dispositions underpinning safe and responsible AI practices. A single author evaluated each occupational standard concerning the CC2020 dispositions, focusing on the "Behaviour" statements for the standard. A mark of ○ signifies that the rater found no evidence of the disposition within the occupational standard, whereas ● signifies clear evidence of the disposition within the standard. A partial match ◐ may signify evidence of knowledge or skills which reasonably imply the underpinning disposition, but that the disposition is absent within the behavioural statements of the standard. A summary of our findings is shown in Table 4 and the full coding of each apprenticeship standard will be made available in a Zenodo publication alongside the full version of the paper [1]. Occupational standards are mapped to the education levels used in England, Wales and Northern Ireland; Level 3 is equivalent to a UK A-Level or T-Level qualification or an Advanced Placement (AP) course in the USA. Levels 4-6 are equivalent to the first, second and final year of an undergraduate degree respectively, (as opposed to the US four-year degree structure). In contrast, Level 7 is equivalent to a postgraduate Masters level qualification.

We see within Table 4 that there is clear and consistent coverage of *Collaborative* and *Professional* dispositions across occupational standards at all levels. This is expected given the employer-led nature of the occupational standards, where collaboration and professionalism are often cited as areas of improvement among graduates. Across many other dispositions, we typically see dispositions increasing in prominence as the educational level of the standard - and seniority/specialisation of the role - increases. For example, we see greater emphasis on the *Inventive* disposition at these higher levels. This is indicative not only of the more advanced level of training, but also of the greater levels of autonomy and influence individuals in these occupations would hold. The next subsection of the report extends this argument, as it points to some directions for IT professionalism that the rise of AI may trigger.

[1] Zenodo deposit to coincide with the camera-ready edition of the paper and incorporating occupational standards updates up to the final date of paper preparation.

2.6 The Role of Professionalisation of AI Roles

The role of professionalisation and accreditation within computing is well acknowledged [95]. Speaking of digital transformation within the health sector; Davies et al. remark; *"In order to professionalise the workforce in this area, digital competencies need to be built into training from early on and be underpinned by frameworks that help to guide regulators and professional bodies and support educational providers to deliver them"* [25]. A clear and consistent embedding of the competencies required of IT professionals within the accreditation of taught programmes (e.g. degrees) and in schemes of professional registration holds the potential to champion emerging sound practice and consistency in the field.

However, the impact of artificial intelligence on the workforce is widespread, and even for the disciplines considered *'cognate'* for data science and technical AI roles, there are several professional and governing bodies operating at national and/or international levels. Furthermore, individuals identifying as professionals in AI may originate outside of typical cognate disciplines.

This presents a risk of fragmentation which could harm working professionals and employers alike. If individual professional and governing bodies independently define competencies, this will undermine the value of professionalisation for hiring organisations, who may receive applications from individuals accredited by different bodies, with a disparity in the underpinning. Furthermore, a lack of consistency across sectors could inhibit IT professional's ability to move between sectors. Finally, such fragmentation could disproportionately disadvantage industry sectors for which AI adoption is currently limited, with the problem exacerbated by less mature professionalisation routes within the sector's bodies.

Below, we highlight one response to this challenge, originating from the context of the United Kingdom, but whose membership has now expanded to include international counterparts.

2.6.1 Alliance for Data Science Professionals. A cross-body alliance of professional bodies and institutes have worked together to collaboratively define and maintain the standards needed to ensure an ethical and well-governed approach to data science, so that the public, organisations and governments can have confidence in how their data is used. The Alliance for Data Science Professionals (AfDSP) was setup in 2021 as a collaboration between The Royal Statistical Society (RSS), BCS (The Chartered Institute for IT), the Operational Research Society (ORS), the Institute of Mathematics and its Applications (IMA), Alan Turing Institute, National Physical Laboratory (NPL) with support from the Royal Society and the Royal Academy of Engineering. It has since expanded to include the Sangar Institute and the American Statistical Association as its members. The Alliance has developed certifications for data science professionals, and its ongoing work informs the accreditation of data science degrees and training courses.

Table 6: Interview Structure

Interview Questions
Demographic Information
Section 1: Understanding AI
Definition of AI and its Use in the IT Professional Context.
Reasons and Motivations behind Adopting AI.
Challenges/Opportunities Related to Integrating AI in their Role
Section 2: Work Engagement and AI
AI's Influence on Workplace Dynamics.
Changes in Task Division and Responsibilities Due to AI.
Section 3: Socio-Technical Work Dynamics
Human-System Interaction and Collaboration.
Section 4: Professional Development and Competencies
Need for Professional Development.
Important Competencies.
AI-related training and support.

All members contribute to standards development but only the four learned societies can award certification. The AfDSP offers two levels of professional certification: the Data Science Professional and the Advanced Data Science Professional. Within the AfDSP scheme, individuals can apply to be certified based on evidence they supply covering education, work experience, Continuing Professional Development (CPD) and evidence that they meet the competencies in several of the skill areas above, plus their level of responsibilities. Individuals apply through the most appropriate Alliance member organisation and fees are dictated by that member.

The report now addresses the complementary and more empirical part of the study, moving to the voices of the professionals we interviewed.

3 Interview Study Methodology

This study employed a qualitative research approach using semi-structured interviews to gather in-depth insights from IT professionals about the impact of AI on their work practices, workplace dynamics, and professional development. The interviews traversed an introductory section, capturing demographic information about the interviewees and their context followed by four primary topic groups: 1) understanding AI; 2) work engagement and AI; 3) socio-technical work dynamics; and 4) professional development and competencies. The interviews concluded with a closing question, allowing the candidates to discuss other relevant issues that came to mind or topics that had not been covered. A brief structure of the interview section can be found in Table 6 and the full interview schedule is available in a Zenodo repository [20].

3.1 Interview Design and Development

The interview guide was developed through a collaborative process involving most members of the research team. Initial questions were formulated based on the study's objectives and relevant literature. The guide was pilot tested with two participants, and feedback from these pilots was used to refine the questions to ensure clarity and relevance. The interviews were conducted using Zoom or Teams between March and May of 2024.

3.2 Recording and Transcription

Before each interview, participants were briefed on the purpose and asked to provide consent for recording the session. The briefing included an explanation of the study's objectives, the confidentiality measures in place, and the voluntary nature of participation. After obtaining participants' consent, the interviews were audio-recorded and transcribed verbatim. Participants were informed that they could withdraw from the study at any time without any consequences. A total of 47 interviews were conducted, with each interview lasting between 30 to 60 minutes. The recordings were transcribed using Zoom, and each transcript was reviewed by multiple researchers to ensure accuracy.

3.3 Ethical Vetting and Data Storage Agreements

Interview recordings and transcriptions from the two countries participating in the original data collection have been collected as a result of the respondent's participation in the study under the ethical protocols applied by each institution. To protect the confidentiality of participants, a de-identification process was implemented. Each interview recording was first transcribed verbatim. The transcription process involved replacing personally identifiable information (PII) with unique codes. This included names and any other information that could potentially identify the participants. The de-identified transcripts were then reviewed by multiple researchers to ensure that no PII remained and that the data was thoroughly anonymized.

The Auckland University of Technology and Eastern Institute of Technology, New Zealand, have approved the data collection for this multi-institutional multinational research project. In Sweden, universities do not approve studies, and the study was instead approved by the Swedish National Ethical Authority (2023-06103-01), ensuring compliance with national ethical standards. The data collected in this study, including both audio recordings and transcripts, will be stored securely for a period following the publication of the research findings. This duration complies with institutional and funding body requirements for data retention. After this period, all data will be permanently deleted from digital storage, ensuring that it cannot be recovered or reconstructed.

A common data-sharing agreement stipulating requirements for using the data was signed so that working group participants could access the de-identified transcript data stored at Uppsala University in a secure repository. The data-sharing agreement outlines strict controls over data access to ensure that only authorized personnel can access the de-identified transcript data. Access is restricted to members of the research team whose institutions have signed the agreement.

3.4 Participants

3.4.1 Criteria for Participant Selection. Participants were selected based on specific criteria to ensure the relevance and quality of the data collected. Firstly, they had to be currently employed in IT-related roles, encompassing sectors such as IT services, IT consulting, finance, government, telecommunication, and health. Additionally, participants were required to have some level of experience or exposure to AI technologies in their professional roles, as the study focuses on the impacts of AI in their workplace. Geographically, participants were based in either Sweden or New Zealand, ensuring a diverse representation of industry sectors and job roles. All participants voluntarily agreed to participate in the study and provided informed consent for recording and transcribing their interviews.

3.4.2 Exclusion of Participants with No AI Exposure. During the analysis of the interviews, 3 participants were excluded, and their interviews were removed from the data set because it became clear that they lacked exposure to AI technologies. It is important to note that participants who initially stated they do not use AI but later mentioned interacting with AI during their interview were not excluded. As a result, some participants self-reported no exposure to AI, yet in their responses, they discussed interactions with one or more AI systems. This exclusion is justified for several reasons. Primarily, the study aims to investigate the impacts of AI on the work practices of IT professionals. Including participants without AI exposure would not provide relevant insights into these impacts. Furthermore, including such participants could introduce variability that may obscure the specific effects and implications of AI, making the data less comparable and consistent.

The exclusion of participants with no AI exposure has several implications for the study. On the positive side, it ensures that the data collected is directly relevant to the study's objectives, allowing for clearer and more focused insights into the impacts of AI on work practices. However, it also means that the study may not fully represent the broader IT workforce, particularly those who have not yet interacted with AI technologies. There was some inconsistency in the excluded respondents' answers, indicating that they existed in a work environment where GenAI was on the horizon and being actively discussed and explored by colleagues or the wider organization. This highlights a potential area for future research, where investigating the experiences and perceptions of IT professionals without direct AI exposure could provide a baseline for understanding the differences and potential barriers to AI adoption within the industry.

3.4.3 Description of Participants Included. Initially, 47 interviews were conducted; however, following the exclusion of 3 participants due to a lack of AI exposure, the data presented here pertains solely to the 44 participants who were included in the final analysis. Our participants were based in Sweden (23 participants) and New Zealand (21 participants).

As summarized in Table 7, the included IT professionals came from a diverse range of industry sectors, with the largest group, 18 participants, working in IT services. Additionally, five participants were from IT consulting, four from finance, three from government and telecommunication, and two from the health sector. There were also six participants from various other sectors. In addition, we asked participants for information about their specific roles in the company they work. We determined for each coded job role the best match to a Skills Framework for the Information Age (SFIA) role[2]. While SFIA is a UK/European originated competency framework cf. [9], it has global applicability, is in active use in New Zealand [4], and in the O*NET online portal [34] similar classifications of job roles in the U.S. context could be found. We had a diverse group of respondents, covering 22 different roles. The most common roles were solution designer – more senior developers/UX team leads; software developers and digital consultants, as illustrated in Figure 1. We also explored the distribution of roles by country, finding that the distribution was largely consistent across sites apart from Solution Designer, with UX & Team Leader roles more common in Sweden and Digital Educator roles more common in New Zealand. In terms of their organization size, measured by headcount, 25 participants were from organizations with more than 250 employees, nine from organizations with fewer than 250 employees, five from organizations with fewer than 50 employees, and four from organizations with fewer than ten employees. Four participants did not provide information on the size of their organization.

To better understand our participants, we asked them about their years of experience in IT and AI. The majority of participants reported having over 20 years of experience in the IT field. Furthermore, 16 participants indicated they had between 1 and 10 years of experience, while 5 participants reported having between 10 and 20 years of experience. Two participants did not respond to this question. Regarding their years of experience in AI, the vast majority (27) reported having between one and 10 years of experience, with ten having less than a year of experience, and interestingly, only 2 reported having 10 to 20 years of experience and more than 20 years of experience. Three participants did not specify. Moreover, we asked our participants about their experience with GenAI, 8 participants reported using AI for 1 to 6 months, 12 for 6 to 12 months, 10 for 12 to 24 months and 3 for more than 24 months. A further 3 participants reported no experience with GenAI, and 7 did not respond.

3.5 Data Analysis

The collected data were analyzed using qualitative techniques described by Seaman [98], Braun and Clarke [11] and Cruzes and Dybå [24]. All interviews were transcribed using online transcription tools complying with the security standards of each university. The transcription resulted in approximately 112 pages of text (A4 format, 10-point font, single line-spacing). The transcripts were analyzed in parallel by all authors and several analytical memos were written. The memos established an audit trail of the analysis and facilitated a process of peer debriefing for the researchers [104].

A data analysis protocol was developed to guide the working group members, and the full protocol was uploaded to Zenodo for reference [20]. Template analysis was adopted as one strategy in the protocol. For instance, King et al., [68] presenting the approach termed "Template Analysis" have observed that:

> "Thematic analysis is widely acknowledged as an accessible and useful approach to the analysis of rich and meaningful qualitative data—indeed, Clarke and Braun [18] describe thematic analysis as the 'basic' method of qualitative data analysis.
> …the principal focus of all thematic analysis approaches is on identifying, organizing, and interpreting themes in detailed qualitative (textual) data to highlight and convey key messages. In this chapter, our focus is on

[2]https://sfia-online.org/en/tools-and-resources/standard-industry-skills-profiles/european-union/sfia-and-eu-ict-role-profiles

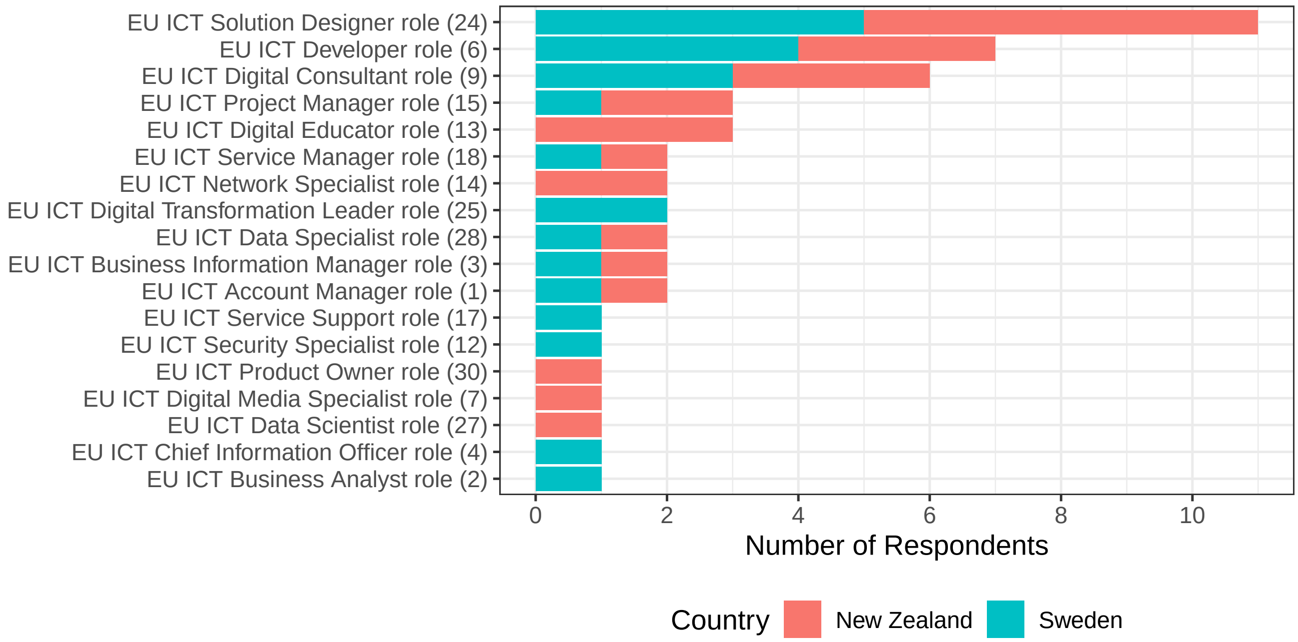

Figure 1: Role by Country. Number of SFIA roles in the parentheses

> Template Analysis as a particular style of thematic analysis" [68]

They also distinguished between Generic Template Analysis as a method, and as applied within a broader research methodology such as 'grounded theory' or 'Interpretative Phenomenological Analysis' (IPA). In its favour they further argued that issues about differing philosophical, theoretical or methodological positions can be better accommodated, as noted below:

> "Generic styles of thematic analysis can provide researchers more flexibility and adaptability to the particular requirements of their own work—rather than applying a methodology as a whole package." [68]

In addition, the implications for choosing between inductive and deductive forms of reasoning in template analysis were elaborated.

> "Forms of thematic analysis vary in the extent to which they use inductive or deductive reasoning: where different approaches to thematic analysis position themselves on this inductive-deductive continuum depends very much upon the methodological approach being taken... Generic approaches to thematic analysis (such as Template Analysis) can, in contrast, be used from a variety of methodological positions and therefore do not have a single fixed position on this continuum" [68].

The process of coding in template analysis is also not prescriptive over coding approaches and does not stipulate a "sequence of coding levels or an explicit distinction between descriptive and interpretive coding" [68]. In template analysis, the general steps in the process are defined by King et al. [68] as below:

> "The procedural steps that are characteristically followed in Template Analysis are:
> - Familiarization with the data
> - Preliminary coding
> - Clustering
> - Developing the initial template
> - Modifying the template
> - Defining the 'final' template
> - Using the template to interpret the data
> - Writing-up."

For the working group's study, the three authors, allocated to a data analysis sub-group, conducted the three steps before developing the initial template "Familiarization with the data, preliminary coding, clustering", using a subset of the transcript data, to derive an initial template using a defined spreadsheet for coding each transcript.

The template was refined as the process progressed, as noted by (King et al. [68]):

> "Revisions might include: re-defining themes to increase or narrow their scope (shown through moving them up or down hierarchical levels), moving themes between clusters, adding new themes—or even entire new clusters—and deleting themes that have become redundant as the template has developed."

Version one of the template allowed for the coding of each question in the interviews. Each row would relate to a question, with a suitable code derived by the analyst from the respondent's data. Multiple codes in corresponding rows could be derived for each question. For some questions, a predefined set of deductive codes could be considered as an initial set of codes for that question, for

Table 7: Demographics of the interviewees.

Country		SE	NZ
Sweden	23		
New Zealand	21		
Work Sector			
IT services	18	10	8
IT consulting	4	2	2
Education	6	3	3
Finance	3	0	3
Government	3	2	1
Telecommunication	3	1	2
Other	7	5	2
Organisation Size [headcount]			
>=250	22	12	10
<250	9	5	4
<50	5	3	2
<10	4	2	3
Did not specify	4	2	2
Years of Experience in IT			
1 to 10	15	10	5
10 to 20	5	2	3
More than 20	23	11	12
Did not specify	1	0	1
Years of Experience in AI			
0 to 1	10	4	6
1 to 10	27	16	11
10 to 20	2	0	2
More than 20	2	0	2
Did not specify	3	3	0
Months of Experience with GenAI			
1 to 6	8	6	2
6 to 12	12	3	9
12 to 24	10	7	3
More than 24	4	2	2
No experience	3	1	2
Did not specify	7	4	3

other questions a more inductive strategy might be more suitable. Version two of the template again allowed for coding of each question but added contextual information to support each coded row. This coding stage (termed coding cycle one), for producing raw codes, would typically code by phrase excerpted from the transcript relating to each question. The template has also been adapted for programmatic extraction and pooling of data, (By labelling each line of the spreadsheet with the transcript id, overall section/subsection, or interview section,/subsection and an ignore character '%' for template comment data or blank lines). More details are provided in the full protocol [20]. For coding cycle two (the thematic extraction stage) when the scripts had been developed, the pooled data for each question was considered for coding and extracting themes. For the coding, it was considered preferable to assign questions to sub-groups. This enabled group analysis and greater topic focus, for instance, a question on 'AI-related training and support', (c.f. Table 6) was analyzed by the sub-group responsible for the topic of competencies. Subgroup members typically worked in pairs or as a group to arrive at a consensus on the derived codes and themes.

The process of thematic analysis broadly followed the stages recommended by Braun and Clarke [10] and Cruzes and Dyba [24]. The process was tempered by the needs of the working group to adopt a form of "Qualitative pragmatism" [11], and apply that within its two cycles of coding and theme development.

Step 1: Data familiarisation.
Step 2: Obtain codes.
Step 3: Searching for themes.
Step 4: Review themes.
Step 5: Defining and naming themes.
Step 6: Reporting. [10]

The themes emerging from the interviews underscore the complexity of AI integration, including its technical, social, and professional dimensions. Building on these insights, the next section examines how these factors manifest in workplace practices and influence professional roles.

4 Results

The extracted data were analysed following the three key dimensions of AI integration in IT workplaces: i) understanding AI technologies, ii) navigating socio-technical work dynamics, and iii) addressing professional development needs. The findings reveal the multifaceted impact of AI, including its influence on workplace interactions, task management, and the evolving competencies required of IT professionals. Building on these insights, the next section explores these themes in greater depth, focusing on their implications for workplace practices and professional roles

4.1 Understanding AI and its Use in Practice

In this section, we discuss the second research question:

RQ2. How is AI currently used by IT practitioners, including the use of specific tools, motivations and challenges to adoption?

4.1.1 Definition of AI and its Use in the IT Professional Context. The interviews provided insights into how IT professionals define AI in their professional context. Eight main definitional themes emerged from the data. Complementing this analysis was a description of any specific AI technologies or tools currently implemented or utilised in the respondent's work, which resulted in a complementary set of seven more user-oriented themes. A summary of the themes can be found in Table 8 and are further discussed below.

Assisting: Most IT professionals defined AI as a tool that optimizes day-to-day tasks and makes their lives easier, which would act as a supporting tool. They noted that *"[AI] can be your good assistant while you are doing your work, so like a tool or a machine which makes your work"* (IA004). Some IT professionals highlighted that it helps them increase their *"efficiency by simplifying their work"* (IE016) *"and increase [their] productivity on the way I do work"* (IE002). One IT professional also noted that AI helps to *"formulate sentences better, be it in English or Swedish or sometimes in other languages and improve my writing when I'm communicating, writing emails or like writing summaries"* (IU010).

Generating content: Other IT professionals defined AI as a system that generates content like text or code for them. They

Table 8: Themes emerged related to defining AI and its use

Theme	Description
Assisting	**AI is a system that helps and makes life/work easier**
Custom models	AI models tailored to specific tasks or industries for enhanced productivity
Vendor products	AI solutions provided by third-party companies to assist in various workflows
Concerns	**Concerns about privacy and security of AI**
Data and Information	**AI is a system that is using a data and process information**
Generating content	**AI is a system that can generate text, code or images**
Custom models	AI models trained to generate domain-specific content
Vendor products	Pre-built content-generation tools offered by AI vendors
Intelligent Machines/Tools	AI is an autonomous or intelligent machine or tool
Normalisation	**AI is part of our lives**
Smart behaviors	AI is a system that has smart behaviors such as problem-solving, decision making and learning
AI Technologies	**AI is a system that uses technologies such as ML, LLMs and NLP**
Custom model barriers	Challenges in developing and deploying custom AI models
Proprietary product	AI systems developed in-house using proprietary algorithms and technologies
Vendor product	AI platforms provided by vendors
Outside work use*	**They use AI outside of the work**
Not used*	**Not used AI**

*Themes only discussed in the use of AI

mentioned that AI is *"writing tests, based on a description of the behavior I'm wanting, help with test-driven development"* (IA002). Others specifically mentioned ChatGPT, explaining that *"something like ChatGPT uses to ask questions on any topic immediately"* (IE010). Some also mentioned that they use AI to generate ideas or images (IE010, IU003).

Data/Information: Interviewees mentioned that AI is *"some form of trained intelligence that is trained on data that is not hard-coded but draws its own conclusions and arrives at answers based on training from real data from the same field"* (IU011). They further elaborate that *"it doesn't think for itself, but rather it relies on the on the collection of vast amounts of data or information"* (IU008). Others explained that AI is *"a way to efficiently get some sort of summary of a large amount of information that is more or less relevant to what I'm asking for"* (IU007). Some also remarked on the huge amount of data AI uses, specifically saying that *"it is a huge damn amount of collected structured information, a gigantic amount of structured information that has been collected"* (IU008). Other IT professionals acknowledged the importance of the data, noting that *" [...] data plays a more important role"* (IU006).

Smart behaviors: Some defined AI, mentioning examples of smart behaviors it may have. They reported behaviors such as problem-solving, noting that *"one usually referred to AI as some kind of smart solution to a problem"* (IU0023). Others discussed the ability of AI to learn, mentioning that *"AI is something that adapts, learns and gets better with time"* (IU004). A few also referred to AI as a decision-making system or algorithm. One IT professional cited that *"[AI is] when you can get a machine to make its own decisions"* (IU017). A handful of IT professionals also discussed that AI can analyze and interpret visual information, noting that *"interpret visual information, plot out OCR numbers and such, and read it in somewhere, that's probably AI"* (IU018).

AI technologies: Others discussed specific AI technologies, such as Machine Learning and Deep Learning, when trying to give a definition of AI. Responses mentioned that the definition of AI has changed over time and *"and it was called Machine Learning for a while, what is now called AI"* (IU009). Others also mentioned NLP and LLMs technologies in their definitions, saying that *"[AI is] large language models, some kind of machine centered learning"* (IE012) or distinguish them by noting that *"I prefer to use LLMs or statistical models instead of AI"* (IU015). Several IT professionals referred to NLP systems that *"are actually AI, [...] ChatGPT is one I think"* (IU018), or *"chatbots that can basically help our customer experience"* (IU021). One acknowledged that *"AI is quite broad and many people think of generative AI and ChatGPT when you say AI now"* (IU023).

Autonomous/Intelligent machines/tools: The general sentiment that emerged from this theme is that interviewees perceive AI as a tool or a machine with a sense of intelligence. Responses in this theme noted that *"It hasn't assumed any human form or any bot form bot is a way to term it, but it is basically a smart search engine that compiles"* (IE011). Some also defined AI as *"[a] software which stimulates the human brains like how people learn stuff"* (IU006). A few participants defined AI as a machine that *"do things that similar to what human intelligence would do but would do it faster"* (IE013) and has *"superpowers or power to make our jobs easier"* (IE015).

Concerns: In their attempt to define AI, they noted that they had some concerns about it. Some mentioned that they are *writing anything complex. I don't trust it* (IA002). Others also discussed privacy issues (IA002). One IT professional highlighted that *"AI [is] an intelligence that we can both control and not control"* (IU022) and *"we can't just let it go out of hands in terms of the workforce."* (IA003).

Normalisation: Some interviewees highlighted that AI is *"[a] tool that promises to deliver certain capabilities, but then [we] need to go and learn what the limitations are"* (IA003) adding that *"definitely [it is] something that we need to catch up with"* (IA003).

More user-oriented themes were derived to relate these perceptions of AI technology to its use in practice.

General work process support - custom models: The notions of **"assisting"** and **"generating content"** were evident through a focus on the broad supporting role of technology in work processes. The high-level theme of **General work process support - custom models** for instance had examples of specific models supporting local needs *"doing the Maori Analysis So they use that train language model to analyse the Maori corpus"* (IA001), and *"I'm across that technology to a certain extent, but the AI concept that they've used is for filtering out parcels based on size dimensions"* (IE011).

General work process support - vendor products: Again the notions of **assisting** and **generating content** in supporting work processes were evident through the use of more vendor provided technology. Examples included: *"a lot of project management software that I use now have AI functionality"*(IE010), and *"automatic transcription"* (IU002).

Specific technology and process support - vendor product: Here, the themes of **assisting** and **generating content** were more closely tied to a specific vendor-provided product than a work process, examples included: *"So copilot is a specific tool which is basically only used to generate code, right? ...It is the large language model behind COPILOT"* (IA004), and *"Mistral Large language model with multiple expert models built into it"*(IA002).

Specific technology and process support - proprietary product: Here again the themes of **assisting** and **generating content** are more closely tied to a specific proprietary product than a work process, for example, *"xyz model - used to be called abc which we used to implement both for code suggestions and e-mail suggestions and document suggestions and everything else"* (IE003), *"ChatGPT-like web service on our intranet. It's command-prompt based and is being developed continuously"* (IU016).

Normalisation: An interesting theme relates to the extent to which novel technologies remain so, or just become lost and normalised in the set of technologies in use during everyday practice. *"We just like they just become part of the tools. It's only the ones that are at the edge that you notice at all. As soon as they pass that threshold then they just become part of your normal toolkit"* (IE017).

Outside work use: A further theme relates to the distinction between sanctioned or required use for work, as opposed to use for personal interest. *"I rather test or almost play around a bit with tools before my own work"* (IU008).

Not used at this stage: This, almost counter, theme reflects the reality for some respondents that they did not have much to contribute as AI technologies were not in active use in their contexts, for instance, *"Not specifically"* (IE005).

Furthermore, interviewees were asked whether they were aware of specific technologies or tools that have AI technologies invisibly embedded and whether they were implemented or utilised in their work. Three themes emerged from the responses and can be seen in Table 9.

Used tools. There is an uneven awareness of AI functionality embedded in other tools. One of the respondents mentioned up to 7 different tools embedding AI, mostly general tools. However, most respondents mentioned only one or no tools. Microsoft tools were the most mentioned, with 7 professionals explicitly mentioning Microsoft co-pilot or its integration in Microsoft Office. Most of the tools that were mentioned are general purpose, for example, Grammarly and Zoom. Only few mentioned tools that are specific for a domain, like Turnitin, used in the educational context, or tools used in the area of Geographic Information System (GIS). While in some cases the IT professionals are mentioning specific tools, in many other cases they seem to think about AI tools in terms of tasks and processes that need to be supported, for example, *"office tools transcribing, auto-correcting etc"* (IA002).

Not used & Lack of Awareness: Several professionals reported that they do not use tools with AI functionality invisibly embedded. However, they also admit, in some cases, that they are not aware of the integration of AI in the tools that are used. Some respondents explicitly mention that they do not know. *"when we work with the scripts and we install PowerShell modules, they might be some sort of AI in them"*(IA003) *"But does Office include AI? Or does Miro include AI? … I don't know whether it's a bunch of IF-statements or if it's really AI"* (IU008). Still, they reflect on the uncertainties connected to what type of AI is embedded in tools and in which ones, *"What type of AI or what type of machine learning or large language models don't know?"*(IA003). These responses seem to indicate that even IT professionals were not certain about whether AI is integrated into the tools they use. So there is an issue with the opacity of AI use embedded in software, which may even remove the option of choice in adopting AI. The motivations for adoption are discussed next.

4.1.2 Reasons and Motivations Behind Adopting AI. When asked about the main reasons or motivation behind adopting AI in their workplace and/or organisation the interviewees discussed 9 themes (see Table 10). Some respondents identify very specific needs to be met by using AI, for example, *"summarize text"* (IA001) or *"data analysis"* (IE006). However, for most of the respondents, the motivations are broader and can be related to: 1) the product, e.g., *"creating product value"* (IA002); 2) work processes, e.g., *"to help the people who are working. For example, I am a developer, and we have copilot for our assistance"* (IA004); and 3) the market, e.g., *"the future is ringing and if you don't keep up with that development you will fall behind"* (IU023).

Most respondents report utilitarian reasons behind adopting AI, like increased productivity, reduced costs, saved time, and efficiency, e.g. *"We can compile research in ten minutes instead of two weeks"* (IU011). In other cases, the motivations are intrinsic, mainly connected to professional development and interest, for example, *"software developers love, you know, the latest tech. So, there's an element of that"* (IA002); or *"It is mainly to bring us to learn and embrace this new technology"*(IU021).

Some respondents underline the need to explore the space of possibility offered by AI, for example, *"Because again, there's a lot of use cases and ways you can use AI, so being in the know in terms of, you know, like how do you use it properly and what specific use cases does it make sense to use AI?"* (IE019). Exploring the space of possibilities also requires addressing issues connected with responsible use, e.g. *"It's going to happen one way or the other, and rather than having a complete, lawless, Wild West where anything goes, we want to try and get ahead of this, figure out the tools that we're comfortable with and the ways that we're comfortable with people using them. So, we can say, hey, look, you want to use AI, these are the tools that are OK to use"* (IE012).

Table 9: Themes emerged related to specific technologies or tools that have AI functionality

Theme	Description
Lack of Awareness	**Uncertain about integration**
What, where	uncertainty about what LLM is integrated and where
No Use	**Professionals explicitly mention not using tools of this type**
Used Tool	**Tools that are used and invisibly embed AI functionality**
Specific Task/Process	Generic tool or family of tools, to support a task or a process, e.g., writing, summarizing
Specific Product	Explicitly mentioning a tool from a vendor

Table 10: Themes emerged related main reasons or motivations behind adopting AI

Theme	Description
Benefit	**Who benefits from adoption**
Challenge	**Challenges coming with AI like responsible use and the cost.**
Driver	**Who drives adoption**
Generic Work Process	**Using AI in general to automate, assist, in general, improve work processes in the company**
Intrinsic Motivation	**Motivation that is intrinsic to the IT professional (or perceived as such)**
Curiosity	Curiosity for new technology
Learning	Interest to learn new technology and new ways of learning
Market	**The need to stay competitive**
Product	**Aiming at getting a better product**
Specific Task/Process	**Explicit task or process such as searching, finding or summarize information**
Utilitarian	**Motivations that are connected to a utilitarian purpose**
Efficiency	Increasing efficiency
Productivity	increase productivity
Reduce Costs	Reducing costs for the company
Time	Reduce time required to getting things done
Work Environment	**More satisfied workers**

For some using AI seems to be pushed on them by the general interest, more an external requirement to stay competitive than a real interest, e.g., *"Partly because it is a buzzword right now"* (IU017). This does not necessarily imply a negative attitude, with people still thinking that this might bring benefits in the future.

Adoption might be driven by a strategic commitment of the organization, like in *"it's also centrally stated that we are going to spend a lot of money on this"* ((IU014). However, the drive might come bottom-up, e.g., *"we have started using AI in some way or another. And then the leadership has adapted to it"* (IU009).

When reflecting on motivations to use, some respondents reflected on who benefits from use. In some cases, the benefit is internal, for example, when productivity is increased. In other cases, the beneficiaries are external, for example, customers getting better service or better advice from consultant companies.

It should be noted that adoption is often emerging, and motivation might increase and change as the value of using AI becomes clearer.

While the first set of responses concerned motivations behind adopting AI at the organizational or industry level, the second set of responses focused on the practitioners' motivations from their perspectives. Many of the broader themes in Table 10 were echoed at the level of individual practice, but the focus was different and closer to the experience of the respondents. So, the representation of these themes in the data had examples of specific personal drivers for adopted practices.

As an example of a **specific/task process** to be supported, we consider - *"Avoiding the need to write boring code"* (IA002). Reflecting the **intrinsic motivation** for adoption - *"because I am enthusiastic about learning new things"* (IA004), *"fun to know how things work"* (IU002). *"Partly because I think it's exciting technologies"* (IU022), *"to learn through dialogue"* (IA003).

The utilitarian theme recurs with the need to increase productivity and efficiency, *"you get something out of it anyway made into a product or result very quickly which effictivizes my day. which allows me to focus on other things"* (IU020).

However, in addition to these echoes of broader themes at the individual level, we see new themes emerging. In the context of competitiveness, the focus here shifts from the product and **"market"** to the notion of **retaining personal currency and competitiveness**. For instance, *"everybody needs to one way or another we will all be AI either users or producers or you know prompting but all of us will need to do something with AI pretty shortly"*(IU021), *"I need to make a more personal journey to be relevant. Because it's going to be about understanding AI. To understand how to manage the tools that come with AI. One needs to learn how to ask the right questions so that there is value in what we get out of an AI product"* (IU024), *"To learn the scope, rather than being scared of what AI can do for us. Rather, how can you use it to your advantage"* (IA003).

Some specific themes emerged as we inquired into the personal motivations driving adoption. **Area of research**, one respondent saw the whole area of AI as a focus for research - *"I'm encouraging* *some of the other staff to do research in this area because we are teaching it as part of the Bachelor program"* (IE013). **Low risk review** was also a theme, *"Yeah, it's. It's like like one of the powerful aspects of doing code reviews is looking at someone else's code and seeing how they've done it and being able to say, oh, that's a good way. I never thought of that"* (IA002).

We further identified an intriguing response related to the double-edged aspect of motivating collaboration with AI and co-operation as opposed to coercion *"compliant collaborator but it's more of a belligerent collaborator"* (IE017).

4.1.3 Challenges or Opportunities related to Integrating AI in their Role. Respondents highlighted a range of challenges and opportunities associated with integrating AI into their roles. While challenges were more prominently discussed, this could reflect the sequencing of the interview questions, which addressed potential issues after exploring AI's applications and benefits.

Opportunities: The opportunities identified align closely with motivations for AI adoption, such as the utility-driven benefits discussed earlier and the potential for creating superior products. Some IT professionals emphasized the potential to combine AI with existing products or to develop entirely new ones. For example, one respondent noted, *"We are looking into new products that are entirely AI-based. And they simply wouldn't be able to exist otherwise. It's only really been the past year that such opportunities have come up"* (IU008). Key themes related to these opportunities are summarized in Table 11.

Challenges: The challenges identified were diverse, encompassing both familiar and emerging issues (see Table 12). Concerns included privacy, safety, data ownership, and intellectual property rights. For example, one respondent mentioned the cost and resource intensity of advanced language models: *"So I can use it for free for the ordinary person though, that's probably beyond them"* (IA001).

Another recurring theme was trust in AI systems. As one professional remarked, *"And then when it comes to analyzing data, that is where I have my biggest fears regarding AI. I don't trust it fully"* (IU010). This lack of trust is often tied to AI's "black box" nature, which makes it challenging to evaluate outcomes, correct errors, and ensure reliability. One respondent expressed frustration with inconsistencies: *"When you're facing a problem that you can't solve on your own and think it would be great to have them, they don't work. Or it works, but then you spend a lot of time going back to catch up"* (IU015).

Broader concerns included human rights, role disruption, and societal impacts. For instance, one respondent remarked on the threat to creative professions: *"There is concern, especially with the artists feeling like they will be... automated out of a job"*. Others voiced fears about general intelligence, such as *"If we manage to create a general intelligence and human beings are no longer the most intelligent, it could possibly mean a problem for humanity on a global scale"* (IU009). Legislative challenges were also noted, including regulatory demands for transparency in AI use, as highlighted by *"The big challenge… is going to be the insistence by government and others when they put in regulation to ensure that if you use generative AI or any form of AI, you can at any later date replicate its use and obtain the same answers"* (IE004).

A significant challenge identified by many IT professionals was the lack of knowledge and the continuous need to learn. One respondent stressed the importance of understanding AI processes: *"You can't have a tool or an AI working in the background without understanding what is happening"* (IU005). This challenge is amplified by the rapid pace of AI advancements, as noted by another professional: *"Not just reading about it, but trying to do... practice and try stuff that is quite time-consuming and is changing very, very quickly. Like unbelievably quickly, I honestly can't believe it"* (IA002).

This fast-paced evolution of AI, while challenging, was also seen as an opportunity. For instance, it encourages individuals, teams, and organizations to develop a competitive edge through continuous learning. One respondent reflected, *"The smarter it gets, the more you need to catch up... you know, they say they are able to do certain things, but they're really not... So it's an advantage, being able to know what tool to use for what"* (IA003).

Similarly, the rapid innovation cycle fosters creativity and adaptability, as noted by another professional: *"We also see that we are looking ahead and keeping pace... perhaps we cannot do what we want today, but perhaps we can do it in two months with the greatest probability… The time horizon becomes shorter and shorter. It's not ten years of development but perhaps a couple of months next year"* (IU008).

While the lack of skills poses a challenge, many respondents showed a willingness to self-train. As one noted, *"Seeing the opportunities in the AI, the staff are willing to train themselves"* (IE009). However, the same respondent emphasized the need for structured support: *"There should be some kind of training provided to people who are ready to train themselves up because of the opportunities it provides."*

Table 12 outlines the key challenges of AI integration, including data quality, lack of transparency, ethical concerns, and skill gaps. It categorizes these barriers thematically and provides examples from participant responses.

4.2 Impact of AI on Workplace Dynamics, Task Division, and Human-System Interaction

Building on the insights into the opportunities and challenges this section explores the socio-technical dynamics of human-system interaction, emphasizing collaboration and adaptation. Specifically, it addresses the third research question:

RQ3. How does the integration of AI influence workplace dynamics, task division, and human-system interaction among IT professionals?

We examine the multifaceted effects of AI on workplace dynamics for IT professionals, leveraging insights drawn from the conducted interviews. The analysis is organized around three core themes: 1) the influence of AI on workplace dynamics, 2) shifts in task division and responsibilities driven by AI integration, and 3) the nature of human-system interaction and collaboration in AI-enhanced workplaces. A detailed summary of the super-themes and sub-themes identified from the interviews is provided in Table 13.

For instance, IT professionals highlighted how AI tools enhance efficiency in daily work tasks by either reducing the number of tasks they need to complete (i.e., **Task Reduction**) or by offering

Table 11: Themes emerged related to the opportunities for integrating AI

Theme	Description
Learning	**Opportunities on learning**
Self-training	Learning by self-training thanks to IT professional interest and curiosity
No Human Replacement	**AI not replacing human beings**
Utilitarian-time	**Opportunities that connected to utilitarian issues**
Efficiency	Increase efficiency
Productivity	Increase productivity
Time	Reduce time
Process	**Opportunities to improve working processes**
Assist	Assistance with getting the work done
Automation	Automating some of the tasks, especially the repetitive ones
Creativity	More creativity
Extend Capabilities	Extending human capabilities, better thinking
Less procrastination	AI helping to get started and reducing procrastination
Product	**Opportunities to create a better/new product**
Better Quality	Better documentation
Integration	Opportunities arising from Integrating AI in a new product
New Opportunities	Access to new opportunities

Table 12: Themes emerged related to the challenges for integrating AI

Theme	Description
Investment	**Investment required to start using AI and keep updated**
Learning	**Challenges connected to learning**
Experience to Use and Evaluate	Prior experience is needed to evaluate AI tools and their results
Keep Updated	Need to stay informed about rapidly evolving AI technologies
Lack of Knowledge	General lack of understanding or education around AI
Specific Skills	Specialized skills are needed to implement, operate, or interpret AI
Stay Competitive	Continuous learning and adaptation are required to stay competitive
Time	Time required to learn the new tools
Legal	**Legal concerns that challenge the adoption of AI tools**
Comply with Regulations	Emerging regulations might be based on unrealistic expectations
Data ownership	Uncertainty or disputes about who owns the data processed or generated by AI systems
IPR	Issues regarding Intellectual Property Rights for AI-generated content
Privacy	Concerns about how personal data is handled by AI
Product/Outcome	**Issues related to the quality, safety, accuracy and security of the outcomes of AI tools**
Responsibility	**Issues connected to responsibility with the model and the outcome**
Trust	**Concerns whether we can trust AI**
Blackbox	AI as a blackbox
Critical Thinking	Need to reflect critically on the outcomes
Experience to interpret results	Need to have experience to interpret outcomes
Other	**Other codes e.g. human rights, role disruption, resistance and lack of guidelines**

enhanced support for task execution (i.e., **Task Assistance**). Subthemes were similarly derived for the remaining super-themes, reflecting a comprehensive analysis of workplace dynamics in the context of AI adoption.

4.2.1 AI's Influence on Workplace Dynamics. In this subsection, we examine how AI technologies have reshaped the overall work of IT professionals. The interviews revealed diverse experiences and perceptions, with AI impacting work processes, efficiency, and task management.

Changes in workplace: Change as a theme was noticeable in the interviews, with many professionals commenting on the observed or expected transformation of workplace dynamics due to AI. The majority of the professionals said that they did not notice a significant change in their work dynamics. However, most of them acknowledged the potential for future impact, depending on how individuals and teams adapt to AI technologies. They believe that the influence of AI is forthcoming. Expectations for these changes vary from personal changes (e.g., thought processes, communication patterns, or competitiveness between people) to

Table 13: Themes found related to Impact of AI on Workplace Dynamics, Task Division and Human-System Interaction

Theme	Description
Changes in Workplace	**Potential differences observed due to the introduction of AI at work**
Disparity	Potential divide within the workforce due to some using AI and others do not
Future Change	Changes are anticipated in the future
No Change	No change has been observed or anticipated at workplace
Over-reliance	The tendency to rely too much on AI performing your work-related activities
Redundancy/Displacement	Concerns that AI will replace humans in their tasks
Collaboration	**AI's role in communication between colleagues at workplace**
Increased Collaboration	Increase in collaboration between colleagues due to the use of AI collaboration tools
Reduced Collaboration	Reduction in collaboration between colleagues due to the use of AI tools
Communication	**AI's role in communication between colleagues at workplace**
Decreased Communication	Reduced human communication due to the use of AI
Human Like	Interacting with AI feels human like
Increased Communication	Communication increased due to the use of AI
Efficiency in Workplace	**AI's role in making tasks more efficient**
Task Assistance	AI's role in assisting humans in work-related activities
Task Reduction	AI's role in reducing human labor needs
Implementation Issues	**Challenges and barriers in the implementation of AI.**
Management	**The impact of AI on management practices**
Responsibilities	The impact of AI on distribution of responsibilities
Task Distribution	The impact of AI on distribution of tasks
Power Dynamics in Workplace	Potential impact in power dynamics due to developed skills/competencies in AI
AI skills & Competencies	The role of AI competencies affect an individual's value within an organization
Attracting Funding	Proposals based on AI technology attract more funding
Status Change	Extensive knowledge of AI can lead in a change of status
Others	**Isolated emerged themes**
Context Dependency	Efficiency of AI tools is context-dependent
Data Dependency	AI tools will potentially not work well on emerging tasks due to limited training datasets
Time Wastage	Spending time on using AI for work tasks but not getting useful results

organizational changes, like team structures or roles and responsibilities. For instance, a notable observation was the expectation that AI would soon necessitate reorganization within workplaces, introducing data-driven approaches that will significantly influence task management and decision-making processes (IU006). Some expected that AI's impact would initially be at lower levels of the organizational hierarchy and later affect the seniors (IE012). Several respondents also indicated that the changes would depend on the interest and adaptability of the people involved (IU024, IE011).

Moreover, some respondents highlighted the emerging disparity between AI users and non-users, suggesting that those who integrate AI into their workflows are likely to outpace their peers, potentially creating a divide within the workforce (IE011, IU009). An example is IE011's expression: *"I think the AI has now created a barrier of AI users and non-users. Then you have a difference where you have the people engaged in technology. And project management is heavily engaged in AI use whereas your senior management are slow adaptors of this technology, although they see a benefit in it."* Similarly, one IT professional explained this issue as *"One might think that people who don't want to use AI might be left behind or left out. In that way, it could affect relationships. I wouldn't say that it's something I've noticed directly. If we give it a bit more time it will become an A and a B team."* (IU009). This disparity underscores the importance of adaptability and continuous learning in leveraging AI to maintain competitiveness (IU017).

Professionals also expressed concerns about the extent of AI's influence. For instance, one concern was not knowing the inner workings and being over-reliant. As the AI and Large Language Models (LLM) become smarter and more complex, they may not understand their inner workings or see how far is too far in terms of what AI can do for or take from them (IA003). The IT professionals also underlined the need to carefully consider the prompts, saying *"Ultimately, it is just gathering your data. It is taking to its central repository and from there, it is building the answers. So, we still need to be careful about what prompts we are putting forward in it and yeah so, but people are taking it very like, you know with welcoming kind of gesture."* (IA004).

Despite some uncertainty and concerns, there is a clear, welcoming attitude towards AI. According to professionals, it is expected to be adopted faster than any previous technology, necessitating adjustments in expectations due to its diverse impacts.

Communication and collaboration: The influence of AI on communication within workplaces was another key theme. Professionals highlighted both positive and negative aspects. On the one hand, AI tools such as Miro or Slack integration, summarizing, and transcription services could potentially foster a more communicative environment by stimulating discussions and idea generation

(IA002, IU004, IU014). However, there were concerns that over-reliance on AI might reduce human interaction, as people might prefer consulting AI over colleagues for basic information, allowing quicker access to information without waiting for colleagues to respond (IU003, IU019). A similar comment referred to this issue as more validation of one's thoughts before expressing oneself (IU014). This shift has led to more specific and meaningful human interactions when they do occur, as people are likely to turn to AI for straightforward answers and consult colleagues for more complex or nuanced discussions (IU019). So, AI seems to support collaboration by serving as a kickstarter for ideas, which are validated and expanded upon with colleagues (IU014).

AI has also encouraged deeper engagement among team members, prompting more discussions about AI and its applications across all levels of the organization, from managers to agile teams. This dynamic seems to positively affect team structures, creating an open and positive environment where new technologies and discoveries are actively shared. (IU004, IE015).

Despite concerns that AI might lead to laziness, the need for validation of AI-generated information encourages employees to critically engage with content and collaborate more effectively, ultimately strengthening team cohesion and communication (IU017).

Efficiency in workplace: The theme of efficiency was also mentioned in the interviews. Professionals acknowledged that AI has the potential to significantly enhance productivity and efficiency by speeding up decision-making processes and providing better insights through data-driven results (IE019). One professional mentioned that AI allows people to do more without feeling threatened, thus fostering a more productive work environment (IE010). However, there were also concerns like *"several orders of magnitude of increased productivity that we just don't have a clue how to deal with."* (IE017). The practical value of implementing AI tools in everyday tasks was also noted, emphasizing the importance and valuation of hands-on experience in maximizing AI's potential (IU014).

While the integration of AI presents some challenges, its benefits in enhancing productivity, decision-making, and process efficiency are undeniable. It was also interesting to see that these benefits may result in higher expectations, which was expressed as *"some colleagues may expect me to, to go in Kraftful and like know about what our customers are saying there, for instance, and combine that with the answers to our customer service, which, like I'm the one managing, uh, so probably it has changed expectations a bit and probably increased expectations a bit"* (IU010). One of the professionals underlined this issue saying that; *"As a leader, I had to calibrate my expectation cause they are really diverse"* (IE002).

Power dynamics in the workplace: The impact of AI on power dynamics within organizations was a recurring theme. While some believe that power relations might remain unchanged (IU002), there is a growing consensus that AI competencies significantly enhance an individual's value within an organization. Skills in AI are increasingly desirable and can lead to greater recognition and opportunities (IU004). Individuals or roles that leverage AI effectively for decision-making gain a competitive edge, as their ability to provide clear, credible answers based on AI insights positions them for success (IU011).

Leveraging AI internally provides a competitive advantage and helps individuals get their proposals approved, attracting more investment towards AI-integrated technologies (IU015). This is also expressed by *"there is a power structure around those who drive AI. They get funding and it is a growing part of our business, which makes us perhaps exclude other parts. We deprioritize other areas that receive less focus"* (IU011).

Additionally, the arrival of AI is expected to narrow the gap between senior management and other employees (IU014). Those with extensive knowledge of AI experience a change in status, reflecting the growing importance of AI expertise in the organizational hierarchy (IU015). On the other hand, one professional pointed out its negative effect on experts as *"I think that beginners get better with AI while experts get worse. Yes, that was exactly it. It's kind of fun because if I'm an expert and I ask AI something and it says something, and I think that's wrong. Then I trust it more than I trust myself. That's somewhat interesting. I would say it's definitely possible that it affects power relations"* (IU023).

AI seems to shift power dynamics by valuing AI competencies and centralizing power around AI-driven projects and roles.

4.2.2 Changes in Task Division and Responsibilities Due to AI. The interviews provided insights into how AI has affected the division of organizational tasks and responsibilities. Five key themes emerged from the data: efficiency and task reduction, no significant change, management and communication, increased responsibilities or opportunities, and implementation issues. These themes illustrate the varied impact of AI on work dynamics, highlighting both the positive changes and the challenges organizations face.

Efficiency: The interviews revealed that implementing AI has increased efficiency and reduced the need for human labor in specific organizational tasks (**for task reduction**). Many IT professionals highlighted how AI has streamlined processes, resulting in fewer people performing tasks that previously needed multiple individuals. One IT professional remarked on the impact AI has had on task efficiency: *"The duty that used to be assigned to two or more people can now be performed by one person"* (IE002) and *"it is reduced the amount of time required. So instead of sitting in, in front of your screen for five hours, now you're done in one hour so"* (IE011). This reduction in the number of people needed for particular tasks highlights the efficiency gains and underscores a significant shift in how work is distributed. Additionally, reducing mundane and repetitive tasks was a point among respondents. These efficiency gains are not limited to reducing labor but also extend to how employees manage their time and workload. IT professionals indicated that AI's role in making tasks more efficient helps them concentrate on responsibilities that require human insight. *"GenAI handle a larger part of my administrative work from recruitment to creating presentations and various types of service materials and so on. Then I could absolutely focus even more on customer relations and such."* (IU020).

AI is reported to help with different tasks, and tasks at work are divided between humans and AI. Some respondents are rather generic, mentioning, for example, a generic increase in productivity. Others are more specific. For example, a respondent reports using ChatGPT to support tasks, from spreadsheets to performance reviews. Tools like ChatGPT are reported to help with tasks that one can already perform but somehow improve them. For example, *"it came up with a good some good ideas, some of which I used.*

So again, that improved my practice. Although I could have done it myself"(IA002). In other cases, AI allows performing tasks that would have been difficult without it. Again, in the words of IA002, *"I've never done a detailed performance review in my life, and I got ChatGPT [...] Reasonably low effort without having to go to someone and look stupid [...]"*.

Changes in workplace: The interviews revealed that for many respondents, AI implementation has yet to result in significant changes in the division of tasks or responsibilities within their teams or organizations. This theme captures the sentiment that, despite the potential of AI, many roles and tasks remain largely unaffected by its implementation. Several IT professionals explicitly stated that they had not noticed any changes: *"No, I wouldn't have noticed. Not yet anyway"* (IU025) *"I think not, not at this stage. We still follow the hierarchy of who's go, what permissions, and who can do what"* (IA003), *"Remain the same and it because it is still treated as a tool to assist developers"* (IA004).

Management: Some interviews revealed that implementing AI has changed how management distributes organizational tasks (**Distribution of Tasks**). This theme reflects the organizational adjustments as teams adapt to AI technologies, explicitly allocating responsibilities. IT professionals specifically noted changes in manager task distribution and that some senior management distributes more difficult tasks to less skilled team members due to them being able to use AI, like in this quote from one IT professional: *"I'd say the senior management that distributes the tasks trusts more difficult tasks to lower members of the team simply because they have access to AI now"* (IE003).

Furthermore, the interviews revealed that implementing AI has allowed employees to take on new **Responsibilities**, and actively engage with AI applications. This theme highlights how AI is changing the division of tasks and creating new avenues for professional growth and development within organizations. Several IT professionals indicated that AI has enabled them to assume responsibilities they previously could not: *"I can take on responsibilities which I previously couldn't"* (IE010). Other respondents noted their proactive engagement with AI, leading to new roles and tasks: *"Maybe because of AI I have taken the lead in doing the AI applications so that because of the opportunities that I have found that they are useful for the customers"*(IE009) and *"Those who want to take advantage of it get the opportunity to do so. If it's related to AI. Because we need more people who are involved and act as ambassadors for it"* (IU002). These responses suggest that AI fosters an environment where employees can expand their skill sets and face new challenges. Leveraging AI tools has allowed some employees to step into leadership roles or become more involved in AI-related projects. The use of AI tools also creates some new responsibilities. For example, *"I am a manager of those who primarily use AI technology. For me, AI has resulted in me ending up with various tricky questions around legal issues"* (IU011).

Implementation issues: The interviews revealed that challenges and barriers to implementing AI have impacted the division of organizational tasks and responsibilities. This theme highlights the difficulties teams face as they attempt to integrate AI technologies into their workflows, often leading to delays or incomplete adoption. Several IT professionals pointed out that the lack of proper implementation has prevented significant changes in task division: *"We don't have any specific that companies encouraging people to use of like"* (IE005). The IT professionals suggest that the absence of a clear strategy or support from management has hindered the integration of AI, leaving traditional task distributions unchanged.

Another common issue mentioned was the lack of management engagement with AI applications: *"Management don't engage in this application on a daily basis"* (IE011). This lack of engagement from management can stall the broader adoption of AI, preventing it from reshaping task responsibilities and workflows.

Moreover, issues with communication about AI implementation were also a common concern among respondents. These communication challenges affect the clarity and effectiveness of how tasks are reassigned: *"So maybe it doesn't make it negative, but it's clear that there are conversations that might not happen because I ask ChatGPT instead"* (IU019) and *"...we still have a lot of work-related questions. So we ask everywhere in different Slack channels. Okay. So we have a lot of communication. Yeah yeah. That cannot be replaced with ChatGPT"* (IU006). These responses indicate that while AI has influenced how tasks are allocated by management, ongoing communication challenges impact the division of tasks and responsibilities.

4.2.3 Human-System Interaction and Collaboration in the AI-Enhanced Workplace. From the interviews, we extracted IT professionals' perceptions of how their interaction with AI has shaped their workplace environment. These perceptions encompassed several themes: enhanced efficiency and task assistance, human-like interaction and support, reduced human collaboration and interaction, no significant change in existing practices, and the potential for time wastage. Additionally, isolated responses highlighted concerns about context and data dependency as well as the possibility of AI leading to human replacement in certain roles.

Efficiency in workplace: The professionals felt that the use of AI tools helped them be more efficient at their everyday professional tasks since they can get **Task Assistance**. For example, one respondent mentioned *"machine's often an intermediary, so holding a meeting, transcribing, summarising the transcription, and then sending that out to people it's helped that whole"* (IA002). Another mentioned, *"[...] They tend to be relying on automation let's say generating codes rather than writing it from scratch. Well to be honest there's nothing wrong with that as long as you produce the output as a leader"* (IE002).

Several professionals noted that AI tools assist significantly with programming tasks. For instance, one respondent mentioned, *"Don't write boilerplate code anymore..."* (IE003). Beyond programming, AI tools were also seen as enhancing work processes and influencing attitudes toward work. For example, one professional shared, *"I struggle a bit with procrastination sometimes. So, [...] the kick from the GenAI [...] once I have described to them what I need and getting them to start a task, that's priceless for me [...]"* (IU004).

Communication: It was intriguing to observe that some professionals perceived AI tools as offering assistance in a manner that felt very **Human-Like**. One professional noted, *"You're like working—each AI seems to have a different, almost personality"* (IE010). Another shared the experience of being mindful of their tone when interacting with AI, stating, *"Yes, it feels like a human sometimes, so you always want to be nice with your language"* (IU019).

Collaboration: The general sentiment among professionals points to **Reduced Collaboration**, as individuals are relying more on AI tools like ChatGPT for answers rather than interacting with colleagues. One participant likened it to virtual team interactions, stating, *"It is like chatting to your colleague on Teams, right? You can just chat with him in human language, and it can just give you the answer. [...]"* (IA004). Another simply remarked, *"People [are] less collaborative with each other"* (IE018).

Changes in Workplace: Some professionals observed **No Change** in their workplace interaction or collaboration dynamics, even with the adoption of AI. While acknowledging AI's assistance with specific tasks, they noted that usual practices remained unchanged. For instance, one respondent mentioned, *"I don't think Stack Overflow will go away because the reason behind it is that I consider Stack Overflow as a data repository, right? [...]"* (IA004).

Others: Although most professionals were positive about using AI at work, some highlighted its potential to contribute to **Time Wastage**. One participant shared an example: *"To be more efficient in certain tasks, but like I say, you know sometimes it takes [you] in a loop, so we ask Microsoft Copilot, can you do this in Azure? It will be like yes, and it will tell you go here and go there and go there, and then you go in and Azure in that place doesn't exist."* (IA003).

One professional noted that the effectiveness of these tools is highly **Context Dependent**, explaining, *"So in the AI language, it is called the context of your chat, and then once it has understood the context, it can start giving you more precise answers"* (IA004). The same participant emphasized the **Data Dependency** of AI tools, pointing out that their performance relies on existing datasets, which may limit their utility for novel tasks. For instance, they remarked, *"Data is a very important content for these models for getting trained, and for example, I am saying this because, say for example, tomorrow a new language comes out, [a] new programming language comes out."* (IA004).

4.3 Professional Development and Competencies

Building on the findings from earlier sections, this part of the report examines how AI integration influences professional growth and identifies the evolving competencies necessary to navigate the transformations brought about by AI in the workplace. It addresses the fourth research question:

RQ4. What are the implications for education and IT professionals of integrating AI on their needs for professional development and developing new professional competencies?

Thus, in this section, we explore the need for changes in professional development due to the emergence of AI. Moreover, we investigate the in-demand competencies adapting to AI-induced changes.

Figure 2 illustrates the connections between the interview questions in Section 4.3 and how the results offer insights into professional competencies and the potential need for changes in computing curricula. The responses to the first question emphasize the necessity for updates in professional development strategies to address shifts in the competency landscape due to the rise of GenAI. This section also underlines the importance of exploring specific competencies in demand within the information technology field (Q2). Each identified competency was mapped to the expected level of skills required.

Notably, emerging competencies such as digital literacy and prompt engineering were found to be in high demand. This prompted further investigation into whether IT professionals had received training in these GenAI-related skills (Q3). The themes were mapped according to the vocabulary used in the competency model defined in the Computing Curricula (CC2020). According to CC2020, competency is defined as the intersection of knowledge, skills, and dispositions in the context of accomplishing a task [35]. These three components — "know-what", "know-how" and "know-why" — are also considered core dimensions of competency in models such as IT2017, CoLEAF, CKC, and CS2023, with slight variations in each model [40, 71, 72, 88].

By synthesizing the insights from the interviews with those from the literature review, we propose revisions to the computing competency model in Section **??**, which will inform potential curricular changes in computing education.

4.3.1 Need for Professional Development. When asked about the need for changes in professional development due to the integration of AI, over 90% of the IT professionals responded positively (Fig. 2). One primary reason cited was the need to *"keep up with possibilities and the ever-changing landscape"* (IA002). Another professional expressed a *"desire to keep up with the technology, the trends, and the tools to be able to leverage it as much as possible in the future as it becomes more relevant to what I do"* (IU012). Additionally, the demand from customers was highlighted as a significant factor. As one IT professional put it, *"When I meet many new customers or interested parties, AI is often something they ask about. So, for our part, we have to be up-to-date on the subject both internally and externally, otherwise, we'll fall behind."* (IU013).

A few IT professionals mentioned the need for correct professional development, with an emphasis that *"the professional development has to be calibrated according to diverse team members' needs"* (IE002). The tailored training can be achieved through *"private tutor"* (IA002), *"specialized workshops"*(IE013) or *"in-depth courses"*(IU002). By leveraging the benefits of AI, IT professionals can shift their focus to bigger things, as one IT professional highlighted *"people who are adapting to the proper use of it, they are now focusing on bigger things. For example, if a machine can write code for me, then I will use my brain to make the architecture of that code more secure and efficient."* (IA004).

It is also worth noting that very few IT professionals stated that no changes are needed for professional development. The few responses citing no need for changes were typically due to the professionals' extensive experience in the field or because their goals for professional development diverged from the integration of AI.

4.3.2 Important Competencies. As most IT professionals pointed out the need for professional development related to AI, we further explored the competencies that have become more important or in demand due to AI, from their perspectives (Fig. 2). Each competency that has emerged or increased in importance was mapped to the

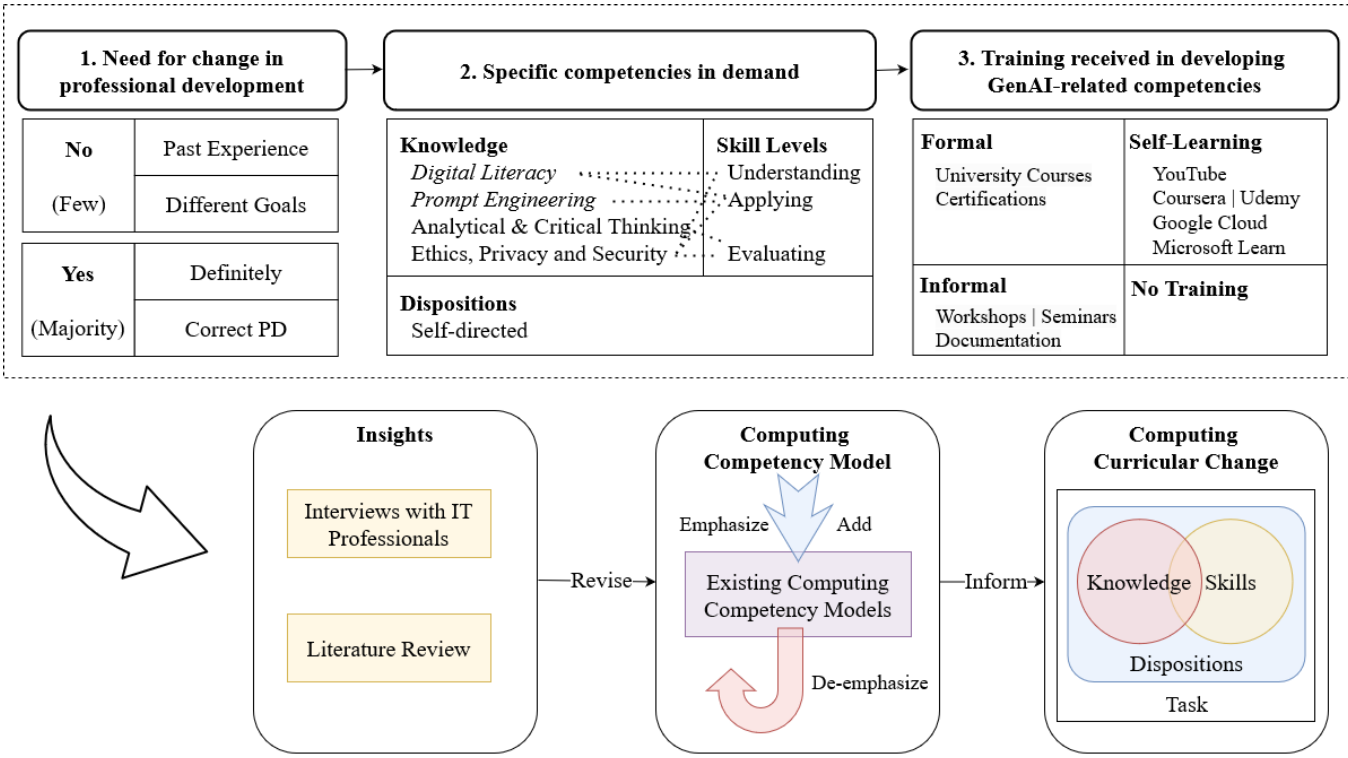

Figure 2: The connections between our interview questions in Section 4.3 and the workflow for implications of computing curricular change. The italicized competencies are newly emerged from data compared to existing competency models.

expected skill levels, such as understanding, applying, and evaluating. Despite the rapid adoption and evolution of AI, however, its impact on competencies for computing graduates has not been well captured by existing competency models.

When asked, *"What specific skills or knowledge areas (competencies) have become more important or in demand due to AI?"*, two new themes emerged from the interviews: **digital literacy** and **prompt engineering**, both of which can be mapped to the professional knowledge area. Additionally, two existing 'professional knowledge areas'—*analytical and critical thinking* and *ethics, privacy, and security*—were heavily emphasized by IT professionals. In support of these professional knowledge areas, two existing 'skills'—*analyzing and evaluating*—were also mentioned across multiple interviews. Although the questions did not specifically inquire about changes in dispositions, a few professionals highlighted the importance of being *self-directed.*

Digital Literacy: IT professionals discussed the importance of understanding AI, including its workings, uses, strengths, weaknesses, and impacts. For example, IE015 remarked that we need *"a broad understanding of what AI is and how it works"*. In addition to this general understanding of AI, IU008 emphasized the importance of knowing how to use AI for tasks such as qualitative coding of interviews and creating presentations. IE012 elaborated on the importance of understanding *"What's it (Generative AI) good at? What's it bad at?"*, which led to *"How do I get the most out of it?"*. One IT professional pointed out that before fully understanding the changes GenAI might bring, *"we don't think we would approve any kind of change in the system"* (IU005). Based on these responses, the skill level for digital literacy can be mapped to *understanding* and *applying.*

Prompt Engineering: Many IT professionals identified prompt engineering as a critical competency due to the rise of AI. For example, IT professional IE002 stated that the number one skill everyone should learn is prompt engineering, stressing that *"without the right prompt, you won't get the best of the AI"*. Similarly, IU002 remarked that *"you will get answers based on how you ask the question"*. The cognitive level of prompt engineering is mapped to *applying*. One IT professional mentioned using it for *"analysis-type documentation"* (IE013). Another noted that prompt engineering is necessary for *"how am I actually going to achieve the same goal and then using the tools to help your code and debug to get to that end goal?"* (IE015).

Analytical and Critical Thinking: Analytical and critical thinking involves judging, filtering, and validating the information, as well as reasoning through what is being done. For example, IE013 explained, *"I think the students need to understand what they're doing and the reasoning and the formula behind what they're doing"*. Another IT professional, IA002, added that *"Judgment evaluation, the credibility of information and information sources becomes really important"*. This process involves evaluating the information to judge whether *"they are wrong"* (IA001) and assessing the *"credibility of information and information sources"* (IA002), which places the skill level at the *evaluation* level.

Ethics, Privacy, and Security: Several IT professionals emphasized the need to cultivate a mindset focused on ethics, privacy, and security. They stressed the importance of being aware of biases in AI and the moral implications of technologies like deepfakes, noting the need to *"prevent misuse - fake news, scams, and hacking"* (IA001). Concerns about privacy and caution regarding data sharing were also highlighted. For example, IE002 mentioned that *"security protocols have to be set"* because their employees had not yet been trained on new forms of infrastructure. This competency involves understanding the issues, applying the knowledge when interacting with GenAI tools, and evaluating biased information.

Decreased Importance of Syntax: Some professionals noted that *"knowing the syntax of different languages in your head has become less important"* (IU017). They emphasized that the focus has shifted from lower-level tasks to higher-level thinking, such as *"how to bring the whole project together and how to use these extremely powerful tools"* (IE010). Nonetheless, many professionals believe that it is still important to have basic coding knowledge, as one explained: *"I think you still need some basic understanding of what you are dealing with"* (IU018). Another added that *"the code that it gives you might not all be safe"* (IA003).

4.3.3 AI-related training and support. The responses of IT professionals regarding the training or support received in developing AI-related competencies or adapting to AI-induced changes are summarized in this section. The responses are categorized into formal training, informal training, self-learning, and lack of training or support (Fig. 2).

Formal training: Some IT professionals have engaged in structured and formal education to build their AI competencies. Universities or specialized training institutions typically offer these courses, providing a comprehensive and in-depth approach to AI learning. For instance, one IT professional noted, *"I actually found a course at my university, a master's level course...focused on ethics implications and applications"* (IE012). A few others mentioned certification courses from the Australian Computer Society and Microsoft. One IT professional mentioned, *"We actually have a large platform with a lot of courses and very good ones. We have even bought courses from Harvard and other renowned universities but also from companies where we can go online and educate ourselves"* (IU002).

Informal training: Some organizations provide informal training, including workshops, training sessions, and guidelines to help employees adapt to AI technologies. However, the extent and quality of such support vary significantly across organizations. Examples include, *"When Copilot was introduced, there were a couple of sessions"* (IA004), *"We get some training from Microsoft and organized workshops from Google"* (IE009), *"Internal guidance on 'Guidelines on how to use AI within the company"* (IU013), and *"Workshops and team learning sessions"* (IE013, IE015). Some IT professionals mentioned learning from the documentation provided by the tool suppliers, for instance, *"Lectures from suppliers to utilize their technology"* (IU014), *Tool tips from the provider after new release"* (IE003). Some organizations have encouraged employees to take relevant courses to adapt to AI-induced changes. Examples include, *"Company encourages to sign up Microsoft's AI course"* (IE008), *"We had mandatory AI training that we had to attend [...] Previously, we had a Center of Excellence for various types of technologies and capabilities. And AI is one such branch there now"* (IU020).

Self-learning: Most IT professionals mentioned self-directed learning methods, utilizing free or accessible resources such as YouTube tutorials, personal research, and self-study. This approach reflects a proactive attitude towards gaining AI skills independently. IT professionals highlighted, *"Everything is self-learning"* (IE010), *"Self-taught and play with it"* (IE003), *"Using YouTube tutorials"* (IE003), and *"I have spent a lot of time talking to engineers in computer science and playing with the tools"* (IE012). Many of these self-learners have utilized online platforms to acquire AI skills. Examples include *"Coursera courses"* (IA001), *"Google Cloud training"* (IA001), *"Courses on how to use AI"* (IU004), and *"I was going through the training Microsoft learn material to upskill myself in the Azure space"* (IE009). These platforms offer flexibility and a wide range of courses catering to various aspects of AI.

No training: A noticeable number of IT professionals reported receiving no training or support from their organizations, indicating a significant gap that leaves employees to rely on their initiative for AI skill development. For instance, some stated, *"I've received no support"* (IA002), *"No formal training was given"* (IE002), *"No training by the company"* (IE018), and *"Nothing at work. Everyone was just doing everything in their own time"* (IA002).

In summary, due to the rapid advancement of AI, most IT professionals identified a need for change in professional development. However, there has not been consistent training or support across the industry sector. *"Not any specific in-house training"* (IU013) and *"training struggles to keep up"* (IU011) were highlighted concerns. Most of the IT professionals had no training or learned by themselves. In addition, the correct form of professional development is important, as pointed out by IT professionals. According to the interviews, a few competencies in the existing competency model must be emphasized. They are analytical and critical thinking, ethics, privacy and security, and being self-directed. Two new competencies, namely digital literacy and prompt engineering, must be added. Syntax can be de-emphasized, which can create space for higher levels of thinking.

5 Discussion

In this work, a mixed-methods approach was employed to address the research objectives, combining a systematic review of academic and grey literature with an interview survey. The literature review provided a foundation for understanding current practices, challenges, and competencies related to AI integration in IT workplaces. In-depth qualitative interviews with IT professionals from New Zealand and Sweden offered valuable insights into their experiences and perspectives. The interview study was organized around three main topics: 1) understanding AI, 2) sociotechnical work dynamics, and 3) professional development and competencies. This section summarizes the key findings for the four research questions guiding the study, and the issues arising.

- *RQ1.* What is the evidence from the academic and grey literature that current AI competencies capture and reflect the needs of professional practice in the Computing and IT industry?
- *RQ2.* How is AI currently used by IT professionals, including the use of specific tools, motivations and challenges to adoption?

RQ3. How does the integration of AI influence workplace dynamics, task division, and human-system interaction among IT professionals?

RQ4. What are the implications for education and IT professionals of integrating AI on their needs for professional development and developing new professional competencies?

5.1 AI Perceptions and Use - Academic and Practitioner Perspectives

An analysis of the results across the interview questions reveals several recurring themes and issues. For instance, the concept of *AI-based assistive tools* supporting the duties of IT professionals and software developers, highlighted in the academic literature (Section 2.2), is mirrored in the empirical data from the interviews (Section 4.1) under *Understanding AI and its Use in Practice.*

Practitioners viewed AI as a *support tool assisting* in their work, aligning with previous research that recognizes AI's role in assisting with complex tasks in daily life [64]. IT professionals shared their experiences, emphasizing AI's effectiveness in *generating content*—whether code or text. They also noted how AI supports broader work processes, such as custom models for local use cases (data analysis, data filtering), as well as vendor products for project management or automated transcription. This finding aligns with previous studies that show AI's potential for generating content, even among non-experts [65]. Furthermore, IT professionals mentioned more specific forms of *technology and process support*, like *Copilot* for code generation or proprietary solutions, such as local chatbots.

On a more critical note, both the academic literature and empirical data reveal concerns about the *explainability of AI assistants* and the *lack of transparency*, with responses suggesting uncertainty, even among IT professionals, about the extent to which AI is truly integrated into systems.

Reflecting the novelty of generative AI technologies, themes like *not used at this stage* or *outside work use* emerged, with practitioners distinguishing between *institutionally adopted AI tools for work* and *AI used primarily for personal interest.* Looking ahead, some professionals expressed skepticism about whether this *novel technologies* would remain distinct or simply become normalized within the broader set of everyday tools used in professional practice.

5.2 AI in the workplace – Human Considerations

The competencies required by IT professionals working with generative AI (genAI) technologies encompass multiple dimensions, including those related to product development, such as the design, creation, deployment, and maintenance of AI-based systems. These competencies involve specialized disciplinary knowledge and expertise to ensure product quality, integration, and the ability to identify improvement opportunities. On a broader level, professionals must develop knowledge to manage risks associated with the quality, safety, accuracy, and security of AI outputs. Awareness of legal, ethical, regulatory, and compliance issues is also critical in the responsible use of AI models and their outcomes.

Professional responsibility and continuous learning were prominent themes in the literature and practitioner interviews. As noted in the Data Lab personas discussed in Section 2.6.6, IT professionals are expected to demonstrate a strong commitment to ongoing learning, keeping pace with emerging AI technologies [105]. This expectation aligns with the long-established principles in the IEEE Computer Society and ACM Software Engineering Code of Ethics [43], which emphasize lifelong learning and ethical practices in the profession. The interviewees similarly agreed on the importance of ethics, privacy, and security when working with AI technologies. These findings echo the critical competencies outlined in the CC2020 framework, notably the professional disposition of being *Professional*, defined as acting with integrity, commitment, and dedication to the tasks at hand [39].

While practitioners acknowledged the need for learning in a fast-evolving field, they expressed mixed views on available training and professional development. Many reported a lack of formal training and recognized that much of their learning was driven by personal curiosity and the intrinsic motivation to stay updated, develop expertise, and remain competitive in the field. As such, organizational support for learning appeared to be limited, often relying on the self-directed learning and professional drive of employees.

In addition to professionalism, the competencies demanded by IT professionals working with genAI span technical skills such as *digital literacy* and *prompt engineering*, as well as more foundational skills in *analytical and critical thinking*. Both the literature and the interviewees emphasized the importance of responsible judgment and discretion when evaluating AI-generated information. As Prather et al. [93] and Azaiz et al. [5] have highlighted, critical thinking is essential to mitigate the risks of blindly accepting AI-generated content, underscoring the need for IT professionals to be discerning and self-directed in their professional development.

The study reveals that AI adoption in the workplace varies widely, from personal experimentation to full organizational commitment. While IT professionals are generally positive about the technology and the professional challenges it brings, they express a significant need for upskilling to meet the evolving demands of AI-driven roles. Concerns about AI technologies, such as privacy, security, transparency, and the potential for job displacement, were noted but were generally outweighed by enthusiasm and curiosity for learning. Notably, the environmental and intellectual property concerns surrounding AI were largely absent or muted, except in organizations where AI use was not yet sanctioned.

Key themes identified in the study include AI as an assistive tool, the need for transparency in AI systems, privacy and security issues, and the drive for increased productivity and efficiency. The study also highlighted the changing power dynamics in workplaces, the evolving need for new competencies, and the importance of frameworks and curriculum changes to meet the demands of AI technologies. The critical role of competency frameworks in guiding professional development and preparing IT professionals for an AI-driven environment was emphasized, along with the need for educational institutions to adapt their curricula to address these new challenges.

When examining the use and impact of AI in the workplace, along with the opportunities and challenges it presents, a broader range of themes emerged, building upon the earlier focus on AI technology and its applications. A key driver for AI adoption was the utilitarian-time rationale, with themes such as efficiency and productivity prominently featured. Respondents highlighted opportunities to *increase productivity, enhance efficiency, and reduce time spent on tasks.*

Drawing from the **SPACE** framework, as outlined by Ziegler et al. [112] and Forsgren et al. [36], which defines five dimensions of productivity—**Satisfaction and well-being**, **Performance**, **Activity**, **Communication and collaboration**, and **Efficiency and flow**—the interview data reflected some of these dimensions. For example, *Satisfaction and well-being* were evident in themes like *self-training driven by IT professionals' curiosity. Communication and collaboration* also surfaced, with subthemes discussing how *interacting with AI feels human-like*, as well as both *increased and decreased communication* with colleagues.

This suggests that balancing **Performance** and **Efficiency** with the human need for **Communication and collaboration**, as well as ensuring **Satisfaction and well-being**, will be critical in the conscious management of AI adoption in the workplace.

5.3 Professional Development and Competencies

By integrating insights from both the literature and interview data, the AI-related competencies required by IT professionals encompass both *product dimensions* – the issues associated with *the design, creation, deployment, and maintenance of AI-based systems* and *outcome* dimensions, which involve managing risks associated with the *quality, safety, accuracy, and security* of AI-generated results. These competencies include specialist disciplinary knowledge and expertise to ensure product quality, and integration and to take advantage of improvement opportunities. This also necessitated a strong awareness of legal, ethical, regulatory, and compliance duties relating to the responsible use of models and their outcomes.

The professional responsibility and earning theme emerged prominently in both competency frameworks and practitioners' perspectives. For example, the data lab personas cited in Section 2.6.6 highlight that *"They will demonstrate a strong commitment to continuous learning, and maintaining awareness of emerging AI technologies"* [105]. This emphasis on lifelong professional development has long been enshrined in the IEEE Computer Society and ACM Software Engineering Code of Ethics [43], which states: *"8. Self. Software engineers shall participate in lifelong learning regarding the practice of their profession and shall promote an ethical approach to the practice of the profession".* Ozkaya, the Editor in Chief of *IEEE Software*, more recently emphasized that avoiding an *"AI winter"* depends *"on our ability to practice software engineering and computer science through the highest level of ethics and responsible practices".* Practitioners interviewed echoed the importance of addressing ethics, privacy, and security concerns when working with AI technologies. Reflecting these demands, one of the critical CC2020 dispositions identified is being *Professional*, defined as ***"With Professionalism / Work ethic: Reflecting qualities connected with trained and skilled people: Acting honestly, with integrity, commitment, determination and dedication to what is required to achieve a task"*** [39].

However, regarding learning and professional development, practitioners expressed mixed opinions. While acknowledging the need to upskill in a rapidly evolving field, they reported challenges such as a lack of knowledge, time constraints, and varying motivations. Learning efforts were often driven by *IT professional interest and curiosity* or the desire *to stay updated, evaluate tools, and remain competitive.* Strategies varied, ranging from formal and informal training to self-directed learning or, in some cases, no structured training. This indicates that organizational support for professional development remains limited, relying heavily on individual initiative. Practitioners also emphasized the need for *development needs to be addressed* and the importance of *technically challenging work* [100] to maintain engagement.

In addition to professionalism, IT professionals working with genAI technologies and products require a diverse set of competencies. These range from technical skills, such as *"digital literacy"* and *"prompt engineering"*, to the *"professional and foundational knowledge"* outlined in CC2020 [35], particularly *"analytical and critical thinking".* Another essential disposition is being *"responsible"*, defined as ***"With Judgement / Discretion / Responsible / Rectitude: Reflecting on conditions and concerns, then acting according to what is appropriate to the situation. Making responsible assessments and taking actions using professional knowledge, experience, understanding, and common sense"*** [39]. This need is underscored in the literature. For instance, Prather et al. [93] found that the use of ChatGPT with novice programming students widened the gap between those who critically evaluate chatbot responses and those who uncritically accept them. Similarly, Azaiz et al. [5] highlighted the limitations of AI-generated feedback for novice programmers, noting that *"48 percent of the generated feedback is incomplete and/or not fully correct, containing incorrect classifications, redundancies, inconsistencies, or problematic explanations [...] To conclude, using GPT-4 Turbo for automatically generating feedback does not seem to be advisable".* One respondent, in discussing *critical thinking* (Section 4.3.2), emphasized the importance of *"Judgement evaluation, the credibility of information, and information sources".* Given the fast-paced nature of AI development, fostering self-directed learning [39] is another critical competency. The literature and interview data align in pointing to evolving frameworks that can guide competency development. Models such as the *data skills for work personas* [105], discussed in Section 2.6.6, offer a foundation for competency frameworks and curriculum innovation addressing AI-specific needs.

Key findings reveal that the adoption of genAI technologies ranges from personal experimentation to full institutional commitment. These technologies are reshaping job roles and professional practices, necessitating new competencies and significant upskilling among IT professionals. Respondents were generally positive about genAI's potential and were actively investing time in self-learning. Although some concerns were raised, enthusiastic perspectives were more prevalent than skeptical ones. For example, notable absences in the discussions included concerns about the environmental impact of large language models [16, 73] and muted concerns about intellectual property rights [21], except in organizations where genAI use was unsanctioned. The Canadian Government's recommendation for federal institutions to *"Verify the legality of the method used to obtain data for training AI models and make sure you have permission to use the data for this purpose"* [86] presents a challenging benchmark.

Additional issues, such as labor exploitation in LLM development, were not mentioned by respondents. As highlighted by [86], *"The development and quality assurance practices of some generative AI models have also been associated with socio-economic harms such as exploitative labor practices. For example, data-labeling or annotation requires extensive manual input, and this work is often outsourced to countries where workers are paid very low wages."* Recurring themes included AI as assisting humans, concerns over privacy and security, task-specific AI applications, lack of transparency in embedded AI technologies, productivity enhancement, intrinsic motivation to learn, legal issues, trust in black-box technology, workplace efficiency, collaboration, shifting power dynamics, evolving competencies, and curriculum changes. Specific to privacy concerns, the ACM's tech brief complements its principles for genAI [22], observing a significant challenge: *"Traditional approaches to anonymization, de-identification, and disclosure control fail to protect information at its current scale and are entirely unable to deal with new ways of utilizing information, such as generative AI"* [3].

This study underscores the critical role of competency frameworks in guiding professional development and ensuring preparedness for an AI-driven environment. It also highlights the pressing need for educational institutions to adapt curricula to meet these evolving demands.

6 Implications

As this study highlights, the integration of AI into workplace dynamics showcases a broad spectrum of impacts. Professionals' experiences vary significantly: some report transformative changes in their workflows, while the majority see little to no immediate effect. This disparity primarily stems from the differing stages of AI implementation across organizations. Early adopters tend to experience more significant disruptions and advancements, whereas those in the early stages of adoption may not yet perceive noticeable changes.

6.1 Implications for IT professionals' Competencies

6.1.1 Future-Proofing IT Careers: Embracing AI for Sustained Professional Relevance. To stay competitive in the evolving job market, IT professionals must commit to continuous skill development and knowledge enhancement to keep pace with advancements in AI. This demands a proactive approach to lifelong learning, enabling them to adapt to the new roles and responsibilities that AI technologies introduce. By staying informed and agile, professionals can effectively integrate AI into their workflows, harnessing its potential to enhance efficiency, innovation, and overall effectiveness in their practice.

6.1.2 AI Implementation Hurdles - Navigating Organizational barriers. The implementation of AI technologies often encounters significant organizational barriers, including the absence of clear AI strategies and insufficient managerial support. Addressing these challenges requires a balanced approach that combines top-down and bottom-up initiatives. A top-down approach, driven by senior management, is essential for setting a strategic vision, defining clear goals, and allocating the necessary resources for AI adoption. This leadership establishes a supportive culture that prioritizes AI integration as a core organizational objective. Conversely, a bottom-up approach leverages the creativity and initiative of employees and teams, encouraging experimentation with AI tools through pilot projects. These grassroots efforts can demonstrate tangible benefits, build internal expertise, and foster a sense of ownership among staff. By integrating both approaches, organizations can overcome barriers more effectively. Senior management provides the strategic framework and resource allocation, while employees' practical experimentation generates actionable insights and validates AI's value in real-world applications. This synergy ensures smoother AI adoption, accelerates its integration into workflows, and maximizes organizational benefits.

6.1.3 Impact on Workload and Stress Levels. AI has the potential to alleviate the burden of repetitive tasks, enabling employees to focus on more complex and meaningful responsibilities. However, this shift can also lead to heightened expectations and increased workloads, potentially straining employees. To harness the benefits of AI without compromising employee well-being, organizations must actively address these challenges by promoting balanced workloads and implementing strategies to prevent burnout.

6.1.4 Addressing Ethical and Security Concerns. AI adoption in the workplace introduces ethical and security challenges that IT professionals must adeptly manage. Navigating these complexities demands a thorough understanding of AI's broader implications and a strong adherence to ethical practices. Organizations play a critical role in this by embedding ethics and security as core components of their AI strategies, cultivating a culture of accountability and responsibility among employees. A coordinated top-down approach is essential, ensuring IT professionals have access to targeted training opportunities on ethics and security in the context of AI technologies. Such initiatives can help address reservations, mitigate concerns, and enable professionals to engage with AI confidently and responsibly.

6.2 Implications for Computing Education

As AI continues to reshape professional competencies, educational institutions must update their curricula to equip students with the necessary AI-related skills, knowledge, and dispositions. This ensures that future professionals are well-prepared to navigate the rapidly evolving technological landscape. Key updates should include the development of new modules focused on AI literacy, the integration of AI skills across disciplines, and fostering a mindset of self-directed learning. By emphasizing these areas, institutions can better prepare students to adapt to AI-driven changes and excel in their careers.

6.2.1 Prompt Engineering. Prompt engineering has emerged as a critical competence highlighted by IT professionals, who recognize that the quality of output generated by GenAI tools largely depends on the effectiveness of the prompts. This insight is supported by several studies [23, 27, 28]. For example, in a programming course, the success rate of students solving problems on their first attempt using Copilot was found to be less than 50%, with performance varying across different problem categories. However, with prompt engineering, success rates improved to varying degrees depending on the problem type. Notably, students who were most reliant on GenAI tools but lacked the skill to modify prompts after receiving incorrect code were found to struggle the most [66]. Another study [23] proposed a framework that encouraged programming students to learn autonomously through conversations with large language models (LLMs). The findings suggested that prompt engineering helped students develop computational thinking skills and exposed them to new programming constructs [28].

Given the fast-evolving nature of GenAI tools, prompt engineering should be considered a fundamental professional competence in computing education, as well as in other educational domains. It is tied to a range of other competencies, such as understanding the consequences of relying on GenAI-generated answers. The interviewees in our study seem to view their current professional competence as a safeguard, ensuring that the answers provided by AI tools are utilized correctly. Some studies have highlighted the educational implications of teaching prompt engineering in computing education. For instance, Shen et al. [101] suggested instructing students in prompt engineering techniques such as breaking tasks into smaller prompts, providing additional context, and eliminating unnecessary information. These strategies have been shown to improve the quality of code generated by AI tools, further underscoring the importance of prompt engineering in fostering both technical and cognitive skills.

6.2.2 Digital Literacy. Digital literacy encompasses a wide range of competencies, including an understanding of AI—how it functions, how to use it, its strengths and weaknesses, and its broader societal impacts. It is increasingly recognized as essential for AI-related components in digital literacy to be at an advanced level in computing education [14].

AI literacy is defined as a *"set of competencies that enable 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"* [77]. Similarly, Chiu et al. [17] defined AI literacy as *"an individual's ability to clearly explain how AI technologies work and impact society, as well as to use them ethically and responsibly and to effectively communicate and collaborate with them in any setting. It focuses on knowing (i.e. knowledge and skills)."* From both professional and academic perspectives, it is clear that understanding how AI technologies impact society should be an integral part of the education system. As the literature suggests, this understanding can help learners develop a sense of responsibility when using GenAI tools [62].

6.2.3 Sustainability. Very few professionals mentioned the implications of GenAI on the environment and sustainability, despite the growing concerns associated with its use. It is estimated that with 11 million requests per hour, AI systems produce 12.8k metric tons of carbon dioxide emissions annually [16]. Additionally, Li and colleagues have raised concerns about the substantial amount of water consumed to power AI's energy-intensive data centers [75], which contributes significantly to environmental impact. The gap between professionals' awareness and the environmental consequences of GenAI should be addressed. Reducing carbon dioxide emissions and water usage could be achieved through optimizing infrastructure [73] or by educating users to limit non-essential usage.

Ozkaya [89] has further observed concerns related to the carbon footprint, noting that *"Research in different training techniques, algorithmic efficiencies, and varying allocation of computing resources during training will likely increase. In addition, improved data collection and storage techniques are anticipated to eventually reduce the impact of LLMs on the environment, but development of such techniques is still in their early phases."* However, the primary focus of AI research has predominantly been on accuracy and efficiency, with environmental impact being a lower priority. As Strubel and colleagues reported: *"AAAI 2019 also held a computational sustainability track last year, comprising 0.4 percent of technical track papers."*

Raising awareness of sustainability is critical when learners use GenAI, as it ensures that this technology is applied responsibly and ethically. GenAI can consume significant computational resources, resulting in a substantial environmental impact due to the energy required for training and running these models. By understanding sustainability, learners can make informed decisions about how and when to use GenAI, opting for energy-efficient methods and optimizing processes to minimize waste. Moreover, this awareness encourages the development of AI solutions that prioritize environmental and social well-being.

6.2.4 Ethics, Privacy, and Security. It became clear that many IT professionals were in a "honeymoon" phase, viewing GenAI as the "shining new toy." Interviewees often had to be prompted to even consider ethical, privacy, and security issues. While we lack data on the educational backgrounds of the interviewees, we hypothesize that this reflects a gap in preparation for addressing these concerns. Literature suggests that ethical, privacy, and security aspects should be embedded in computer science (CS) curricula, as many CS students currently lack sufficient training in these areas [61, 63, 70]. To adequately prepare students to consider these issues, a holistic approach to ethics, privacy, and security is essential and should be integrated throughout the computing curriculum.

GenAI may become so ubiquitous that it exposes users to risks without them even being aware of it [8]. Developing a comprehensive framework for GenAI ethics education could address this issue. Nguyen et al. [83] examined ethical guidelines and reports from international organizations and identified seven principles related to GenAI in education: governance and stewardship, transparency and accountability, sustainability and proportionality, privacy, security and safety, inclusiveness, and human-centered GenAI education. These principles should be considered when designing discipline-specific or interdisciplinary frameworks for integrating GenAI ethics into educational programs.

6.2.5 Self-directed. In the interviews, it became evident that most IT professionals had to rely on self-directed learning methods. This approach highlights a common necessity in the fast-evolving field of computing. Our study underscores that the ability to upskill and enhance one's professional competencies should be viewed as an essential learning objective in computing education.

Prasad and Sane [92] proposed a framework for designing interventions that promote self-regulation and problem-solving in learners. The behaviors associated with being self-directed, such as critical self-assessment, proactive planning, self-review against guidelines and goals, successful problem-solving, and the effective use of external resources, are not always consistently demonstrated by students [67]. Therefore, further research is needed to understand how to support students in developing and applying dispositions like self-direction in their learning processes.

6.2.6 From Coding to Critical Thinking: Evolving Skills for the AI Era. Novice learners in programming often encounter various metacognitive challenges. If GenAI tools end up replacing critical thinking in programming problem-solving rather than supporting it, these metacognitive difficulties could be exacerbated, as highlighted by Prather et al. [93]. Some students perceive that ChatGPT enhances their critical thinking skills, rather than replacing them [93], though data suggests that this is not always the case. The misconceptions that form while interacting with GenAI tools can further deepen the metacognitive challenges faced by novice learners, widening the gap between students who are on track for success and those who are already struggling [93].

While traditional coding skills remain crucial, there is an increasing emphasis on cultivating higher-order thinking skills, such as critical analysis, problem-solving, and the ability to evaluate AI-generated outputs. This shift reflects the growing need for graduates not only to use AI tools, but also to understand, critique, and validate the results they produce.

6.2.7 Interdisciplinary Approach. The varied impacts of AI on workplace dynamics underscore the importance of adopting an interdisciplinary approach in computing education. Students should be introduced to concepts from business, psychology, and organizational behavior to gain a deeper understanding of the broader implications of AI integration. Such a holistic education will better equip them to navigate the complex environments where AI technologies are deployed.

The value of an interdisciplinary approach is highlighted by insights from many of the interviewees, who mentioned that they are now engaging in areas where they previously needed to consult with others. This shift has two key aspects: first, they may become overly reliant on the capabilities of AI, and second, they may develop a broader interest in the bigger picture. Both aspects have important implications for education, particularly in terms of cultivating the ability to navigate complex environments. Additionally, it emphasizes the need for students to develop the skills necessary for constructive collaboration across disciplines, especially when leveraging AI as a tool for interdisciplinary work.

7 Limitations

This study has several limitations that should be acknowledged. Firstly, the use of AI among IT professionals is still relatively immature. The rapid evolution of AI technologies means that the landscape is continually changing, and professionals' experiences and perceptions today may differ significantly in the near future.

Secondly, while diverse, the 47-person sample size may not fully capture the wide range of experiences and challenges faced by IT professionals globally. The participants were primarily based in New Zealand and Sweden, which may limit the findings' applicability to other regions with different technological, cultural, and organizational contexts.

Thirdly, the study's structuring of analysts into sub-groups of authors may have influenced the findings. By dividing analysts into sub-groups focused on specific questions or themes, there is a potential risk of creating silos in the data interpretation process. This segmentation might have led to fragmented insights and reduced the holistic understanding of the data, affecting the comprehensiveness of the findings.

Fourthly, using purposeful and snowball sampling techniques could introduce bias. While useful for targeting specific groups, purposeful sampling may limit the generalizability of the findings as it does not provide a random or representative sample of the broader population of IT professionals. Snowball sampling may lead to a less diverse sample as participants are likely to refer individuals within their networks who may share similar views and experiences. Nonetheless the set of respondents cover a broad range of roles recognised within the SFIA framework [99], with some 22 roles represented, and concentrations in the software developer and more senior team leading and User Experience profiles, plus digital consultant which gives confidence that the results present a balanced view of IT professional perspectives.

Lastly, the study's reliance on self-reported interview data introduces the potential for bias. Participants' responses may be influenced by their desire to present themselves in a particular light, which can affect the accuracy and objectivity of the reported data.

8 Future Work

To build upon the findings of this study, several avenues for future research are proposed:

(1) Personas: Developing detailed personas based on the diverse experiences and profiles of IT professionals will provide deeper insights into how different groups interact with AI. These personas can help tailor AI training programs and tools to meet the specific needs of various user segments better.
(2) Evaluate the findings of the interviews with respect to the AI Skills for Business Competency Framework from the UK [59]
(3) Influence of Country, Organization Size, and Experience: Further analysis will explore how factors such as country, organization size, and the level of IT or AI experience influence the use and acceptance of AI. Understanding these dynamics can help organizations and educational institutions tailor their approaches to different contexts and backgrounds.
(4) Longitudinal Follow-Up Study: A follow-up longitudinal study will track changes over time, providing insights into how AI adoption and its impacts evolve. This will help identify long-term trends, benefits, and challenges, offering a more comprehensive view of AI's role in the IT profession.
(5) Investigating Work Engagement: Identifying effective strategies to support employees in adapting to AI-driven changes with a special focus on work engagement

9 Conclusion

GenAI technologies have promised significantly enhanced efficiency and productivity in IT work environments through automation and intelligent tools. However, the extent of these changes is heterogeneous across different professional contexts, with some practitioners experiencing more substantial transformations than others.

The pervasive adoption of AI mandates a comprehensive shift in the competencies required of IT professionals. There is an emergent demand for expertise in GenAI-related technologies, including machine learning, natural language processing, and data analytics. Complementing this computing knowledge are a need for increased digital literacy and expertise in prompt engineering. Furthermore, professional knowledge, skills and dispositions ranging from critical thinking, being self-directed, having problem-solving skills and judgment, to an acute awareness of ethical, privacy, and security issues have become indispensable.

Incorporating GenAI has redefined workplace dynamics, potentially fostering a dichotomy between AI-adept and non-AI-adept professionals. This schism could engender shifts in organizational power structures, affording those proficient in AI a distinct competitive advantage.

Despite GenAI's clear benefits in enhancing efficiency and automating tasks, several challenges remain. These include the risk of biased decision making with resultant harm, time wastage due to inaccurate GenAI outputs, and the imperative for ongoing education to keep pace with rapid technological advancements.

This study emphasizes the critical need for continuous professional development. IT professionals must engage in formal and informal training regimes and self-directed learning to sustain their relevance in a rapidly evolving professional landscape.

9.1 Contributions of This Report

This report has studied the fast-moving landscape of emerging technologies and tools associated with GenAI. It presents a snapshot from mid-2024 of the adoption of GenAI technologies, and the perceptions and experiences of a set of IT Professionals in the two *small advanced economies*[47] of New Zealand and Sweden involved in the adaptation of their work practices. Complementing this set of 47 interviews, have been systematic and multi-vocal literature reviews, to establish what evidence exists within the academic and grey literature that current AI competencies capture and reflect the needs of professional practice in the Computing and IT industry. Overall the report provides an empirical picture of evolving practice in the field of GenAI as an emerging technology and an accompanying critical analysis. So the report is grounded in the realities of practitioners occupying diverse roles within the *Information Technology Industry* [32], complemented by a research-based investigation. Of course, the advent of emerging technologies in the IT industry is not new, and as the SFIA foundation has observed *"Over the years, from SFIA v1 to SFIA v8, the lifecycle of new technologies and working practices has been observed. SFIA's regular updates have allowed for niche skills to evolve from specialist areas to more generic skills, eventually breaking down into more granular and focused activities within broader skill areas".* [37]. So recognising this typical process of evolution from novel technology to adaptation, it is intended that the report will provide a useful resource for educators, practitioners and policymakers and chart the way for future research and developments in practice.

Acknowledgments

The AFA funded project Work engagement in automation, robotics and AI (AROA, dnr 220244).and the Uppsala University Strategic Activities Fund for EDU-AI are gratefully acknowledged, as are the contribution of the interviewees from each country.

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