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Artificial Intelligence and the Evolution of Skills

Skills needed for information systems development

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Artificial Intelligence and the Evolution of Skills: Skills needed for information systems development

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ABSTRACT:
This master thesis investigates the evolving skills required for Information Systems Development (ISD) in the context of increasing integration of Artificial Intelligence (AI). Utilizing a mixed-methods approach, the study combines quantitative analysis of job advertisements with qualitative insights from interviews with ISD managers. The job advertisements, sourced from the Swedish market, focus on roles relevant to system development, while the interviews provide deeper perspectives on AI's impact on skill requirements. The findings reveal that AI acts both as a facilitator and disruptor within ISD. AI tools automate routine coding tasks, shifting the focus towards more analytical and integrative roles, but also raise concerns about potential deskilling, particularly among junior developers. Job advertisements indicate a growing demand for AI-related skills such as data management, machine learning, and design, alongside essential programming skills like Python and Java. Additionally, the study emphasizes the increasing importance of soft skills, such as adaptability, communication, and problem-solving, in an AI-driven job market. This research contributes to the field by highlighting the need for continuous learning and adaptation and by identifying emerging roles in ISD driven by AI advancements.

AI Contribution statement:

OpenAI Whisper was used for the transcription of interviews and ChatGPT was used to summarize research articles. Quotes from these were used in the prior research chapter. ChatGPT was also used to generate Python code used in handling the data in the quantitative part of the study, as described in section 3.3.

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1 Introduction

This chapter introduces the area of inquiry through sub sections background, problem area and the research questions, purpose and delimitations.

1.1 Background

The rise of artificial intelligence (AI) in the 21st century has transitioned from symbolic AI to data-driven approaches, including neural networks and deep learning (Jarrahi, 2018). As technology evolves, the focus has shifted towards human-AI symbiosis, where AI enhances human decision-making rather than replacing it (Jarrahi, 2018; Cabrero-Daniel, Fazelidehkordi & Nouri, 2024). This transformation is significantly impacting the workplace, presenting both opportunities and challenges across various industries (Agrawal, Gans, & Goldfarb, 2022).

Adapting to this new reality involves upskilling by learning how to use AI tools and developing expertise in AI-related fields. This is crucial for both individuals and businesses to remain competitive in an AI-driven market (Agrawal, Gans, & Goldfarb, 2022). Tools like ChatGPT from OpenAI can generate text, answer questions, and assist with coding (Agrawal, Gans, & Goldfarb, 2022). Benbya and McKelvey (2006) explain that software systems are emergent entities, highlighting that building software is a complex and evolving venture requiring agile adaptations to new realities as new requirements emerge. They emphasize that developers can dynamically expand these systems by iterating on requirements through deep involvement in the processes of gathering them. According to Riemenschneider and Armstrong (2021), Information systems (IS) developers are defined by their involvement in dynamic and demanding work where things constantly shift. Lee and Truex (2021) agree, adding that the developer's experience significantly impacts how they handle different modes of thinking.

Assyne, Ghanbari, and Pulkkinen (2022) categorize competencies into hard and soft skills. They define soft competencies as the ability to empathize with others in context and hard competencies as technical skills and knowledge. They also assert that education lags behind industry in meeting Software Engineering requirements. Educational institutions face challenges in adapting to these changes. They must balance the need to provide a broad education that includes fundamental technical skills while also incorporating emerging technologies (Niederman, Ferratt & Trauth, 2016).

The cyclical nature of technological innovation has influenced the skill sets required by IS developers. Each new wave of technology introduces new technical skills, followed by skills needed to build user-friendly interfaces, and eventually, skills to develop applications leveraging these technologies for organizational goals (Niederman et al., 2016). Technology companies are increasingly facing a shortage of necessary skills (Ebert & Hemel, 2023). This deficiency is exacerbated by the rapid pace of technological change. Without the right competencies, companies encounter quality issues and struggle to deliver innovative solutions, resulting in a competitive disadvantage.

1.2 Problem area

The field of information system development (ISD) is evolving over time. Earlier research (Gallivan, Truex & Kvasny, 2004; Niederman et al. 2016; Acemoglu & Restrepo, 2018) have observed that new technologies affect what kind of skills are needed for system development. The demand for different software languages evolve over time and breakthroughs in technological research opens up new opportunities for businesses.

Inadequate competencies is the primary short-term and midterm challenge for technology companies (Ebert & Hemel, 2023). This gap affects innovation and competitiveness, exacerbated by rapid technological changes such as the rise of generative AI and low-code practices. This is a problem as the implementation of AI systems requires team members to have a variety of skills, from technical, to interpersonal, to managerial (Ebert & Hemel, 2023; Merhi, 2023). Niederman et al. (2016) observed that technological innovation required highly specialized technical skills initially. But over time, as the technology matured, there was a growing emphasis on creating user-friendly interfaces that shielded end users from the technical complexities.

While AI in software development brings novelty and creativity to the work, it also introduces significant technical challenges, such as hallucinations where the model generates incorrect or fictitious output that appears plausible (Fan et al., 2023). This is particularly problematic in software engineering, where such outputs can introduce bugs and errors in software systems. Cabrero-Daniel et al. (2024) emphasize the importance of contextual understanding, domain knowledge, and human oversight in integrating generative AI within the software management pipeline. Artificial intelligence as it is used within the field of ISD implies a variety of different technologies based on machine learning code. The introduction of the ML algorithms in the firm's data analysis enables the processing of larger data sets and more timely analyses. However, this shift also required the development of new skills and roles, particularly in data science and algorithm management (Grønsund & Aanestad, 2020; Shollo et al., 2022). The adoption of AI tools is characterized by significant changes in skill demands, as some previously sought skills become obsolete while new skills emerge (Acemoglu et al., 2022).

There have been studies of the effects of AI on the job market, but they are generally focused on the US market and are several years old at this point (Acemoglu et al., 2022; Alekseeva et al., 2021; Montandon et al., 2021). Similarly to the work of Montandon et al. (2021), this master thesis focuses on the dynamic demand of different soft and hard skills for system developers. The increasing prevalence of AI in system development necessitates a thorough understanding of the evolving skill sets required in the industry. As AI technologies continue to integrate into various aspects of system development, from coding to project management, the specific competencies in demand are shifting (Acemoglu et al., 2022).

Understanding these dynamic skill's requirements is crucial for policymakers, educators, and industry leaders to make informed decisions about education and training. This alignment will not only enhance the employability of developers but also boost innovation and productivity in the field of information system development.

1.3 Research questions

In order to identify skills presently in demand this study aims to answer the following research questions:

Q1: How do ISD managers view the effects of AI on the required skills of IS developers?

Q2: What skills are associated with AI in ISD job advertisements?

Q3: How are the required skills for IS developers affected by AI?

1.4 Purpose

This study aims to identify how the skills that firms look for when hiring IS developers are affected by the development of artificial intelligence. This will be done through a mixed methodology. One part consists of interviews with ISD managers from Swedish firms. The second part being the study of job advertisements for ISD positions, looking at the soft and hard skills mentioned in the texts. The analysis of the collected data will focus on the changing characteristics of IS developers.

1.5 Delimitations

The scope of this master thesis focuses on identifying the impact of AI on the skills required for IS developers. This master thesis does not go into the specific phases of ISD or the distinct roles developers play within these phases. Instead, it broadly addresses the changing skill demands without granular examination of each ISD phase and role.

The study predominantly focuses on the effects of AI on the skills demanded from IS developers, particularly through the analysis of job advertisements and interviews with ISD managers. This approach does not encompass the full spectrum of skills required across different contexts and industries. The emphasis on job ads from the Swedish market may not capture global trends and variations in skill requirements. The dynamic landscape of AI also means that skill requirements can change swiftly, and this study provides a snapshot rather than a comprehensive longitudinal analysis.

2 Prior research

This chapter discusses prior research in the areas of IS/IT skills, hard and soft skills, ISD and Software Engineering Teams and AI as a disruptor in knowledge work.

2.1 ISD and software engineering teams

Hassan and Mathiassen (2018) define Information Systems Development (ISD) as "The integrated social and technical practices of conceptualizing and realizing information technology-based systems, and managing the associated changes and implications to accomplish specific goals in organizational contexts.“ (Hassan & Mathiassen, 2018, p.178) which they view as concentrated on the construction of the Information System. They describe ISD as being an iterative process with more social and organizational focus, where different roles within a team, working together in developing a system to fit with the different aspects of organizational demands.

Taking the socio-technical view of ISD Benbya and McKelvey (2006) emphasizes the reduction of complexity to allow for changes of the system. They posit that change is a constant, the requirements change based on the environment such as business systems alignment. They liken the design of an information system to an ongoing process and requires ease restructuring the system which they achieve through modular design principles.

In ISD Windeler, Maruping and Venkatesh (2017) posit that developers perform best when they are well hence stress is an important factor for developers. They explain that clear leadership helps with creating order among all the complexity and multifaceted tasks developers perform, complexity which can cause stress. They present that clarity about their role and responsibilities in their work is important as with feeling in control they feel less stressed. They say that avoiding unclear organizational hierarchies is beneficial for developers but the leadership should be attentive to these developers' concerns and to allow developers to take part in decision making which may also help them deal with situations better as they can reason about issues in a different and adaptive way.

Rezvani and Khosravi (2019) introduces the concept of stress, emotional intelligence and trust and that they are all important components when it comes to an efficient ISD team. They also say that a clear workload that is manageable and planned as well as IS developers are understood and developers can rely on each other. They pose that the work environment of IS developers is highly dynamic where they have to take on various roles with blurry lines and to have to use a wide variety of skill sets to fulfill these requirements. They state that stress resistance and emotional intelligence makes it easier to understand colleagues. This aids in forming trust and to communicate. This further strengthens the ability to handle the dynamic environments that developers find themselves in. Rezvani and Khosravi (2019) mean that the mentioned aspects increase performance as teamwork becomes more efficient, providing clarity of task leading to less stress.

Tiwana and McLean (2005) presents how expertise can be integrated into a team, meaning that it is not enough to add experienced IS developers but that the expertise must be made part of the group. They mean that ISD team members with similar technical and domain expertise coming from similarities of tacit and explicit knowledge understand each other well as with different forms of expertise and role background may think differently about the same topic or even have prejudices against them, if these aspects of variance between ISD team members can be overcome people with different backgrounds and heterogeneous expertise may complement each other creating opportunity for creativity.

According to Licorish and MacDonell (2017) the efficiency of development tasks performed comes down to how software tasks are resolved by the teams, how they work and communicate and structure themselves to meet dynamic demands and integrate other IS developers in the work done. This is in contrast to their observation that certain tasks require quite different structures, skills and interaction to solve depending on the situation. Further, they find that the same people solving software bugs were more collaborative and talked more and were at the same time proficient in developing new software quicker as it is a communication intensive task to create new solutions.

2.2 IS/IT skills

For programmers from the IS discipline in the 1990s, Todd, McKeen and Gallupe (1995) explains that IS developers need both technical skills and soft skills although soft skills have increased in importance. Akman and Turhan (2018) agree that both soft and hard Skills depend on the context they are used in. There is a need to deal with a growing and more specific quality set of requirements on IS developers (Montandon et al., 2021). In their paper, Lee and Mirchandani (2010) explains that things are in an ongoing change in IT and that their study is relevant to its time. They say that IS has undergone changes in the areas of focus, over time the complexity of IT has grown and different IT trends and methodology paradigms have emerged. Aasheim, Williams and Butler (2009) finds that while needing social soft Skills, especially junior developers, need a wide technical background with many different technologies, juniors do not need business level skills or such skills like leadership within their cohort. Other roles, such as requirement analysts, need more soft skills in order to fill their role in the development process (Klendauer et al., 2012).

2.2.1 Hard skills

Some hard skills relevant for development jobs were “programming languages, libraries and frameworks” (Montandon et al., 2021, p.4). Todd, McKeen and Gallupe (1995) say that developers need to know has become wider and more specific as technology has developed, so when the article was written a variety of technical skills in certain areas was asked for. Lee and Mirchandani (2010) give an example where the language of C has diminished while mobile and web technologies have increased in prominence as hard skills needed. They say that except for web and mobile technologies, the authors propose that hard skills such as C programming languages are still relevant along with databases and systems design as they are still represented.

Changing an already known skill set is difficult. As Armstrong and Hardgrave (2007) states, in their paper on the topic of transitioning between programming paradigms, changing your thinking is harder than continuing improving with similar skills. They pose that two similar but different programming languages may be confusing to a developer, needing what they call a mindshift to reframe their understanding.

2.2.2 Soft skills

Borges and Gratão de Souza (2024) states that the need for soft skills is large within Software Engineering, so further development and education of IS developers is important as they facilitate the development of systems. In their study Aghaee and Karunaratne (2023) find that the new work force coming out of academia does not have the soft skills asked for by the market leading to a poorly equipped workforce and there is also a lack of understanding what soft skills are among this emerging workforce. Furthermore, Aghaee and Karunaratne (2023) find that students do not know what soft skills are or how to improve them. They mean that defining soft skills is difficult as it contains a plethora of attributes and traits relating to the person's character and their ability to interact and handle tasks towards solving issues within a context of social constraints.

Neufeld and Haggerty (2001) in their work define the importance of the performance of teams and the learning that working in teams can provide, through deeper introspective about their activities, team skills are important to facilitate this. The effective use of soft skills when developing Information Systems is of high importance for in the case of communication where on one side conveying ideas as well as information and on the other to gain compliance from different stakeholders (Galster et al., 2023). For negotiation and ease of teaching "... Software Engineering programs tend to emphasize communication and team skill …" (Galster et al., 2023, p.12). Akman and Turhan (2018) present different soft skills expected from new graduates, skills that facilitate communication are important, languages such as English to communicate and be able to use the same language for the profession to communicate efficiently, time management are important along with cooperation, adaptability and ability to work together as a teamwork setting. Ford et al. (2021) observed that communication and collaboration skills also became more critical as developers had to rely entirely on digital communication tools during the covid-19 pandemic.

Aasheim, Williams and Butler (2009) say that communication, creative thinking, analytical ability, problem solving, teamwork and "... interpersonal and personal skills/traits ..." (Aasheim, Williams & Butler, 2009, p.51) are important, after these come technical skills, these skill sets are both encouraged to be improved when possible. They discuss the need for "honesty/integrity" (Aasheim, Williams & Butler, 2009, p.52), a personal value but important for what they say are ethical and legal reasons. Some less critical soft skills are, according to Akman and Turhan (2018), problem solving and leadership. This is because they are not expected from entry level developers. Some soft skills mentioned in the literature are communication (Todd, McKeen & Gallupe, 1995; Montandon et al., 2021; Lee & Mirchandani, 2010, Lee & Mirchandani, 2010), problem solving (Todd, McKeen & Gallupe, 1995; Montandon et al., 2021), collaboration (Todd, McKeen & Gallupe, 1995) and interpersonal (Lee & Mirchandani, 2010; Aasheim, Williams & Butler, 2009; Borges and Gratão de Souza, 2024), creativity (Aasheim, Williams & Butler, 2009; Borges & Gratão de Souza, 2024; Juárez-Ramírez, et al., 2022), emotional intelligence (Juarez-Ramirez et al., 2022), critical thinking (Juarez-Ramirez et al., 2022; Borges & Gratão de Souza, 2024), leadership (Borges & Gratão de Souza, 2024; Montandon et al., 2021) and judgment and decision making (Juarez-Ramirez et al., 2022).

2.2.3 Entry level skills

A number of studies have been conducted on the relation between IS curricula and the job market expectations of junior system developers (Mardis et al., 2017; Burns et al., 2018; Steen & Pierce, 2023). Mardis et al. (2018) compared university programs with ACM/IEEE curriculum guidelines. They argue that employers value soft skills like critical thinking, problem solving, teamwork, and communication. But these skills were rarely seen as learning outcomes in the programs analyzed. In their analysis of job advertisements, Mardis et al. (2018) observed that technical competencies such as system integration and architecture, programming fundamentals, and systems administration were frequently mentioned.

Burns et al. (2018) similarly compared the alignment between the knowledge and skills required by employers of recent graduates from undergraduate Information Systems (IS) programs and the current ACM/AIS Information Systems Curriculum Guidelines. The research highlights that soft skills are highly valued by employers such as problem-solving and teamwork. Furthermore, two-thirds of the job listings emphasized the need for excellent written and oral communication skills. When comparing these findings with the 2010 ACM/AIS IS curriculum guidelines, it becomes apparent that the curriculum is more focused on specific hard skills, while employers are looking for a broader range of soft skills and general technical competencies.

Steen and Pierce (2023) compared the IS 2010 Curriculum Guidelines, the IS2020 Competency Model, and employer expectations as expressed in Swedish IS job advertisements. The job ads underscore the critical importance of soft skills, with traits such as being communicative, cooperative, and proficient in Swedish and English being highly valued. These traits are mentioned in nearly all job ads. Technical skills remain a core requirement, with a particular focus on cloud infrastructure, operating systems, and software development tools such as Docker, Jira, and Git. These areas align with the IS2020 report's emphasis on emerging technologies and development competencies. Programming skills are consistently important. However, the depth and specificity of programming knowledge expected by employers are not as comprehensive as the requirements outlined in the IS2020 Competency Model.

Other studies focus more on the skills demanded by employers. Litecky et al. (2004) studied the hiring process for Information Systems positions, focusing on the demand for both technical skills, as advertised, and soft skills, which are often crucial in the final hiring decisions. The study's survey of IS managers revealed that while technical skills are necessary, people-oriented and organizational skills are more valued in practice.

Technical skills remain a critical component in both the IS and Data Analytics job markets. Litecky, Igou & Aken (2012) emphasize the need for technical knowledge in MIS, with a significant focus on security, testing, and programming. They studied the skills demanded in the Management Information Systems (MIS) job market, utilizing data mining techniques to analyze U.S. job advertisements. They observed a relatively lower demand for specific programming skills, compared to general IT positions, suggesting that MIS professionals are expected to have a foundational understanding of programming concepts rather than specialized programming expertise (Litecky et al., 2012). Similarly, Dong and Triche (2020) identify a robust demand for proficiency in tools like Python, Tableau, and R among entry-level data analysts, highlighting the importance of these skills for data visualization and analysis.

In contrast, Jones, Leonard, and Lang (2018) note that while technical skills are necessary, they are often secondary to soft skills for entry-level IS positions. The most commonly required technical skills are basic proficiency in Microsoft Office and foundational knowledge in database management and SQL, which aligns with the findings of Litecky et al. (2012) regarding the consistent demand for general technical competencies.

Business skills are particularly emphasized in the MIS job market. Litecky et al. (2012) report that managing/supervision skills, project management, and customer support are among the top requirements, indicating a strong need for IS developers to possess a solid understanding of business operations and project management principles. Goles, Hawk, and Kaiser (2007) further support this by highlighting that while for entry-level employees, technical skills such as programming and system testing are still important, there is also a strong emphasis on communication and project management skills. This suggests that even new hires are expected to have a well-rounded skill set that includes both technical proficiency and the ability to interact effectively with clients.

Neufeld and Haggerty (2001) present the perspective that even though individual skills matter in this as to work as a team you need interpersonal and collaborative skills, something that can be missing in formal training of new graduates entering the job market. According to Aasheim, Williams and Butler (2009) the IT field is growing in both width and need for IS developers, but new graduates are lacking in some relevant skills which increases the need for internships. Akman and Turhan (2018) talks about new graduates' skills expectations within the team, on their own, and that while both are important, individuals make up and are components of the teams that they are part of so there is an inherent dependency between the two from the team to the individual.

The longitudinal analysis by Dong and Triche (2020) reveals significant trends in the data analytics job market, such as the increasing demand for skills in Python, Tableau, and R, while older technologies like Microsoft Access and Cognos decline in popularity. This trend underscores the rapid evolution of technological requirements and the need for continuous skill development to stay relevant in the field. Similarly, Goles, Hawk and Kaiser (2007) and Litecky et al. (2012) highlight the shifting landscape of required skills, suggesting that both IS and data analytics professionals need to adapt to new tools and methodologies continually. The studies collectively emphasize the importance of aligning academic curricula with industry trends to prepare graduates for the challenges of the modern job market.

The study conducted by Kennan et al. (2007) involved a content analysis of job advertisements to determine the knowledge, skills, and competencies required for early career Information Systems graduates. The results revealed a significant demand for both technical knowledge and communication skills. In terms of qualifications and experience, two-thirds of the ads specified a requirement for academic qualifications, while almost half sought candidates with some experience in IS work. This requirement for experience, even for positions aimed at recent graduates, underscores the importance of practical, hands-on experience in addition to formal education.

2.3 Artificial intelligence

2.3.1 Defining artificial intelligence

Artificial intelligence (AI) can be defined as systems that imitate cognitive tasks and decisions originally completed by humans (Mehri, 2023). Opportunities for AI are immense, particularly in enhancing productivity and creating new forms of work that focus on human-AI collaboration (Dwivedi et al., 2021).

Generative AI is a type of artificial intelligence that can generate various forms of content such as text, images and audio based on input data (Cabrero-Daniel et al., 2024). This AI utilizes large language models (LLMs), which are self-supervised deep-learning algorithms trained on extensive datasets. LLMs are typically based on architectures such as transformers, which utilize mechanisms like self-attention to capture relationships between words and contextual information within the text (Fan et al., 2023). AI systems can independently interpret and learn from external data to achieve specific outcomes through flexible adaptation (Dwivedi et al., 2021). One major issue however is the potential for unauthorized access to user conversations and data breaches (Gupta et al., 2023).

LLMs are trained on extensive datasets that encompass a broad range of textual data, enabling them to perform various language-related tasks (Fan et al., 2023). Their application in specific fields such as software engineering highlights challenges such as hallucination, where models produce incorrect but plausible outputs. Addressing these challenges requires robust evaluation techniques according to Fan et al. (2023). From a legal standpoint, the use of GenAI tools raises issues related to data protection laws and regulations (Gupta et al., 2023). Dwivedi et al. (2021) also notes that AI's rapid development often outpaces society's ability to adapt, leading to issues like algorithmic bias and lacking transparency and accountability.

While there are many different AI alternatives such as Natural Language Processing and Expert Systems, the most common type of AI methods used in studies is Machine Learning (ML) (Collins et al., 2021). Machine learning can be defined as the ability of computer-based applications to automatically detect patterns in data and to act without explicitly being programmed (Borges et al., 2021). This capability enables systems to acquire their own knowledge from the data, allowing them to make decisions and predictions autonomously.

Shollo et al. (2022) identified three distinct mechanisms through which organizations create value using ML. The first, knowledge creation, focuses on generating models that offer descriptions and explanations, heavily reliant on human interpretation. The second, task augmentation, enhances human tasks with predictive and prescriptive functions, varying in the degree of human involvement. Third, autonomous agents, automates tasks entirely based on algorithmic prescriptions. To successfully implement these mechanisms, organizations need strong data science capabilities and deep domain knowledge (Shollo et al., 2022).

Cabrero-Daniel et al. (2024) emphasizes that while AI tools can assist in routine and analytical tasks, complex decision-making still requires human intervention. This is due to AI's limitations in understanding nuanced contexts and making ethical decisions. While Jarrahi (2018) also believes that AI is best suited for routine tasks, they believe that creative holistic thinking is more suitable for humans. Jarrahi (2018) motivates it as not believing that machines are good decision makers as a long term solution. They believe that since decisions need to be made on all levels in the organization by different people, AI is an ill fit in the role. They reiterate that human domain experts should be adapted or trained to use AI by learning how to use it efficiently.

2.3.2 AI assisted work

Humans use machines to enhance themselves, Fügener et al. (2021) discusses how complementarities between humans and AI can in a similar vein lead to synergetic relationships where the whole is larger than the sum of the parts thereby enhancing human ability. Jain, Padmanabhan, Pavlou & Raghu (2021) posits that combining different types of human and AI logic in a way that complement human abilities, enhancing capabilities and competitive advantage of the firm. They suggest that these impacts could be positive to employment as opposed to more routine work that may be automated. This automation is one type of value generation which Mikalef and Gupta (2021) also believes they are well suited for. Potentially however, users might become less innovative if the knowledge work is outsourced to AI (Fügener et al., 2021).

Bucaioni, Ekedahl, Helander and Nguyen (2024) conducted a number of experiments comparing ChatGPT with human programmers. They conclude that while ChatGPT shows potential as a programming assistant, especially for simpler tasks, it cannot yet replace human programmers for more complex problems. When comparing the AI generated solutions to those by human programmers, the study found that ChatGPT's code was generally less efficient.

Human-AI collaboration in software management involves leveraging AI's capabilities to augment human decision-making processes, thereby enhancing efficiency (Cabrero-Daniel et al., 2024). Laato et al. (2023) found that automation is expected to increase in both software development practices and the systems being developed, emphasizing the creation of scalable software from the start. Developers are likely to work higher on the software stack and focus more on automated tests. Ebert and Louridas (2023) notes that the integration of generative AI into software development must be managed carefully to avoid risks of security breaches and the spread of false information.

AI can be trained continuously to improve its understanding of real-world scenarios, much like training a human colleague (Cabrero-Daniel et al., 2024). This iterative learning process can help AI tools become more adept at handling specific tasks within Agile development workflows (Cabrero-Daniel et al., 2024). Over time, IS developers also develop tools and routines that further simplify technology usage, effectively lowering the barrier for non-technical users (Niederman et al. 2016).

Grønsund and Aanestad (2020) describes a human-machine work configuration called human-in-the-loop, where human experts monitor outputs of AI to make sense of them, guide them and to take accountability for outputs ensuring that it meets requirements. Human-AI collaboration involves integrating AI's computational power with human creativity and decision-making abilities. AI can augment human capabilities by handling repetitive and data-intensive tasks, allowing humans to focus on higher-level cognitive functions such as problem-solving and emotional intelligence (Dwivedi et al., 2021). AI enhances creativity by freeing up human resources from manual tasks, allowing them to engage in innovative activities (Mikalef & Gupta, 2021).

2.3.3 AI skill-gap

Based on a survey of nearly 3,000 industry professionals, Ebert and Hemel (2023) identified inadequate competencies as a primary concern for the technology industry. They argue further that the pandemic intensified these issues, as companies cut training budgets, resulting in a decline in essential skills. A potential mismatch between skills and technologies also has negative effects on productivity (Acemoglu & Restrepo, 2018).

Xue et al. (2022) talks about how AI will affect companies' need for certain skills. They pose that a big shift in skills and knowledge from educated staff is coming as AI allows for higher skilled work to be done by lower skilled IS developers through AI aided work meaning that education is less needed for the same jobs also termed as deskilling. They say that consequences of the integration of AI will mean that tasks change composition and that some reskilling or upskilling will be needed to adapt to these changes, there to produce an adaptive and learning workforce to stay relevant. Main barriers for implementing AI tools have been identified to be hindering company culture and lacking relevant developer skills (Laato, et al., 2023).

New technological innovation triggers a cycle where initial high technical skill demands gradually diminish as technology becomes more user-friendly. This process, referred to as "shielding" by Niederman et al. (2016), reduces the necessity for end users to have deep technical knowledge, enabling them to utilize technology for domain-specific applications without needing to understand the underlying technical complexities. Other research however points towards an ongoing convergence between the roles of data scientists and software engineers (Laato, et al., 2022).

Ebert and Hemel (2023) emphasizes that competencies extend beyond technical know-how to include business acumen and social skills. The shift to remote work has also contributed to decreased productivity and innovation, highlighting the need for balanced hybrid work models and stronger leadership.

2.4 Summary and relevance of prior research

2.4.1 ISD and software engineering teams

ISD is described as an iterative process that combines social and technical practices to meet organizational goals (Hassan & Mathiassen, 2018). This socio-technical view emphasizes the reduction of complexity through modular design principles to accommodate constant change (Benbya & McKelvey, 2006). Effective ISD teams require clear leadership and defined roles to manage stress and enhance performance (Windeler, Maruping & Venkatesh, 2017; Rezvani & Khosravi, 2019). Additionally, integrating expertise within teams promotes creativity and efficiency, as members with diverse backgrounds complement each other's skills (Tiwana & McLean, 2005; Licorish & MacDonell, 2017).

This is relevant to Research Questions Q1 and Q2, which seek to understand how AI affects the required skills for ISD developers and how managers view these changes. Clear leadership, stress management, and the integration of diverse expertise are essential for adapting to the evolving skill demands influenced by AI.

2.4.2 IS/IT skills

IS developers need a blend of technical and soft skills to adapt to the evolving demands of the field. Technical skills such as programming languages, libraries, and frameworks are foundational, but their relevance can change over time (Todd, McKeen & Gallupe, 1995; Montandon et al., 2021; Lee & Mirchandani, 2010). Armstrong and Hardgrave (2007) emphasize the challenges of transitioning between programming paradigms, highlighting the need for cognitive flexibility.

Soft skills, including communication, problem-solving, teamwork, and emotional intelligence, are increasingly crucial (Borges & Gratão de Souza, 2024; Aghaee & Karunaratne, 2023). These skills facilitate collaboration and adaptability within teams, addressing the dynamic requirements of ISD projects (Neufeld & Haggerty, 2001; Galster et al., 2023).

This is relevant to Research Questions Q1, Q2, and Q3, as they investigate the impact of AI on both hard and soft skills required for IS developers, as well as the skills highlighted in job advertisements.

2.4.3 Artificial Intelligence

AI technologies, including generative AI and machine learning, are reshaping skill requirements in ISD. AI systems can perform cognitive tasks, enhance productivity, and create new forms of work focused on human-AI collaboration (Dwivedi et al., 2021; Cabrero-Daniel et al., 2024). The integration of AI necessitates new skills in data science, algorithm management, and human oversight (Shollo et al., 2022). While AI can augment routine tasks, complex decision-making and ethical considerations still require human intervention (Jarrahi, 2018; Cabrero-Daniel et al., 2024).

AI's rapid development introduces challenges such as hallucinations in generative models and data protection issues (Fan et al., 2023; Gupta et al., 2023). Human-AI collaboration involves leveraging AI's computational power to enhance human creativity and decision-making abilities (Dwivedi et al., 2021; Mikalef & Gupta, 2021).

The skill gap posed by AI adoption underscores the need for continuous education and training to keep pace with technological advancements (Ebert & Hemel, 2023; Xue et al., 2022). The shift to remote work further complicates this landscape, highlighting the need for balanced hybrid work models and strong leadership (Ebert & Hemel, 2023).

This is relevant to Research Questions Q1, Q2, and Q3, which focus on understanding the specific skills required for integrating AI into ISD, the perspectives of ISD managers on these changes, and the skills emphasized in job advertisements related to AI.

3 Research Methodology

This chapter explains the methodology and research methods in the study. The early sections present the general considerations of the study, focusing on the research paradigm and research design. Later sections present the methodology of the data collection and analysis in more detail.

3.1 Research strategy

The goal of this master thesis is to examine the skills needed to fill the role of system developer in the age of artificial intelligence. This study employed a convergent mixed methods approach to examine the skills required for system development roles. This approach was chosen to integrate qualitative insights from industry experts with quantitative data from job advertisements, thereby providing a comprehensive understanding of the necessary skills in this field. This study employs a parallel collection and analysis of both qualitative and quantitative data, followed by the merging and interpretation of the result to provide a comprehensive understanding of the research problem (Creswell & Creswell, 2023).

The research methodology serves as the roadmap guiding the investigation to address a specific research question (Recker, 2013). In this study, we adopt a mixed methodology. This approach involves multiple steps, utilizing various data sources and analytical techniques to comprehensively address our research inquiries (Johnson & Onwuegbuzie, 2004). Creswell and Creswell (2023) contends that a mixed-method approach enables researchers to gain a deeper understanding of the research problem by leveraging the strengths of both qualitative and quantitative methods while mitigating their respective weaknesses. The convergent mixed methods approach is particularly suited for this study because it allows for the integration of diverse types of data to offer richer insights. Quantitative data provides a broad overview and generalizability, while qualitative data offers depth and context to the findings.

To study the demand for certain hard and soft skills imply both an understanding of the list of skills as well as the context in which they are demanded. Just listing the skills gives a limited understanding of the attributes and why they are asked for. Some are likely more commonly asked for than others, and the list is likely to change over time given technological change and shifting market demand.

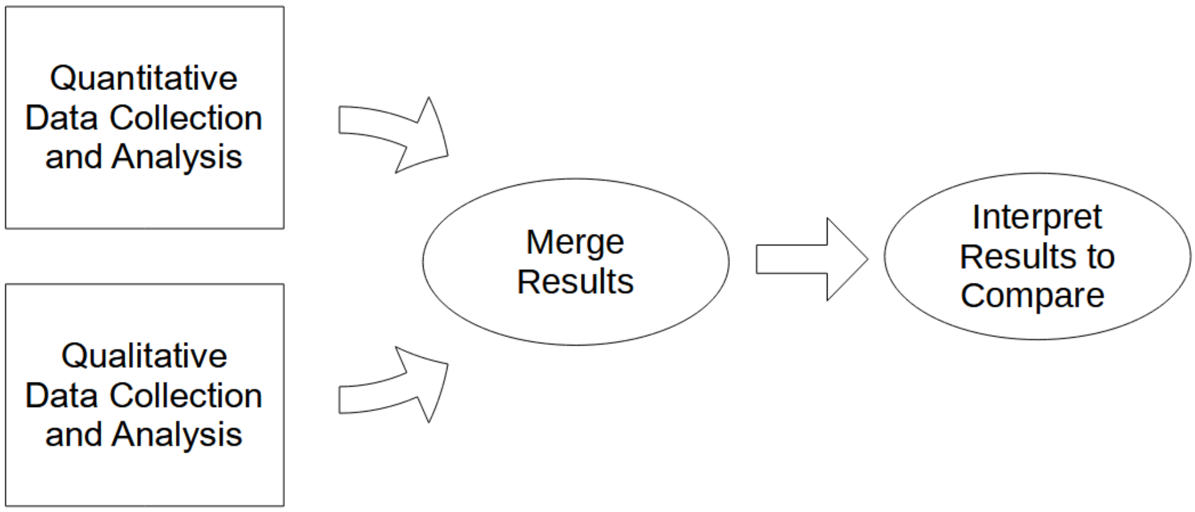

Figure 3.1: Convergent design (adapted from Creswell and Creswell, 2023, p.236)

The study follows a one-phase design where the qualitative and quantitative data is analyzed separately before the results are merged and compared. Figure 3.1 shows the steps as illustrated in Creswell and Creswell (2023, p.236). In this study there will be two parallel collections of data. One part is semi-structured interviews conducted with professionals from the industry. This data will have a qualitative focus. The other part of the study is the collection and analysis of job advertisements. This will focus on the occurrences of different keywords and trends in the prevalence of different skills in the data. This part will take the form of an exploration of quantitative data.

Drawing metainferences is the final and crucial step in the integration process. Metainferences are interpretations or conclusions derived from the integration of the qualitative and quantitative data, rather than from each dataset independently (Creswell & Creswell, 2023). These inferences provide a broader understanding that extends beyond the individual insights from the separate datasets.

3.1.1 Defining skills

In this master thesis there is a notable overlap between different categories of skills. One such overlap is between hard skills and technical skills. While both hard skills and technical skills relate to the competencies required to perform specific tasks effectively (Valle, Vilela, Guerino & Silva, 2023). “Technical skills” can even be understood as a subset of hard skills, particularly focused on proficiency in specific tools. Some prior research focuses more on one or the other. This study will mostly use the term hard skill, but in some sections technical skills are used to be more precise.

Another more complicated division can be done between soft skills and traits. While soft skills are often defined as interpersonal and cognitive abilities (Valle et al., 2023), traits on the other hand, refer to inherent characteristics or qualities of an individual. Traits can likewise be thought of as being subparts of soft skills (Litecky et al., 2004). Both soft skills and traits contribute to how effectively an individual interacts with others, but are partially different types of characteristics. This overlap becomes difficult when analyzing the job advertisement data, as traits are ordered in the data as a separate category from skills. The traits of applicants mentioned in job ads will in this study be discussed in terms of soft skills. The comparison between the different types of skills will be done in the discussion section.

3.1.2 Literature review

The prior research section focused on research published in the senior scholars’ list of premier journals. The authors were mindful of the socio-technical perspective to align the results of searches and focus to the field of Information Systems. The literature search was performed through school databases through LUBsearch, scopus, and through Google Scholar. Terms used to search for were, “knowledge workers”, “programmers”, “developers”, “software engineers”, “skills”, “hard skills”, “soft skills” and “information systems” all in mixed combinations to form boolean statements of strings and “AND” to build precise queries to databases. Furthermore, if a more specific view of the papers of these terms were required then the ”Senior Scholars' List of Premier Journals” (College of Senior Scholars, 2023) were used in a deeper selection to narrow down papers further. There were some adjacent journal such as from the “SIG Recommended Journals” (College of Senior Scholars, 2023), Information Systems education such as Information Systems Education Journal and engineering oriented journals such as the IEEE Software and IEEE Access.

After a potential finding of a piece of literature was found it was reviewed by reading and breaking it down by notes and discussions between the two master thesis authors. The literature was then added to the larger knowledge base of the master thesis. The direction of the review was then discussed and the value of each findings for the master thesis research goal was evaluated.

3.2 Interviews

The first part of the mixed study was a number of interviews with people who can help answer the research questions. This part of the study follows a qualitative methodology in order to study the phenomena of skills in demand within the context of ISD. This is suitable as qualitative interviews make it possible to study the lived context and to access people’s subjective experiences of a phenomena (Bhattacherjee, 2012, Recker, 2013). The interview format leaves room for a degree of subjectivity and makes interpretation the central focus (Recker, 2013). Part of the research problem was studied through quantitative measurements, but the “demand” of skill is a subjective aspect of the labor market. This means that the managers looking to fill the roles of system developers hold information and understanding that cannot be gained by solely focusing on textual sources such as published job advertisements.

A qualitative method was also deemed to be suitable as the research has exploratory aspects and is addressing a phenomenon that is complex and highly contextual (Recker, 2013). While the wider IT-sector follows certain trends and the professional role of developers might be similar, companies differ in size and market fit. This means that there could be hidden complexities to the research subject which need to be studied further.

By following a semi-structured format the interviews can cover some preselected questions while still leaving room for follow up questions and clarifications (Bhattacharjee 2012). The conversational format gave the interviews room for longer explanations which aided in understanding their context and role in their respective company.

3.2.1 Informant selection

The respondent selection process followed purposive sampling where the respondents were chosen on the basis of whether they fit the purpose of the study (Etikan, Musa & Alkassim, 2016). The interviewees were selected on the criteria of having a management role in a technology intensive company. This could for example be smaller software or IT-consulting companies or larger firms with an extensive IT-organization. The people asked to be interviewed had all several years of experience in senior managing roles within their respective companies or similar firms who are managers in higher and base level positions in larger corporations active on the Swedish jobsmarket. The selected companies include both retail, software and consulting and all had more than one thousand employees.

3.2.2 Interview guide

Semi-structured interviews follow a predefined interview protocol with themes and central questions, but leaves room for follow-up questions and discussions (Recker, 2013, Oates et al., 2022). This gives the interviews a structure as well as ensuring some amount of repeatability, while also leaving room for longer answers and follow-up questions (Recker, 2013). It also allows for questions to be said out of order in order for the interview to follow a conversational pace and open up for richer data (Oates, Griffiths & McLean, 2022). The interview guide can be found in appendix 1.

The structure of the interview guide follows the steps described by Myers and Newman (2007). They call for a four step approach to prepare an ”opening”, ”introduction”, ”key questions” and the ”close”. The opening section of our interview guide included general information which the respondent should know before the interview continues. This should set the premise for the interaction and ensure informed consent (Oates et al., 2022). This is also where permission for recording is asked for.

The introductory part of the interviews focuses on simple questions pertaining to personal information about the interviewee such as their position in the organization and prior experience relevant to the subject. Part of the introduction is also, according to Myers and Newman (2007), to give the respondent an understanding of the context of the interview and what the purpose of the research is.

The key questions are ordered under two central themes. The first section focuses on the required skills of IS developers. This part of the interview begins with a focus on more practical questions of how the system development is organized and what roles different individuals have within this process. This gives the researchers contextual information which could help in interpreting later answers and reflections from the interviewees. The practical focus also gives the interview a more comfortable start before asking for more reflective answers later on. After the context is described the interview moves on to the subject of skills.

This gives further information which can be analyzed and compared with later answers and with the job advertisement data.

The second theme is directly tied to the research questions. It pertains to the effects of AI on ISD work. This section is mainly focused on questions meant to draw out reflections from the interviewees on the subject of AI and machine learning and their effects on system development.

The interview ends by asking the interviewees for their general reflections on the development of the IS field and the effects of new technology. The closing question asks if there is anything else that the interview subjects want to say, add or clarify.

3.3.3 Conducting the interviews

The interviews were conducted over Teams with video calls. While facial clues can be seen in this kind of interview it still would be preferable to be able to see the interviewees in their place of work (Bhattacherjee, 2012). This was initially part of the plan but due to sickness and scheduling issues it was deemed necessary to conduct the first interview digitally. All subsequent interviews were done in the same manner in order to keep the material consistent and enable a wider geographical selection of interviewees. All interviews also had their audio recorded. Recording the interview ensures that the researchers focuses their attention on the interviewee and minimizes the potential bias introduced by the written notes or personal recollections (Kvale & Brinkmann, 2009).

All of the interviews were conducted in swedish since both the researchers and the interviewees were native speakers, this enabled the setting to be more relaxed and conversational which should assist in ensuring the interviewees feel comfortable in the process and in elaborating on their answers (Myers and Newman 2007). While the semi-structure enables lengthy reflections there is a risk of losing track of the subject and going on tangent. When this happened the researchers would clarify or ask a new question.

3.2.4 Transcription of interviews

The interviews were recorded and transcribed in order to make further analysis easier. Recker (2013) and Bhattacherjee (2012) both stress the need to secure the data from the interviews in this fashion. While there is no standard procedure for transcribing interviews (Kvale & Brinkmann, 2009), there are technical tools to speed up the process.

Transcription was done with the help of speech to text software. A local instance of Whisper transcribed the recordings from the interviews. The program produced a rough draft of the transcribed interview which was then formatted and anonymized in order to hinder the identification of the respondents. The transcriptions were later proofread and compared to the audio in order to fix the faults in the automated transcription. The text was also cleaned by removing pauses and filler words such as “um”.

3.2.5 Coding of qualitative data

Coding of the data was used to distill the information from the interviews as suggested by Recker (2013). Coding is the use of keywords in order to extract meaning from the expansive material (Kvale & Brinkmann, 2009; Recker, 2013). This enables the emergence of recurring themes or larger patterns (Kvale & Brinkmann, 2009).

The approach to coding in this study included multiple readings of the interview material, during which concepts and themes were identified. Initially, these concepts were drawn from previous research and the concurrent analysis of job advertisements, focusing on categories such as "soft skills" and "hard skills." In the later stages of the analysis, inductive coding was incorporated, following the principles of open coding to uncover and name new concepts that emerged directly from the data (Gibbs, 2007; Recker, 2013).

Inductive coding, as discussed by Gibbs (2007), allows for the generation of codes that are grounded in the data itself, rather than being imposed from pre-existing frameworks. This method is particularly valuable in qualitative research for identifying new patterns that may not have been anticipated (Gibbs, 2007). By employing both concept-driven and inductive approaches, the study ensured that the coding process was comprehensive. Both researchers participated in the coding process, independently reading all transcriptions and contributing to the coding. This collaborative approach enhanced the quality of the coding by incorporating diverse interpretations (Kvale & Brinkmann, 2009).

The thematic coding of the transcripts were performed and based on found concepts in the transcript different response sections were coded with codes pertaining to different areas. The codes were related to a plethora of different concepts relating to the literature and concepts that the respondents brought up in the interviews. Some thematic codes used were “skills”, “soft skills”, “hard skills” and “skill level” as well as “AI effects“ and “AI integration”. It was then used to induce clusterings combined with meanings the extracts with subheadings under the two main themes such as “ISD and Software Engineering Teams” under “Theme 1: Required skills for IS developers”.

The interview transcripts have a comment and a thematic codes column. The theme codes that we induced from the interviews are listed in appendix 2.

3.2.6 Interview numerical coding and length of the interview

The interviews were performed with 7 respondents, 5 interviews within 4 companies. The format is “i.r”, “i” is for the interview number and “r” is for the row as 1.12 is the first interview and the 12th row. The references make clear which of the respondents are focused on by every interview such as using R1 for Respondent 1.

Table 3.1: Interviews

Respondent	Interview	Company	Interview length
R1	1	A	34 minutes
R2	2	A	56 minutes
R3	3	B	58 minutes
R4	3	B	58 minutes
R5	4	C	60 minutes
R6	4	C	60 minutes
R7	5	D	34 minute

3.3 Survey of job advertisements

The second part of the study consists of a quantitative analysis of job advertisements. This study will also focus on the dataset from Arbetsförmedlingen (2024) and select relevant ads based on the Swedish occupation classification system. This means that the data will focus on advertisements directed towards the Swedish job market. The usage of the classification system might also mean that professional positions within IS development might fall outside the scope of this study based on how the ads have been written.

3.3.1 Data collection

The job advertisement data was sourced from the Swedish Public Employment Service (Arbetsförmedlingen – AF) government agency. AF is responsible for matching job seekers with employers looking for hires as well as hosting job advertisements. The ads have been collected from the agency's platform Platsbanken ("The Job Bank") and are available through its open data repository. The dataset used for this study was obtained from a JSONL (JSON Lines) file format. Each line in the JSONL file represents a unique JSON object representing a job advert containing various attributes relevant to our research.

The unprocessed data from the job bank would not just need to be cleaned and sorted but also coded. The Swedish employment agency has however done a lot of work to enable a more efficient usage and analysis of the public data. This includes a coding initiative where the unstructured text of the ads have been processed into "keywords". This enables not only sorting of the ads based on the type of job and job group.

The JobAd Enrichment algorithm (JobTech Development, n.d.A) utilized entity recognition techniques to identify and categorize specific entities mentioned in the job ads, such as job titles, required skills, qualifications, and company names. This makes it possible to also deal with poorly formatted advertisements or where the same keywords are described in several different ways. This "Enrichment " done by JobTech follows the format of preliminary coding of the material making it possible to do content analysis. This code was developed to be a part of commercial job matching-software (JobTech Development, n.d.A), but the open source aspect of the program makes it usable also in an academic environment.

3.3.2 Data preprocessing

The chosen JSONL files contain all available job ads for each year. Processing these take unnecessary processing power so the first step is to only select adverts which are relevant to this study.

ChatGPT was used as a coding assistant when handling and filtering the job advertisement data. The AI-chat was prompted to produce python code which produced either new JSONL objects or excel documents.The study required filtering the data based on specific criteria within the "occupation_group" field. The JSON objects were sorted based on if the field legacy_ams_taxonomy_id included: 2511 or 2512; concept_id: 'UXKZ_3zZ_ipB' or 'DJh5_yyF_hEM'. This is the code for: 'Systemanalytiker och IT-arkitekter m.fl.' and 'Mjukvaru- och systemutvecklare m.fl.'. This is the profession-groups for “system analyst and IT-architects” and “Software and system developers”. Filtering function was implemented that iterated through the JSON objects, checking for the presence of the criteria in the "occupation_group" field. Only the records that met these criteria were selected for further analysis.

The filtered JSON objects were written to a new JSONL file, ensuring that only the relevant data was retained for subsequent analysis. This process involved writing each qualifying JSON object to the output file, maintaining the line-based structure of the JSONL format. After the preprocessing the total number of lines (job adverts) were 224 633 spanning from 2016 to 2023.

3.3.3 Data analysis

After the preprocessing the data was analyzed through descriptive statistics which summarizes the main features of the dataset. This focused on frequencies for categorical attributes as shown in the results section.

The analysis focuses on quantitizing the textual data in order to make the large dataset legible. Quantitizing, as Sandelowski (2000) describes it, is the reduction of a qualitative artifact, such as textual document, into numbers. The text is then no longer “meaningful” in the same way, but on the other hand makes it possible to discern larger patterns or compare different documents in ways not possible for the research before (Sandelowski, 2000). The advert data is not particularly rich, and often use commonly used phrases and job descriptions. This would not lend itself to particularly deep qualitative analysis, but could possibly enable a keyword analysis which shows wider patterns in the data.

The “enriched” data from JobTech Development (n.d.A) include a number of new fields which contain an even more standardized format for keywords. The primary focus was on two attributes: keywords_enriched_skill and keywords_enriched_trait. These attributes contained lists of skills and traits mentioned in the job listings. For each job, these lists were collected and tallied by a python code which ensured that each skill and trait was counted individually. The script iterated over each year’s JSONL file, accumulating the counts of skills and traits in two separate Counter objects. This step ensured that we captured the total occurrences of each skill and trait across all the years under study. After processing all the JSONL files, the aggregated data was exported to Excel files using the pandas library.

Exploratory data analysis was performed to uncover patterns, anomalies, and relationships within the data. Visualization techniques, such as frequency tables and different graphs, were employed to facilitate this exploratory process. This was done via different extractions from the JSONL files into Excel format where graphs and tables could be formatted.

The point of the data analysis is to look for patterns in the data and draw conclusions (Oates et al., 2022). The analysis of the data focused on the skill and traits keywords. The keywords are counted and are of the nominal data type, the data have no actual numerical value in itself (Oates et al., 2022). This means that the possibility for statistical analysis is limited and the only available analysis is that of the frequency of the keywords throughout the material (Oates et al., 2022).

Descriptive statistics focus on describing the frequency counts of each category within the dataset. This initial step allowed us to grasp the overall distribution of keywords and identify any potential patterns. The use of frequencies and percentages can help us understand what skills and traits are mentioned often in the advertisement data set and in what context.

One important part of the analysis is to study possible changes over the last couple of years in order to see if any skills are of especial importance in today's market. Analyzing the effects of AI-tools on system development is the main focus of the second part of the results section.

A critical step in our analysis was identifying adverts that contained the keyword "artificial intelligence". For each line, the keywords_enriched_skill field was split into individual skill and sorted by number of occurrences. Similarly, the keywords_enriched_trait field was processed to extract individual traits. For lines that included "artificial intelligence", the total number of items in both fields was counted. Each unique skill and trait in these lines was tallied, and their occurrences were recorded. The total number of lines containing AI-related skills was also tracked to understand the prevalence of AI-related skills within the dataset.

3.4 Meta-Inference

Mixed methods research employs a combination of qualitative and quantitative methodologies to investigate a phenomenon, leveraging different instruments to gain a holistic understanding (Sandelowski, 2000). The mix of qualitative and quantitative methods can help ensure credibility through the use of triangulation (Recker, 2013). Contradictory information among various sources can serve as a catalyst for future research, prompting further investigation to reconcile discrepancies and deepen our understanding of the subject matter.

The final phase of an integrative data analysis is the integration and analysis of the qualitative and quantitative data. Creswell and Creswell (2023) describe several ways of doing this. A classical method is to compare the different findings and see if they confirm or contradict each other. This side-by-side approach compares the data within the discussion.

However, using different methods within the same study runs the risk of resulting in two different studies within the same paper (Venkatesh et al., 2013). This can be handled by the utilization of a meta-inference approach to the analysis (Venkatesh et al., 2013). Meta-inferences refer to the higher-order conclusions drawn from the integrated data, transcending the insights provided by the separate quantitative and qualitative analyses. Creswell (2022) emphasizes the importance of this step, noting that meta-inferences provide a broader, more nuanced understanding of the research problem by synthesizing the two sets of results.

A problem with mixed methods is that qualitative and quantitative approaches are underpinned by philosophical paradigms that contradict each other (Dawadi et al., 2021). Qualitative science generally focuses on subjective experiences and the meaning individuals ascribe to phenomena, while the quantitative approach is associated with positivism and emphasizes objectivity (Creswell & Creswell, 2023). Sandelowski (2000) argues that the analysis of textual data through a numerical analysis does not necessarily employ assumptions associated with quantitative analysis.

Furthermore, in practice, the comparison of qualitative and quantitative data requires careful consideration to avoid simply juxtaposing the two types of findings without meaningful integration. This is where meta-inference becomes critical. By synthesizing the insights from both datasets, researchers can develop conclusions that are not merely a sum of the parts but offer new perspectives that neither approach could provide independently (Venkatesh et al., 2013).

3.5 Research Quality

The research will focus on interpreting interviews and job advertisement data, which precludes the use of statistical measurements of reliability and validity. Instead, the study will adhere to the guidelines for research quality as outlined by Jan Recker (2013), who identifies four key principles for analyzing non-numerical data: dependability, credibility, confirmability, and transferability.

Dependability (reliability), refers to the ability to reproduce results using the same data. This will be ensured by clearly detailing what data is analyzed and how conclusions are drawn. Following standard procedures and iteratively analyzing the material will further enhance reliability.

Credibility (internal validity) confirms that the researcher's interpretations are well-substantiated, achievable through triangulation, evidence chains, and detailed notes. The use of multiple data sources ensures the empirical method's validity. Confirmability (measurement validity) allows findings to be independently verified by outsiders, through reviewing summaries and conclusions.

Transferability (external validity) assesses whether findings can be generalized to other contexts by providing detailed descriptions of the research environment. Additionally, a high number of respondents enhances generalisability, as noted by Bhattacherjee (2012). However, the purposive sampling used in this study introduces limitations for generalisability. This method is advantageous when researchers have limited resources or time, as discussed by

Etikan et al. (2016). To mitigate this shortcoming, the qualitative data will be complemented with quantitative data from job advertisements.

The structured coding of data will enhance the study's transferability and reliability (Recker, 2013). The qualitative component of this study relied on interviews with ISD managers. While interviews are a powerful tool for gaining in-depth insights, they are inherently subjective (Recker, 2013). The responses provided by interviewees are influenced by their personal experiences, perceptions, and the specific contexts of their organizations. This subjectivity can introduce biases, particularly if the interviewees have strong opinions about the impact of AI on the ISD workforce. For example, managers from larger organizations might emphasize different skills compared to those from smaller companies, based on the specific needs and resources of their respective firms.

Additionally, the interviews were conducted in Swedish and later transcribed and translated. While efforts were made to ensure accuracy, the translation process can sometimes lead to subtle shifts in meaning, which could affect the interpretation of the data. The use of AI tools, such as transcription software, also introduces a layer of potential error, particularly if the software misinterprets or misrecords parts of the conversation.

There is also a potential for bias in the job advertisement data, as not all job openings are listed, and some job advertisements may be influenced by the way HR departments select and present skills. Although the number of open positions and recruitments likely exceeds the number of advertisements in the dataset, the large size of the job database should make it representative of the job market. Employers also use standardized templates for job postings, which may not accurately reflect the full scope of skills required for a position. Additionally, job advertisements tend to emphasize the most desirable or marketable skills, potentially omitting less prominent but equally important competencies.

Furthermore, the data was sourced from a single country (Sweden), which may limit the applicability of the findings to other regions with different labor market dynamics and technological adoption rates. The focus on job advertisements also means that the data primarily reflects the demands of employers rather than the actual skills possessed by employees, which could create a gap between perceived and actual skill requirements.

Open data and coding contribute to the study's replicability, allowing future research to test or contrast the results. Data triangulation is crucial for enhancing the credibility and validity of the findings by incorporating multiple data sources, thereby reducing bias and providing deeper insights into the research topic (Recker, 2013).

However, utilizing different data sources and analytical methods may result in discrepant findings. While this may raise concerns about the reliability of the research design, it also presents an opportunity to identify inherent discrepancies within the phenomenon itself (Sandelowski, 2000). Other websites and social contacts used for recruitment, which may not be visible in the dataset, could also influence the study's findings. Despite these potential biases, the job database's comprehensiveness should adequately represent the job market.

3.6 Ethical considerations

Ethical considerations are fundamental to all research conduct, this study has closely adhered to the considerations prescribed in the methodological literature (Bhattacherjee, 2012; Recker, 2013). The interviewees were informed of the purpose of the interviews and the research for the master thesis. They gave explicit informed consent to be part of the study and be recorded. This consent is needed in order for their interviews to be part of the analysis (Oates et al., 2022; Recker, 2013). Research must ensure that informants are not harmed (Bhattacherjee, 2012). Therefore, all information about interview participants and companies in the job advertisement data will be kept confidential by storing data securely and anonymizing names, organizations, and any private details.

Striving for transparency and honesty is important in research and in this to give as clear and unbiased view of collected data as possible (Recker, 2021). As such the data collected via the interviews was interpreted with as much care as possible as to represent the believed thoughts and meanings of what the respondents were believed to mean. The data from the job advertisements have similarly been described and handled with the aim of showing it in an as unbiased manner as possible.

Giving accreditation to the authors of a work in an appropriate way is highly important as if not doing so and in some way using someone else’s work as one's own it may constitute plagiarism (Recker, 2021). Recker (2021) explains that the best way of avoiding plagiarism is by always pointing to the source that was used as the foundations of one’s own work. Information in the master thesis that is not novel observations but rather information from prior work have their sources cited in the references section.

4 Results

This chapter presents the results of both the interviews and the dataset is presented. In the interview section responses of the 7 respondents of the 5 interviews are presented. In the following part we present the results of data relating to work advertisements from Arbetsförmedlingen.

4.1 Interviews

The following section contains the results of the 5 interviews with the 7 individual managers. This section is divided into two themes with subsections based on clustered references from the transcripts. To reiterate the interview i and the row r creates format i.r, example 1.60.

4.1.1 Theme 1: Required skills for IS developers

This section of the Results chapter talks about the respondents' reasoning around working within development and the relevant skills within the development process. The section starts with a subsection that talks about how teams work with ISD and the second presents how they think about the roles involved in the process then their ideas, hard skills and soft skills are presented.

4.1.1.1 ISD and Software Engineering Teams

From the answers of the majority of the respondents it is seen that communication and interaction with different entities is of high importance to being able to work with ISD. Good demeanor and self-organization are also viewed as beneficial traits where Agile work and Scrum fits this purpose. Some talk about the need for negotiations and discuss how to solve issues together while going through their development process. One respondent also mentioned how opinions of how to proceed may be different depending on the outlook of the group holding it.

Developer teams organize themselves and perform their work in different ways. R1 says they pick what they do themselves but that they often divide easy and hard tasks among themselves (R1, 1.60). R2 explains that they work in an Agile Scrum based manner and that team members have meetings continuously (R2, 2.8). According to R2, the development teams have a lot of customer contact and communications are frequent between the parties where the customer may be the ones contacting (R2, 2.8). R2 says that the developers have to prioritize what issues to deal with, negotiations happen when doing this (R2, 2.12; R2, 2.14).

> *"You have to be a bit outgoing and search for information yourself and find the right people to ask. So having some social skills is good. To be able to build networks to be able to carry out one's job."* R2, 2.48

How the developers act to others may factor into the types of people sought for as they need to fit into a larger social context. R2 says people working with them need to be helpful and be able to network as the structure of the firm is informal and based on social networks (R2, 2.48). They say that social interaction is an important part of the work where helping others tasks is a central theme displayed (R2, 2.50). It is also expected that they handle formal and informal workloads and that they communicate this with their managers for the purpose of project management (R2, 2.50). R2 means that people who like structure may not fit into the organization, as formal processes are not used as much, leading to a mismatch between soft skills and organizational needs (R2, 2.52). They believe that teamwork in software development is needed as one person will not be able to do everything themself (R2, 2.96).

"Now it is so complex that you become very dependent on everyone knowing something and then having to cooperate to reach a solution, the project becomes more complex." R2, 2.96

R4's firm uses Scrum. R4 believes that developers sit in a team in the same place because it speeds up work (R4, 3.17). R4 says that the Scrum team and the Product Owner work close together (R4, 3.11) and especially so if they are located in the Swedish locations (R4, 3.13) R4 says that the Product Owner comes with requirements which they put into a backlog and then depending on the sub role a developer is assigned (R4, 3.10). They negotiate the solution with different parties (R4, 3.10). The developer starts working and when the task is finished it is reviewed by a senior developer and then it is tested by function and then by regression (R4, 3.10).

"There can be very different opinions between Product and Engineering. I don't know how you look at it. My view is that Product is more responsible for the "what". So what are we going to do? Then how we are going to do it. That's what Engineering sits with." R7, 5.26

Contacts occur between functions where opinions may differ, R7 explains that several parties are involved such as Data, Product development and Engineering where Product development and Engineering may have differing ideas of what should be as they both define what is made with strong wills on each side (R7, 5.26).

4.1.1.2 Roles and skill levels in development

Developers communicate with different parties within and around the team. There are a few roles that teams can contain such as Devops and Scrum roles. Team members may also interact with roles adjacent to the teams such as analysts and UX. A developer can have roles within a horizontal plane but also as vertical tiering such as senior developers. These seniors are expected to have slightly different skills profiles than that of juniors.

R4 and R3 explain how different roles interact in their firm. R4 starts by describing how there are several roles involved with development and not necessarily only developer roles, the developer roles are backend and frontend, they list roles such as database admins, testers, DevOps (R4, 3.6), business analysts and architects who work closely with developers (R4, 3.8) and UX (R4, 3.6). Similarly, R7 explains that there are many roles involved in teams' work in a similar way, teams can be composed of software engineers of all levels and they are surrounded with other teams, functions and consumers (R7, 5.22). They explain that the developer mostly communicates with other team members, data analytics or UX but that senior developers have (R7, 5.18) internal and external consumer (R7, 5.20) contact to get a better understanding of what they are to develop (R7, 5.18). They further explain that the other functions are not part of the team but they are still semi integrated with auxiliary functions such as UX and Analytics with varying effectiveness (R7, 5.24). R7 works in an agile manner using Scrum elements such as Sprints and Scrum roles (R7, 5.6). R5 also uses Agile methodology and Scrum so roles such as Scrum Master and the developers in the development team exist, among these there is a UX developer as well (R5, 4.12). R5 says the

Product Owner is sitting with the customer company, as they are a consultancy firm (R5, 4.14). R6 says that there are also business analysts (R6, 4.13). They explain that the business analyst sits outside the team but it is present as a more external information source and stakeholder (R6, 4.19).

"Business analysts often come in quite early to determine the requirements. Perhaps even before the development process has begun. So that you know what you have to do and also that all the requirements from the business can be implemented." R6, 4.19

R4 allows developers to move between roles and view it positively and developers can do it if they like to (R4, 3.48). On switching roles is mentioned by R2, they mean that it is fully up to the developer themself (R2, 2.28). R7 also allows for role change but they motivate it with it both allowing for developing promising developers, to make them more performant but also to assure succession as an investment in the future (R7, 5.42).

The reason to bring on certain developers may differ depending on what is needed, R3 means that senior roles for developers can be for their ability to run projects or for their technical skills set (R3, 3.52). According to R4 developers can do a spectrum of tasks related to certain areas, "some only program, some adapt applications and some are on third party applications" (R4, 3.2). R6 lists some developer roles with a skills focus on areas such as backend and frontend development (R6, 4.5). They say that the development team consists of more roles rather than exclusively pure development based skill profiles (R6, 4.7). Similarly, R2 says that IS developers have different subroles: such as Tech Lead or Code Block Architect, there are also agile roles such as Scrum master, Backlog owner within the ones they can take (R2, 2.6). They state that prior professional experience is viewed as positive within the topic areas as it allows for the taking of subroles within software development (R2, 2.6). In R5's firm's recruitment for their teams there is a clear difference but in practice a person may have broader skill sets (R5, 4.8). They also state that they expect their developers to have the bare minimum skills across the used technologies to perform software delivery even if it is not their main area of work (R5, 4.10).

"Some are very purely developers and some are half bad with the tools. But you always have to be able to use the tools. In your daily work. As in being able to build, deliver the code." R5, 4.10

More senior skill levels may need even more soft skills. R4 finds the ability to reason about one's work as important for senior developers (R4, 3.53). They say that it is also important to be able to communicate well (R4, 3.53). R1 believes skills such as mathematics and being able to handle complexity is more important at more senior levels than showing programming skills (R1, 1.12).

"So many of these tests that we have, they're not that tough on programming but they're tougher on math or complexity. We have a lot of algorithms in our code and a lot of image analysis like this. So we usually go a little deeper into algorithms in particular." R1, 1.12

R7 means that later levels in the career of the developer require more people skills, such as stakeholder management and leadership skills. They mean that it is not only technical issues but also social aspects that matter (R7, 5.16). With seniority comes wisdom to understand and the need for belief in one's ability, R2 explains this by stating that in latter stages of their career it is of more importance that the skills they have are the ability to reflect on their own experiences, more precisely to reflect on "... what has gone well and what has gone badly." (R2, 2.56). They assert that on senior skill levels of a software architect, developers have to be able to stand by their own ideas and perceptions of the solutions developed and to be able to show some confidence in themself and their decisions (R2, 2.58).

"They cannot be like a weather vane that wobbles back and forth, they should be mature enough to stand for it. For what they believe in." R2, 2.58

Some respondents view seniors as the center of wisdom to the team. R5 states seniors have an understanding of their profession (R5, 4.46). R6 states senior team members can be used as a source of knowledge and act as a mentor guiding the team and its members (R6, 4.47). R7 mentions that for senior developers, the technical insight and communicating with the customer is most important while junior engineers have more leeway when they work in the team as they are more replaceable generally (R7, 5.44). R5 says that there is a large number of juniors on the work market but they are looking for more senior staff and candidates with security skills (R5, 4.43). They also state their evaluation of juniors are not so high expectations on junior developers compared with seniors (R5, 4.74).

"But taking in a senior, then we expect that they are effective coders, you shall have knowledge about the occupation, you shall have a thorough and good CV that we can help, you shall be able to sell them, you shall be able to answer, You shall be a leader in a technical way, or whatever it says. There are totally different demands put on seniors." R5, 4.74

R5 says they "sell them", meaning the developers going into a consulting role with other customers. R5 also mentions that juniors may get better results on code tests than experienced people (R5, 4.34). Although the understanding of the actual code is better for seniors (R5, 4.36).

4.1.1.3 Skills

Skills consist of two different subtypes, hard and soft skills. These can be weighed and valued in different ways depending on the context. It is a balancing of the value of social ability and ability to cooperate compared to technical ability.

R2 describes the importance of using a combination of soft skills such as logical reasoning and problem solving and hard skills such as programming (R2, 2.38). To R5 not not only the hard skills matter to them in being able to present the developer as an attractive commodity to customers (R5, 4.39). A larger issue they see is that of the lack of social fit with the team (R3, 3.24). Aspirants need to function well in teams (R1, 1.18). R1 states that being able to handle complexity (R1, 1.14; R1, 1.10) and to be a good human are important aspects for things to work (R1, 1.14). R6 says that people cannot work alone so they need to be able to work together (R6, 4.50). There is a pragmatic balance between soft skills and hard skills here (R6, 4.50).

"It is rarely possible to have people who only work in isolation. But on the other hand, there may be those who are perhaps less good at it who still have a good place in the team. Because they are so technically skilled. And then you can be indulgent with it especially if you have some people around them." R6, 4.50

R6 cooperating over the creation of code is important, following standards is valued highly (R6, 4.38; R6, 4.41). While R4 perspective is that of social ability being vital to accomplish the goals but technical skills they can be learnt (R4, 3.25). R3 agrees that technical skills are not always a large problem with some lack in skills as according to them these skills can be trained (R3, 3.24).

4.1.1.4 Hard skills

Many respondents answer that programming is highly valued by developers after that comes more specific skills like frameworks and related business knowledge. Some respondents also require a broader base skill set to do development related to such things as platforms and tooling. Some of the respondents also bring up some future tooling needs.

R5 states that hard skills is a baseline to get the job then personality and general cognitive capabilities follow after that in importance (R5, 4.55). They state that if the academic background is from Engineering and Information Systems then they are expected to be able to perform programming tasks in different domains such as mobile and cloud (R5, 4.2). In R1's and R2's firm they find that capabilities in programming are of importance and they make sure to test this in aspirants (R1, 1.4; R2, 2.38). R1 says that they look for skills such as object oriented programming skills (R1, 1.6; R1, 1.10) as well as some experience in scripting and SQL databases (R1, 1.6).

R3 suggests that having sufficient knowledge in related areas is enough, arguing that expertise in a particular field or skill, such as proficiency in a specific language, can qualify someone as a viable candidate for jobs requiring similar skill sets (R3, 3.39).

> *"It is enough that there is a basic understanding and competence in terms of development. If you can program Java today, you can certainly learn a framework for building mobile applications and so on. It's just another library, another framework that you need to learn."* R3, 3.39

R3 says that the aspirant only needs to know a programming language such as Java, as this means it is possible for them to learn to program apps within adjacent languages given some training (R3, 3.39). Within the same context and firm, R4 continues this line of reasoning through explaining that internal channels to recruit someone already related to the firm could be accepted to have a broader skills set such as object oriented programming while the sought for skill is Java. To them if the source is external they have higher and more specific standards such as specific frameworks, an example given is Vue (R4, 3.40). The reasoning more specifically is that of business knowledge about the firm being valuable to them so therefore they allow variation in hard skills for internal recruits, it is a pragmatic trade-off for them (R4, 3.42).

> *"If we have someone with experience here, who knows how everything works and which architectural groups exist, and we know that it is a good person, then we can give the opportunity to learn the other part."* R4, 3.42

There can be a variation of depth to the skills developers know, R6 means that some developers have more platform based skill sets and some more specifically development based skills (R6, 4.5). R6 explains that they use code to do a lot of the work with environments, known as "Infrastructure as Code" (R6, 4.5). To match the variety of skills there are plethora of tools a developer needs to understand, R6 further explains that the firm uses IT operations tooling within the development process for DevOps purposes. These tools are such as Jenkins, Azure DevOps, Github, Docker, Kubernetes and Terraform where they use cloud platforms such as GCP, Azure and AWS (R6, 4.3). Some further needs which R5 presents are the need to understand development processes and tools (R5, 4.2).

"Both development environments but also environments in the form of using Jira. Confluence is another type of tool for running software development in a group, in a team." R5, 4.2

Further, hard skills that are needed or looked for, R5 mentions that skills in the newer AI tools are sought for (R5, 4.44). R7 remarks that due to the popularity of technologies such as the systems SAP and ServiceNow, there is competition for the existing talent in the job market (R7, 5.30).

"But I would say SAP we are having difficulties to find, also ServiceNow. Despite it being big now there are not many that have it." R7, 5.30

4.1.1.5 Soft skills

In development interactions are commonplace and so soft skills are closely considered and required. Skills that are germane to the context of soft skills are the ability to work in a team, social abilities, communication, handling, problem solving, being a teamplayer, time management, a positive demeanor and thinking within different perspectives.

R2 has observed that soft skills can be an issue for aspirants of positions in their organization, to them it is considered to be almost equal in weight with the technical skills and lacking in them can be a cause for non-consideration of the aspirant (R2, 2.54).

"We have probably refrained from recruiting people with the right hard skills because the soft skills were too far from what we want in our organization." R2, 2.54

They say that due to how their firm is structured culturally, there are high demands on soft skills, a positive demeanor and openness are in demand to be viable in their organizational culture (R2, 2.20). In their firm there are a lot of interactions where people have to share information with each other directly (R2, 2.18).

R1 has a view of the person and its type for the purpose of group composition and interpersonal dynamics which determine what soft skills are sought after by them (R1, 1.4). Depending on the purpose if detail is needed or more openness is needed they choose a purpose along per case lines (R1, 1.18). They motivate it by explaining that people's personality matters for the way in how the task is done, detailed or holistic thinking and the team composition as how the building blocks of the team shape the whole (R1, 1.22).

"A lot about how the team is built up so that you get a dynamic in it also." R1, 1.22

Some skills that respondents want are cognitive ability, managing pressure and fit into a team environment. R2 finds that the ability to remove oneself from the lower levels of thinking to view things as a whole is beneficial (R2, 2.92). Skills that they say they require are logical thinking, problem solving skills and the ability to manage under pressure (R2, 2.38). R4 also thinks handling pressure in stressful situations is seen as important (R4, 3.30). In later time they have started to want to see not only how aspirants would deal with stress but they have started to prioritize more how developers are functioning within a team setting which they deem to be more important than handling stress (R4, 3.32). In line, R3 are looking for the ability to be a team player and to share knowledge with each other (R3, 3.35).

"Sitting alone with knowledge then you become more indispensable. Which we do not want. We are open. We share knowledge. We help each other and so on. We check very thoroughly for it, so that we get such people that we call team players." R3, 3.35

Communicating their views and ideas is considered important. R3 says that people can be different but they need to be able to communicate (R3, 3.33). R3 states that they value honesty and the ability to be open about what is lacking, to say their opinions about an issue (R3, 3.36). R4 says they value openness about what they think, people need to share their opinion and not that of the manager's opinion (R4, 3.37). It is harder to find people in India or outside the west where people say what they are thinking themselves, they want people to be expressing their thoughts and opinions (R4, 3.37).

"So share it, because it may be better than that of the manager's. And then we should choose the way forward that is the best." R4, 3.37

Teamwork and social ability is valued by R4. R4 thinks communication is seen as an important soft skill as the developer needs to get interaction and get input from a variety of stakeholders, with parties from both within the team and outside the team (R4, 3.25).

"The most important thing is that they fit into the group and have communication skills. So that you can talk to someone, talk to users and make sure you know what the customer wants and what the product owner wants." R4, 3.25

They present social ability, group dynamics and the ability to work with the team are very important aspects to working with development (R4, 3.27). While a foundational level of skill is needed, technical skills can be trained but lacking social ability is considered as being a critical flaw (R4, 3.27). The perspective on soft skills of R5 is that they should be in line with one's position as an IT development consultant, to be able to understand the customer and to be able to cooperate with the team are important activities (R5, 4.49). It is also important to have the ability to handle critique on one's code (R5, 4.49). R5 states being on time and having a positive demeanor are important traits (R5, 4.51). R5 states being dependable is an important trait to have and keeping track of what is going on (R5, 4.53).

"Yes but for example then you have such daily Scrum or stand ups then. That you have in agile work. And is the time 09:00. Then you are at work at 09:00. If there are meetings then you show up at meetings and so on. You keep track of email. You keep track of Slack channels and answer your colleagues and so on." R5, 4.53

4.1.2 Theme 2: Effect of AI on ISD work

This section talks about how AI tools affect the development related skills needed currently and reflections on future orientation. The section starts with going through a clustering of answers that talk about the maturity of their integration of AI tools and use of AI in the organization. The second talks about the challenges of integrating AI tools into the firm and the third talks about general effects on the developers work. The last subsection talks about how the respondents believe the future of development will be.

4.1.2.1 AI maturity

The level of AI maturity in integration of tools into use varies between firms from what respondents convey in their responses. Some are ahead of others in integrating AI tools into their work, some are eager to learn and integrate and some whose attitude is to wait and see.

There are different levels of integration regarding AI tools such as assistants. An example of this is R5's firm whose IS developers use these tools and work closely with Github Copilot to generate code, Azure AI-algorithms, Microsoft 365 suite of tools such as Word and Excel with its offering called Copilot and UX AI tools (R5, 4.76).

"You can say that the majority of our developers use AI in their daily work. And then there are things like GitHub Copilot, for example, which means that in the development tools there is AI support that can look through code, give code suggestions and lots of things like that. So in that context it is used extensively." R5, 4.76

R2 says they have started to use AI assistant tools within their organization for a select group of developers (R2, 2.60). R7 in contrast to this only uses AI assistant tools in the browser and in Outlook but not yet for direct development (R7, 5.50). Similarly R4 uses mostly AI systems embedded directly into products such as SAP (R4, 3.57) and for generating reports (R4, 3.59). They explain that these AI tools can be used by anyone in the firm without specific knowledge requirements other than business rules (R4, 3.64). R7 also mentions that their firm has many components using AI (R7, 5.46), such as ServiceNow (R7, 5.48), but when it comes to using AI tools such as assistants in doing work they believe that there is more space to mature for the AI tool (R7, 5.46).

"I have a dream that Microsoft Copilot would do my job. It is much easier when I can work with the whole Microsoft suite for example. And I do not believe that we are there to have the one AI to rule them all but I really hope for that personal assistant to help a lot and also do it for all coworkers." R7, 5.46

While some view AI tools in a positive way when it comes to integrating them into their work some are not as eager to do so. R6 says that it is the beginning and that they have plans to expand their faculties in the area (R6, 4.79). R5 argues that continued investments must come from consumers of the services as there is a level of hesitancy about security which may hinder further integration (R5, 4.78). R1 says that they are at the moment evaluating how AI assistants can be used in the firm. They want to be involved but the risks are seen as big (R1, 1.24). R7 would rather wait to see what happens in regards to coding assistance tools like Github Copilot (R7, 5.52).

"If you view the whole AI journey that has happened the last two years. And we rather wait while investing more energy in AI in other directions. More to the customer." R7, 5.52

4.1.2.2 Challenges with AI-tools

Safety and security are big themes in how, according to many respondent's firms move forward with AI. There are also mentions of legal issues that they are hesitant about code that is not within their license range. A few of the respondents put part of the responsibility on vetting code on the developer.

Safety and security are of great concern to firms but insights and views of AI's effect on it differs. R6 does not have issues with AI but some of their customers do, therefore they do not want to use it in development (R6, 4.103). To contrast this to something else they claim that the reason for customers being hesitant are scandals involving data that has been published publicly to the cloud (R6, 4.105).

"There were some troublesome cases with some use of AI where information has been published knowingly or unknowingly to the public cloud." R6, 4.105

They see them as great search tools and great for code development but when it comes to general use as part of other tools it should be discreet when sharing privileged information (R6, 4.108). They earlier explained that from a security perspective it is important for information to stay within the right contexts so that it does not leak (R6, 4.83). They continue by saying penetration of system security are concerns and so is Information security and User security (R6, 4.85). On this R5 says there are issues around security policies for how information is accessed and this is in their opinion not as much of a technical issue pertaining to AI but an administrative issue (R5, 4.107). R7 has their way of viewing AI tools integration and they want to improve cyber security readiness and build into the firm in a safe manner (R7, 5.60). They see a great need in improving security around AI tools in a way to imbue confidence in the developer's abilities to integrate it well (R7, 5.70).

"I also believe above all, considering what we see outside the company, what we see in the world, how AI is used and can be used, how do we make it as faithful as possible, i.e. security, not security as in cybersecurity, but more that it feels credible, what we do around AI, so that customers are not afraid of not doing it, that is, that we do it in a credible way." R7, 5.70

They think that a major challenge is the lack of a framework for guidance of how to handle the AI tools and issues pertinent to it within the organization, there needs to be more formal procedure to deal with their usage (R7, 5.72).

Legal issues such as IP protection are considered a few of the respondents. R1 is saying that some people are allowed to use Github Copilot but that it is a lot of analyzing before knowing what code they are allowed to send to get processed from their side to avoid IP leaks and who has which permissions (R1, 1.26). Other issues stem from the risk of getting code into their code base that they do not own themselves which could constitute code license transgressions (R1, 1.44). R1 usually keeps away from performing transgressions such as these by having a list of licenses for which they can use produced by the legal team (R1, 1.28). R1 views this point as AI generated code as dangerous as it can contaminate their codebase with licensed code (R1, 1.44).

"So not that it will go wrong, because of course it's always a risk, but it doesn't matter. But there may be certain code parts that have been patented. Or that is part of an open source suite that has a license that we don't want to accidentally get into ours" R1, 1.44

R5 is also concerned that they would be generating IP protected content (R5, 4.110). R2 has similar views of challenges with AI use regarding IP protection and to introduce licenses which have not been deemed acceptable for their code bases (R2, 2.60). R6 repeats this point as pertinent on the topic as they say that legal factors are something they have to learn about to deal with AI tools in companies (R6, 4.87).

"We also encounter legal requirements, for example. We work with both private and public businesses. We have different regulations for them." R6, 4.87

Developers taking responsibility for the product produced from the use of AI tools is seen as an important path to how to handle potential issues. R2 thinks that taking responsibility for the code produced means taking ownership of it making sure that it is legitimate (R2, 2.76). R1 says they have a course they have to attend before starting to use such AI tools (R1, 1.32). They also state the responsibility is over the code that the developer adds to the codebase (R1, 1.32). To R7 quality controlling what AI writes is of importance (R7, 5.54).

"We always need someone who can actually control the quality and review what is done with AI machine learning. I think that will become even more important." R7, 5.54

R1 believes that critical thinking for the use of AI tools are required by developers (R1, 1.34). R1 puts value in being meticulous which is a trait seen in senior developers because they have a greater ability to evaluate the code produced (R1, 1.36). The AI tool may not understand the human operator (R1, 1.40).

"Some things the AI is not as good at so far. And that's the thing with empathy, for example. You really want that with us. Service-mindedness. Empathy. And understand the user. So those are the ones I think are important too." R1, 1.40

R1 states that juniors can use AI tools in two ways, one is to process it in a critical way and learn from it and another unpreferred way is for these juniors to take the code and use it in a naive way without understanding it (R1, 1.38). R2 thinks that to handle bias of the AI tool there needs to be team work where the team deals with things together to evaluate it (R2, 2.80).

4.1.2.3 Effects of AI on skills

Firstly, AI's effects on the developer are that of higher performance, keeping up with change and gaining a deeper understanding of code. Secondly, according to many respondents critical thinking and analytical skills will be needed to deal with outputs. Thirdly, the changes will happen for developers and how AI changes or does not change the profession.

The effects on development as observed by R5 who have seen in general effectiveness gains of at least 30% if not more (R5, 4.81). They see improvements to safety as given by Github Copilot, getting extra checks on the code as highly beneficial (R5, 4.81; R5, 4.98). Similarly, R4 uses AI tools to gain insight into the code (R4, 3.55).

"As it is looking now I believe that maybe some developers have started using it some, to test the code or to see if there are any improvements." R4, 3.55

Overall there is a need for using diligence and judgment by the developer around the outputs of these tools as of importance. As R1 sees the potential of AI in producing software, they also believe that it will require more base skill to analyze the code generated to handle it (R1, 1.30). R2 continues in the same line, soft skills such as the ability to use critical thinking surrounding AI tools outputs is seen as important (R2, 2.70). R4 likens it to a search engine allowing for accessing information and so code reviews will still be needed to verify outputs (R4, 3.74). R5 in a similar manner posits that being critical and verifying the output for development purposes are important ways of dealing with AI as it is currently (R5, 4.92). R6 also states that the ability to judge the outputs are critical other than that the social aspects stay the same (R6, 4.101). R7 claims that understanding technical aspects will still be important so that holistic systems thinking will persist (R7, 5.56). They imagine that the value goes from skills such as programming languages to understanding the system as a whole (R7, 5.58).

"I don't know if it's the case that you really need to know a coding language in detail. But I think you need more of this systems thinking to understand how to create what you have in mind." R7, 5.58

While reasoning around adaptability of developers R6 says that there has always been a factor of having to learn relevant skills for the profession. To them it is not a new concept to have to keep up with technical developments (R6, 4.115). R2 means that the most adaptable are the free thinkers (R2, 2.72). They further mean the importance of curiosity in developers but also how to effectively use their curiosity with the context of the firm (R2, 2.74).

"Yes, this is interesting. Can we use this? Maybe dig a bit deeper before throwing it out to the team. To connect this problem with this tool. It is about curiosity but taking the idé to another level." R2, 2.74

There are some thoughts from R4 and R3 in interview 3, R4 believes the human hand is still being needed. R4 believes that future impacts on the development of the systems will require someone who can review the program to make sure that it fits the use case on a broader level with another type of understanding of the system's purpose (R4, 3.72). R3 talks about the narrower view and says that basic development work can be done with help of these AI tools but more complex issues require an appropriate skill set to perform (R3, 3.75). There are circumstances when humans will be needed and those are more specific circumstances (R3, 3.77).

"No general business logic but very specific. Where you work a lot with details which I believe are hard to complete with AI." R3, 3.77

4.1.2.4 AI Future

Respondents believe in the transition from solving technical issues to solving people's problems. In this direction, many of the respondents foresee that even if AI tools makes coding less prevalent then soft skills would take more space in activities. Some believe tasks would become more efficient and in this essentially people with lower prior skill levels would benefit from it but juniors' value proposition is in question.

"It may be that you still need to have more depth of understanding in some products technically versus having soft skills, but in other products where you're buying something as a solution or everything is more AI-based, it's more of these soft skills that are important going forward." R7, 5.68

R7 thinks that soft skills needs will grow and hard skills demands will lessen (R7, 5.68). R6 has similar thoughts where less coding and more reasoning focused on what should be done with the team takes center space (R6, 4.100). Similarly, R1 views AI assistants as being a tool to express ideas to and then the utilizers to get a result (R1, 1.52). R1 understanding is that of the product and its purpose will be more important (R1, 1.54). They believe that because development does not only have to be to code, they believe in having empathy and to understand complexity, the requirements and the use case will remain important factors in the process (R1, 1.56).

"But a developer can be so many different things. It doesn't just have to be coding. So in a few years it might not be right there. But you have to be able to understand it and understand what comes out and how to optimize. I still think so. But I think you need people who can think complexly and put complex systems together. So if you recruit smart people who can handle complex things but can also formulate requirements and have empathy and understand the end use." R1, 1.56

They mean that a developer does not only code but they perform tests and they plan and structure things, so changes would be in doing more of these activities if coding becomes a smaller part of the work (R1, 1.58). R2 thinks that the nature of the developer job will become more configuration based but that certain individuals will continue to try to understand the system on a more base level (R2, 2.78). Similarly R7 believes that less specific technical skills will be needed with AI tool's support (R7, 5.62). They further believe that more focus will go to being able to deliver what the consumer actually wants instead of focus on the technology (5.64). They also note that the analytical manner of thinking will still be needed for developers, the methodology to solve problems, even if the code is less important to focus on to do so (R7, 5.66).

The future of development is seen as analytically oriented. R6 believes that once the knowledge of how to use the AI based development tools are known, effectiveness and quality will be higher than it is today (R6, 4.101).

"The big thing today is efficiency. I think you can increase the quality and you can write code faster with the help of AI tools." R6, 4.101

R4 currently has the opinion that it may be slower to use an AI tool at times due to performing corrections on the assistant's product (R4, 3.78) therefore R3 has doubts about the clear future abilities of AI (R3, 3.79). R3 maintains that analyzing results of the AI tool outputs over writing code will be a factor in how code is produced in the future (R3, 3.77). They believe that there will have to be a supervisor likening it to how a pilot flies a plane with auto-pilot on and only intervenes when difficult procedures are done (R4, 3.82). R2 says that using AI to deskill certain tasks such as finding memory leaks in code would save time and prevent changes from tarnishing areas that work in the code (R2, 2.66; R2, 2.68). R2 allows for handling routine tasks but they have fears that this will make people less critical and that it will stifle innovation by relying on the outputs of AI tools (R2; 2.70).

"The AI we've looked at, it's all about retrieving information. If we stop creating things, then soon we will just regurgitate the same information that AI itself has created. It will be a bit biased in the end. I think that you need to continue to be creative but use AI for more routine work. I think that is the first step. And then it is very important to be able to be a little critical in your assessment of what you get." R2, 2.70

The ability of the developers to do more with less is a benefit of AI tools. R7 AI tools will help juniors get into programming and make soft skills more important to what is demanded from seniors (R7, 5.78). R5 thinks that new graduates will lose their leverage on the jobs market as their skill level becomes redundant due to AI tools such as code assistants (R5, 4.94).

"Here you see the risk that recently graduated coders are not really needed anymore. What I said earlier, that they are good at writing code. They may not have all the other skills needed.

But if you then have an AI function in your development environment. Basically, your AI robot writes all the code for you and you sit and verify. Do you then need a fresh graduate, a junior developer?" R5, 4.94

They pose that the demand for new graduates will be lower as one senior developer can do more (R5, 4.96). While R1's belief is more positive stating that junior developers may benefit from AI tools (R1, 1.46). R2's perspective on juniors is that AI assistant tools may be good to use for juniors as they do not know as much, allowing them a head start (R2, 2.78). Although they are concerned about the ability to judge the quality of AI output compared to seniors with experience (R2, 2.78).

"It is possible that it is something that juniors may need a bit of mentorship in how you evaluate the outputs of AI results." R2, 2.78

R6 sees that there are new integrations of the coming AI tools' development environments that allow for customization similarly to Microsoft Copilot Studio, which is a Microsoft 365 customizable environment (R6, 4.118). Other ways AI tools can help and change things within the ISD process is to make other auxiliary tasks more efficient and eliminate a lot of work, such as R5's example of translation of websites can and have become cheaper and more efficient (R5, 4.90). On some believed effects on future roles within ISD, R2 thinks that like that of the videogame industry new roles will spring up eventually (R2, 2.82).

4.2 Job advertisement data

The purpose of this section is to establish a detailed understanding of how the job market for IS developers has evolved over time, with specific attention to the skills and traits that are most frequently sought after by employers. The analysis includes both technical and non-technical competencies.

4.2.1 Number of adverts

A job advertisement describes the expectations of a potential employee. It describes the role that needs to be filled in the company and what is expected of the candidate. The advertisement includes information about the company, such as mission and culture. It also includes lists of qualifications needed to apply and what role the candidate is filling, such as its professional title and related responsibilities.

Table 4.1: Number of advertisements selected for each year as a table

Year	Number of adverts
2016	18949
2017	21711
2018	25895
2019	26297
2020	20736
2021	33733
2022	40915
2023	36397

The dataset includes the number of job advertisements selected each year from 2016 to 2023. In 2016, there were 18,949 advertisements, followed by an increase to 21,711 in 2017. This upward trend continued in subsequent years, with 25,895 advertisements in 2018 and 26,297 in 2019. However, there was a noticeable decline in 2020, with the number of advertisements dropping to 20,736, likely due to the global COVID-19 pandemic impacting hiring practices. The subsequent years saw significant recovery and growth, with 33,733 advertisements in 2021, 40,915 in 2022, and a slight decrease to 36,397 in 2023. This data indicates fluctuations in job market activity, with a general trend of increasing job advertisements over the observed period, except for the dip in 2020.

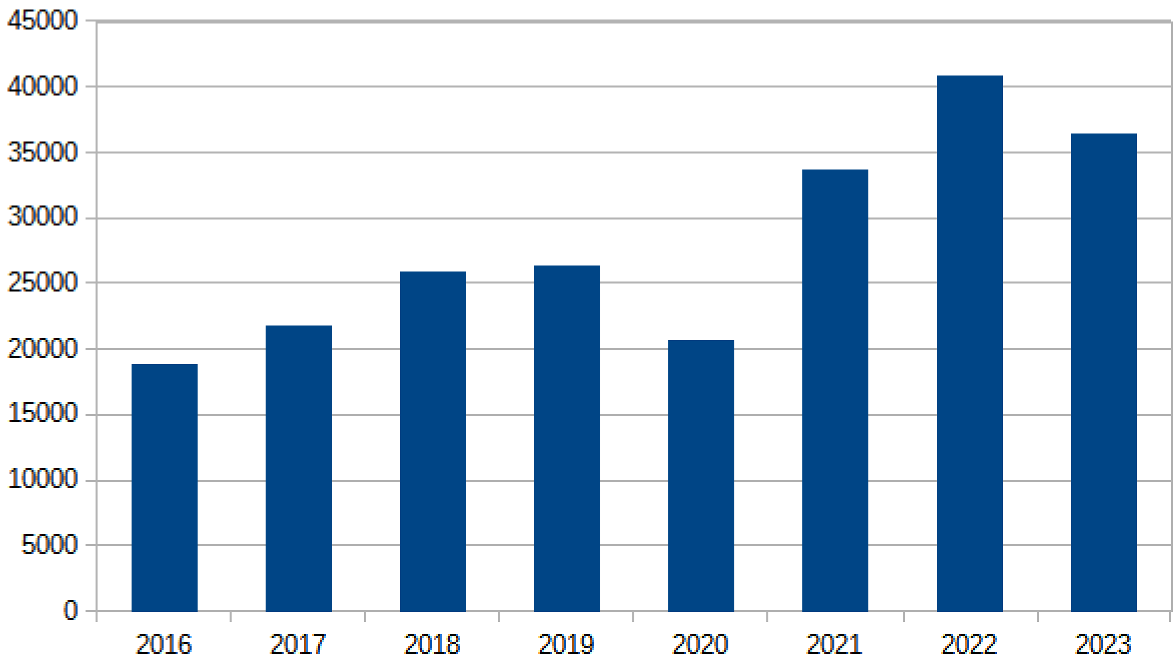

Figure 4.1: Number of advertisements selected for each year as a chart

This bar chart (Figure 4.1) shows the aforementioned trend. There have been a general increase in the number of adverts within the selected occupation groups . There was however an exception in 2020 and 2023.

Table 4.2: Number of skills and traits

Total Number of Skills	Number of Unique Skills	Total Number of Traits	Number of Unique Traits
2438641	14391	422461	383

Table 4.2 provides a summary of the skills and traits mentioned in job advertisements. There are a total of 2,438,641 skills mentioned across various job ads, encompassing 14,391 unique skills. There are 422,461 mentions of traits, with only 383 unique traits in the dataset.

The skewed number of adverts to certain years might affect the outcome of descriptive statistics. Likewise there is more of a focus on “skills” and less on “traits”, making it difficult to study certain aspects of the data such as the distribution of traits across different types of job advertisements.

4.2.2 Technical skills

Keywords were collected from Arbetsförmedlingens JobTech Atlas (JobTech Development, n.d.B). It lists and defines many of the words and titles used in the job advertisement space. Under the heading of “Skills” are different types of subgroups of skills, some of which are of interest and have been included here. The phrases have been sorted by the number of their occurrences in the skills field of the advertisement data over the whole time frame from the year 2016 to 2023. Next to it is the percentage of adverts where the skill is mentioned. Skills that are not mentioned in the data have been omitted.

Table 4.3: Top programming languages

Skill	Count	Percentage
java	34138	15.6%
javascript	29433	13.5%
c#	29425	13.5%
c++	21763	9.9%
python	21341	9.8%
sql	17478	8.0%
css	15031	6.9%
html	12649	5.8%
typescript	8661	4.0%
php	6452	2.9%

Table 4.3 shows the 20 most mentioned programming languages in the data (full list in appendix 3). The dataset provides the distribution of job advertisements mentioning specific programming languages and technologies, along with their respective counts and percentages. "Java" is the most frequently mentioned skill, appearing in 15.6% of the total. Following closely are "JavaScript" and "C#", both with around 13.5% presence. Other significant languages include "C++" (9.9%), "Python" (9.8%), and "SQL" (8.0%).

Reading through table xx it is easy to see that the main languages that have been in demand have been Java, Javascript and the C family of languages. Languages such as Python and SQL have trailed behind. There are a large number of different languages, but a select few are in high demand. These numbers are collected over the whole time period. So as we will see later there are changes in which languages are mentioned the most in job advertisements.

Table 4.4: Top development tools

Skill	Count	Percentage
git	14874	6.8%
scrum	13652	6.2%
node	8689	4.0%
jenkins	4936	2.3%
jira	4122	1.9%
kanban	3570	1.6%
eclipse	1834	0.8%
agila arbetsmetoder	1239	0.6%
unified modeling language	1175	0.5%
active directory	1034	0.5%

Table 4.4 shows the most common development tools for the period (full list in appendix 3). This distribution reflects the varied technological requirements and preferences across different roles and organizations, with a strong emphasis on widely adopted tools and methodologies like Git and Scrum. "Git" appears in 6.8% of advertisements, indicating its critical role in version control. "Scrum," mentioned in 6.2% of advertisements, underscores the importance of agile project management frameworks. "Node" is featured in 4.0% of ads. Other tools like "Jenkins" (2.3%), "Jira" (1.9%), and "Kanban" (1.6%) are also notable, showcasing their relevance in continuous integration, issue tracking, and workflow management, respectively. There are very few tools being mentioned in the ads compared to the frequency of programming languages.

Table 4.5: Top operating systems

Skill	Count	Percentage
linux	12008	5.5%
android	7144	3.3%
ios	5065	2.3%
unix	2212	1.0%
windows server	1334	0.6%
operativsystem	1167	0.5%
rtos	677	0.3%
ubuntu	435	0.2%
jcl	170	0.1%
gnu	163	0.1%

Table 4.5 provides an overview of the occurrence of various operating systems and related technologies in job advertisements (full list in appendix 3). The table shows that the most common operating system mentioned was linux. "Linux" is prominently mentioned, appearing in 5.5% of the total advertisements, indicating its widespread use and importance in the industry. "Android" and "iOS" are also significant, with 3.3% and 2.3% mentions, respectively, reflecting the high demand for mobile operating system expertise. Other than these common operating systems for smartphones are sometimes asked for in terms of skills. It seems generally rare to specify systems in job advertisements.

Table 4.6: Top application platforms

Skill	Count	Percentage
docker	7818	3.6%
sap	2462	1.1%
apache kafka	1721	0.8%
windows server	1334	0.6%
iis	865	0.4%
apache tomcat	828	0.4%
ibm websphere	319	0.1%
google cloud platform	193	0.1%
weblogic server	97	0.0%
windows azure	41	0.0%

Table 4.6 provides an overview of the occurrence of the most commonly mentioned application platforms (full list in appendix 3) "Docker" is the most commonly mentioned, appearing in 3.6% of the advertisements. Other than that it is rare to mention platforms in the job descriptions. "SAP" appears in 1.1% of adverts, reflecting its significant role in enterprise resource planning. Similarly to systems, it is rare to specify platforms in job advertisements.

Table 4.7: Other skills

Skill	Count	Percentage
data	29009	13.3%
agile	16486	7.5%
problemlösning	10233	4.7%
automation	8442	3.9%
open source	6300	2.9%
artificial intelligence	5210	2.4%
machine learning	4596	2.1%
it-arkitektur	2893	1.3%
automatisering	2481	1.1%
test automation	2118	1.0%
testautomatisering	2027	0.9%
ml	1064	0.5%
maskininlärning	612	0.3%
tensorflow	300	0.1%

A selection of other common skills and words associated with artificial intelligence and automation were also searched for in the material (table 4.7). Problem solving (problemlösning) was one of the most common skills in the data set so it has been included here. While it is sorted in the data together with technical skills it might be debatable if it is more of a trait or soft skill.

"Data" is the most frequently mentioned skill of these, appearing in 13.3%. "Agile" methodologies are highlighted in 7.5% of advertisements, indicating their widespread adoption in project management. "Problemlösning" (problem-solving) is mentioned in 4.7% of advertisements. This indicates a demand for analytical skills.

The skills associated with artificial intelligence and automation have a low rate of occurrence over the whole dataset. Contemporary AI-tools such as ChatGPT, GitHub Copilot or AutoML are not present in the skill list.

Table 4.8: Top skills each year by percentage of ads with each skill

2016	2017	2018	2019	2020	2021	2022	2023
svenska (42.6%)	svenska (36.4%)	svenska (31.9%)	svenska (34.7%)	svenska (31.9%)	svenska (26.9%)	svenska (26.7%)	svenska (30.9%)
engelska (39.7%)	engelska (35.6%)	engelska (31.8%)	engelska (32.8%)	engelska (29.2%)	engelska (25.1%)	engelska (24.4%)	engelska (23.5%)
javascript (21.7%)	java (20.8%)	design (18.7%)	design (20.9%)	design (19.4%)	design (17.5%)	design (16.2%)	design (18.4%)
java (20.0%)	javascript (19.1%)	java (17.7%)	java (19.3%)	java (16.0%)	java (12.6%)	data (12.4%)	data (15.1%)
programm ering (18.3%)	design (18.3%)	javascript (15.7%)	javascript (17.3%)	javascript (14.5%)	data (12.3%)	java (11.4%)	python (12.1%)
design (17.8%)	c# (17.0%)	programm ering (15.0%)	c# (16.7%)	c# (13.2%)	c# (11.2%)	python (10.0%)	java (10.9%)
c# (17.3%)	programm ering (16.6%)	c# (14.7%)	.net (13.5%)	data (12.5%)	javascript (10.8%)	c# (9.8%)	.net (10.6%)
.net (13.9%)	.net (14.3%)	.net (12.7%)	data (13.2%)	.net (11.6%)	.net (10.0%)	programm ering (9.3%)	agile (10.4%)
systemutve ckling (13.6%)	arbetslivse rfarenhet (13.3%)	systemutve ckling (12.1%)	programm ering (12.8%)	programm ering (10.2%)	programm ering (9.6%)	.net (9.3%)	c# (10.2%)
data (13.5%)	c++ (13.1%)	data (11.7%)	c++ (12.5%)	back end (10.1%)	arbetslivse rfarenhet (8.9%)	systemutve ckling (8.7%)	react (10.0%)

The most commonly asked for skills are languages such as Swedish and English (table 4.8).Over this period, "svenska" (Swedish) consistently remains a significant skill, peaking at 42.6% in 2016 and fluctuating to 30.9% by 2023. "Engelska" (English) also shows a high prevalence, with a peak of 39.7% in 2016 and a decline to 23.5% by 2023. These languages are the top two most common skills in the whole dataset by a wide margin.

Java and Javascript were the most common programming languages near the beginning of the period but later became less prevalent. "JavaScript" had its highest mention in 2016 at 21.7% but decreased to 14.5% in 2023. Conversely, "Java" saw fluctuations, with its highest presence at 20.8% in 2017 and dropping to 12.6% in 2021.

Python on the other hand grew to become the most asked for programming language by the end of 2023. It is not visible before 2022 but by then it is present in 10% of adverts. The following year Python is in 12.1% of ads. The skill "Data" also exhibits a rising trend in the later years, starting from a low point at 12.4% in 2019 and increasing to 15.1% by 2023.

In this data we can see how the natural languages have stayed at the top with a fairly stable percentage of advertisements mentioning Swedish and English throughout the period. While programming skills were less often specified in the later period.

Table 4.9: Highest increase by year in percentage of ads with each skill

2017	2018	2019	2020	2021	2022	2023
agile (2.5%)	cloud (2.0%)	svenska (2.8%)	microsoft azure (1.0%)	innovation (1.0%)	open source (3.5%)	agile (5.0%)
react (2.2%)	amazon web services (1.9%)	python (2.6%)	vue (0.8%)	typescript (0.6%)	django (2.7%)	svenska (4.2%)
cloud (2.2%)	docker (1.4%)	react (2.5%)	ci/cd (0.7%)	systemveten skap (0.5%)	python (2.2%)	it-arkitektur (3.2%)
python (2.0%)	artificial intelligence (1.1%)	microsoft azure (2.3%)	arkitektur (0.7%)	säkerhetssk ydd (0.5%)	arbetsliv (0.8%)	data (2.8%)
elektronik (1.3%)	git (1.1%)	cloud (2.2%)	sas (0.7%)	kompetensut veckling (0.5%)	konsultuppdr ag (0.7%)	open source (2.7%)
embedded (1.3%)	microsoft azure (1.0%)	amazon web services (2.2%)	lösningsarkit ektur (0.5%)	kundprojekt (0.5%)	typescript (0.7%)	react (2.6%)
innovation (1.3%)	kubernetes (0.8%)	design (2.1%)	gcp (0.5%)	betalningslö sningar (0.3%)	automotive (0.7%)	typescript (2.2%)
linux (1.2%)	agile (0.8%)	agile (2.1%)	typescript (0.4%)	transaktionsl ösningar (0.3%)	nätverk (0.6%)	design (2.1%)
jenkins (1.1%)	automotive (0.8%)	c# (2.0%)	tillverkande företag (0.4%)	mekatronik (0.3%)	säkerhetssky dd (0.6%)	python (2.1%)
5g (1.1%)	ci/cd (0.7%)	kubernetes (1.8%)	amazon web services (0.4%)	embedded (0.3%)	innovation (0.6%)	sales (1.9%)

The table (table 4.9) highlights the skills with the highest yearly increases in job advertisement mentions from 2016 to 2023. First column shows the percentage increase in 2017 compared to 2016. In 2017, "Agile" experienced the most significant growth, increasing by 2.5%, indicating a growing demand for agile methodologies. The skill had some of the highest growth near the beginning of the studied period and near the end. In 2018, "Cloud" saw a notable rise of 2.0%, reflecting the increasing importance of cloud technologies in the job market.

In 2019 there was a significant increase of 2.8% for "Svenska" (Swedish) and in 2020 "Microsoft Azure" grew by 1.0%. "Innovation" also saw a 1.0% rise in the following year. "Open Source" had a substantial increase of 3.5%, showing a larger change in the skills being asked for. The time period ends with a sharp increase for "Agile" in 2023 compared to 2022 with a 5.0% increase, reinforcing its ongoing relevance.

The prevalence of the Python programming language increased over time as we could see in the previous table. “cloud” and cloud services such as Microsoft Azure and Amazon web services also saw some of the most stable increases over the period. This indicates a demand for skills connected to that type of technology.

During 2020 and 2021 there were not any significant changes in the skills mentioned. But as could be seen in table 4.1, 2020 had a steep decrease in the number of published advertisements. This might affect how the changes in asked for skills can be studied.

Table 4.10: Highest decrease by year in percentage of ads with each skill

2017	2018	2019	2020	2021	2022	2023
svenska (-6.2%)	svenska (-4.6%)	programmering (-2.1%)	linux (-6.8%)	svenska (-5.0%)	javascript (-2.6%)	programmering (-1.8%)
engelska (-4.2%)	arbetslivserfarenhet (-4.5%)	systemutveckling (-1.1%)	agile (-4.0%)	engelska (-4.1%)	amazon web services (-1.5%)	css (-1.3%)
javascript (-2.6%)	engelska (-3.8%)	systemvetenskap (-1.1%)	engelska (-3.6%)	javascript (-3.7%)	node (-1.4%)	javascript (-1.3%)
webbutveckling (-2.4%)	javascript (-3.4%)	jakarta ee (-1.1%)	c++ (-3.6%)	java (-3.4%)	c# (-1.4%)	microsoft office (-1.3%)
vidareutbildning (-2.4%)	java (-3.1%)	testdriven utveckling (-0.8%)	c# (-3.5%)	git (-2.7%)	design (-1.3%)	problemlösning (-1.2%)
högskoleutbildning (-1.8%)	radio (-2.4%)	hibernate (-0.8%)	java (-3.3%)	python (-2.3%)	front end (-1.3%)	mission (-0.9%)
css (-1.7%)	c# (-2.3%)	programspråk (-0.8%)	cloud (-3.2%)	angularjs (-2.3%)	java (-1.2%)	engelska (-0.9%)
html5 (-1.7%)	elektronik (-2.2%)	datavetenskap (-0.8%)	javascript (-2.8%)	c# (-2.1%)	css (-1.1%)	present (-0.9%)
programmering (-1.6%)	webbutveckling (-2.1%)	episerver (-0.8%)	högskoleutbildning (-2.8%)	design (-1.9%)	ux (-1.0%)	eftergymnasial utbildning (-0.8%)
html (-1.5%)	högskoleutbildning (-2.0%)	mjukvara (-0.7%)	svenska (-2.8%)	css (-1.9%)	angularjs (-1.0%)	sql (-0.7%)

Table 4.10 shows the skills with the highest yearly decreases in job advertisement mentions between 2016 and 2023. The languages that dominate the data saw a stable decline throughout most of the period. In 2017, "Svenska" (Swedish) experienced the most significant decline, decreasing by 6.2%, and this trend continued in 2018 with a 4.6% drop. The Swedish language had some of the steepest drops of any skill. But as we saw in the earlier table this decline was from a dominant position and followed by an increase in the last year.

In 2019, "Programmering" (programming) saw a decline of 2.1% and the most notable decrease in 2020 was for "Linux," which dropped by 6.8%. This drop for “Linux” had the highest drop of any skill mentioned in the selected data. As seen in the list with skills associating with different operating systems, Linux is the most common operating system mentioned.

The trend from earlier years continued in 2021, with "Svenska" again with a decrease of 5.0%, followed by "Javascript" dropping by 2.6% in 2022. This indicates a fluctuating demand for programming languages and local language skills. In 2023, "Programmering" again saw a decrease, this time by 1.8%, continuing the trend observed in previous years.

Other notable decreases included "Engelska" (English) and "Javascript," which saw multiple years of decline. “Java” also saw multiple years of decline with -3.1% in 2018 and -3.3% in 2020.

4.2.3 Occupations

Table 4.11: Most common occupation in the dataset

Occupation	Count	Percentage
systemutvecklare	114731	51.0748643342697
mjukvaruutvecklare	41884	18.6455240325331
projektledare	22925	10.2055352508314
backend-utvecklare	12393	5.51699883810482
frontendutvecklare	12304	5.47737865763267
civilingenjör	11616	5.17110130746596
lösningsarkitekt	11408	5.07850582950858
it-arkitekt	11366	5.05980866569026
javautvecklare	8633	3.84315750579835
software engineer	6745	3.00267547510829

The dataset presents an analysis of the most common occupations, detailing both the total count and the percentage of each occupation relative to the total number of adverts in the selected dataset (table 4.11). The occupation "systemutvecklare" (systems developer) is the most prevalent, comprising 51.07% of the total, with 114,731 job adverts. Following this, "mjukvaruutvecklare" (software developer) accounts for 18.65%, with 41,884. Other notable occupations include "projektledare" (project manager) at 10.21%, and "backend-utvecklare" (backend developer) and "frontendutvecklare" (frontend developer) at approximately 5.52% and 5.48%, respectively. These findings highlight the significant demand for systems and software developers, which together make up nearly 70% of the total adverts.

Table 4.12: Top skills for 10 most common occupations in the dataset

systemutvecklare	**mjukvaruutvecklare**	**civilingenjör**	**lösningsarkitekt**	**it-arkitekt**	**projektledare**	**software engineer**	**backend-utvecklare**	**fullstack-utvecklare**	**javautvecklare**
svenska (32.6%)	engelska (25.9%)	engelska (35.4%)	svenska (38.3%)	svenska (39.7%)	svenska (42.2%)	design (38.7%)	back end (32.6%)	javascript (39.9%)	java (73.2%)
engelska (29.4%)	c++ (25.3%)	svenska (34.6%)	engelska (28.9%)	engelska (26.6%)	engelska (38.8%)	agile (20.3%)	java (27.5%)	react (36.6%)	svenska (39.0%)
java (21.8%)	svenska (24.9%)	design (18.7%)	design (27.3%)	design (26.5%)	projektledning (31.0%)	c++ (19.8%)	.net (25.3%)	svenska (33.5%)	engelska (32.4%)
c# (20.0%)	design (22.8%)	c++ (17.7%)	arkitektur (19.8%)	it-arkitektur (19.0%)	arbetslivserfarenhet (11.1%)	java (19.6%)	svenska (24.7%)	.net (33.2%)	javascript (20.3%)
javascript (19.3%)	java (17.8%)	systemutveckling (16.6%)	it-arkitektur (15.2%)	arkitektur (18.6%)	budget (10.3%)	data (19.3%)	engelska (21.8%)	c# (30.3%)	git (17.8%)
.net (17.6%)	python (17.0%)	data (16.4%)	data (14.5%)	data (14.1%)	högskoleutbildning (8.4%)	embedded (16.5%)	c# (21.7%)	back end (29.5%)	back end (15.4%)
design (17.4%)	mjukvaruutveckling (16.3%)	programmering (14.6%)	integration (12.6%)	integration (12.1%)	data (8.0%)	python (15.3%)	javascript (16.7%)	engelska (27.9%)	systemutveckling (15.1%)
programmering (17.1%)	c# (15.0%)	python (13.7%)	microsoft azure (11.7%)	microsoft azure (11.1%)	kommunikation (7.9%)	back end (13.2%)	design (15.4%)	front end (27.3%)	jakarta ee (14.9%)
systemutveckling (14.8%)	programmering (15.0%)	mjukvaruutveckling (12.7%)	cloud (9.4%)	cloud (9.2%)	scrum (7.7%)	c# (12.3%)	amazon web services (12.9%)	angularjs (25.2%)	apache maven (14.6%)
back end (12.8%)	data (14.7%)	java (12.6%)	systemutveckling (8.8%)	högskoleutbildning (8.3%)	ekonomi (7.6%)	cloud (11.0%)	sql (12.5%)	java (25.1%)	programmering (14.4%)

Table 4.12 shows the top skills for the 10 most common occupations in the dataset. These occupations include systemutvecklare (system developers), mjukvaruutvecklare (software developers), civilingenjör (civil engineers), lösningsarkitekt (solution architects), it-arkitekt (IT architects), projektledare (project managers), software engineer, backend-utvecklare (backend developers), fullstack-utvecklare (fullstack developers), and javautvecklare (Java developers).

The top skills of the common occupations reflect the specializations of the different roles. Languages are often mentioned in the advertisements from Arbetsförmedlingen (2024). Both Swedish and English are commonly mentioned in the data. The notable exception is "software engineer" which might indicate a more international recruitment in mind.

Different technical skills correspond to different roles. Software engineers require design (38.7%) and agile methodologies (20.3%), highlighting the importance of creativity and agile processes. Backend-utvecklare prioritize back end skills (32.6%) and Java (27.5%), reflecting the technical focus of these positions. Fullstack-utvecklare roles are heavily reliant on JavaScript (39.9%) and React (36.6%), indicating a strong demand for front-end development skills. Javautvecklare unsurprisingly emphasizes Java (73.2%).

4.2.4 Skills associated with artificial intelligence

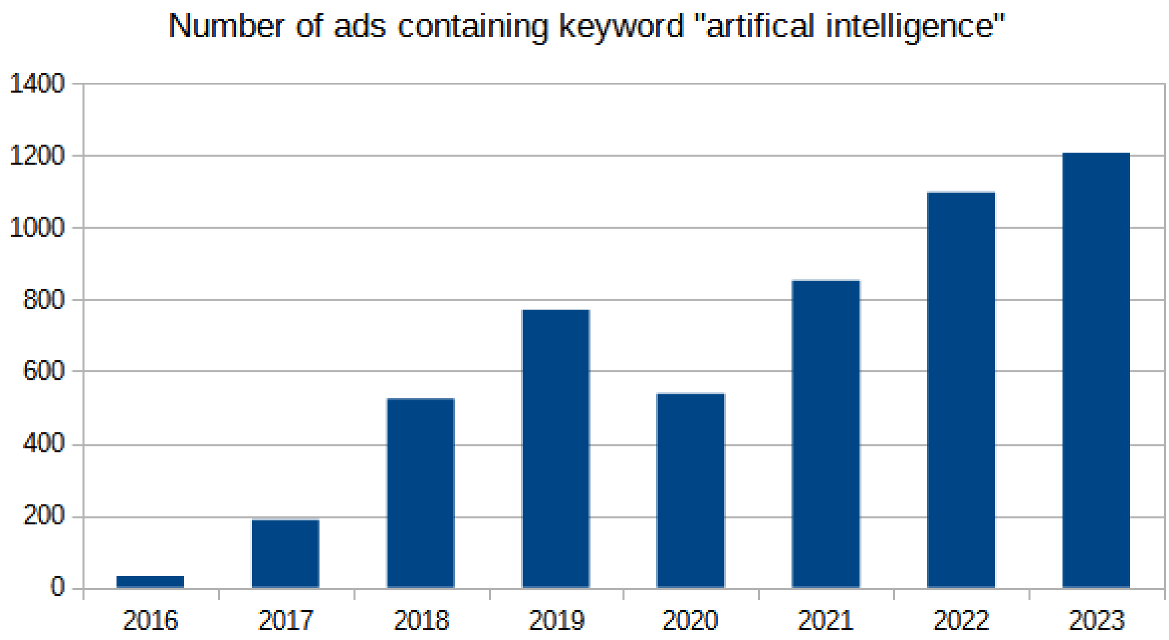

Figure 4.2: Number of ads containing keyword "artificial intelligence"

As we can see in the diagram (Figure 4.2), the number of ads with artificial intelligence mentioned increased over time. From basically being nonexistent in the beginning of the period to having over 1000 adverts per year in the last two years. A major downturn can be seen in 2020 which can be partially attributed to the general drop in a number of adverts that year.

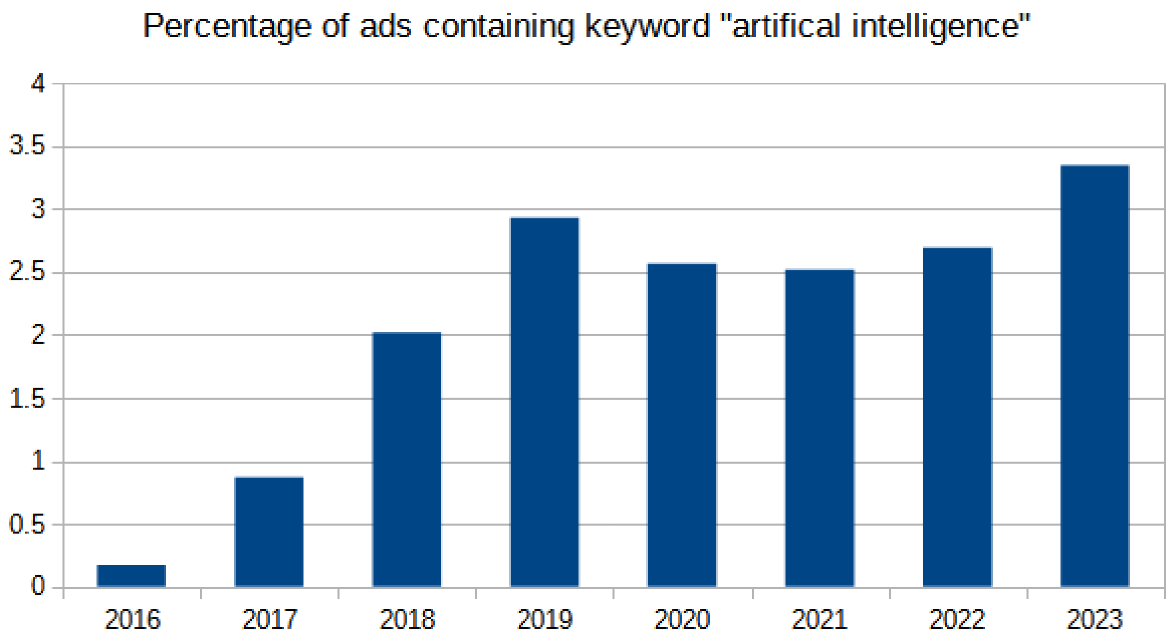

Figure 4.3: Percentage of ads containing keyword "artificial intelligence"

Looking at the percentage of ads with the phrase artificial intelligence, as can be seen in figure 4.3, it shows a less dramatic development since 2019 and onward. The increase in the last couple of years is explainable by the general increase in adverts in the database.

Table 4.13: Skills associated with the phrase "artificial intelligence"

Skill	Occurrences	Percentage
artificial intelligence	5210	100.00%
data	2364	45.37%
machine learning	1693	32.50%
design	1509	28.96%
svenska	1179	22.63%
engelska	1162	22.30%
python	1157	22.21%
java	976	18.73%
cloud	896	17.20%
ml	730	14.01%

Table 4.13 shows the frequency and percentage of advertisements mentioning various skills related to artificial intelligence (the full list can be read in appendix 3). The data reveals that AI is referenced in 5,210 advertisements, making it the baseline (100.00%) for comparing other related skills.

The second most common skill is data, appearing in 45.37%. This indicates that nearly half of AI-related job postings also emphasize data skills. Machine learning is mentioned in 32.50% of adverts. Design skills are highlighted in 28.96%, suggesting the role of user experience and interface design. Python is the most common programming language associated with AI, appearing in 22.21%. This is followed by Java, 18.73%, indicating the relevance of these languages in AI projects. As previously seen, Swedish and English are commonly mentioned in advertisements, 22.63% and 22.30% respectively.

Table 4.14: Top skills associated with artificial intelligence

Skill	Total Percentage	AI Percentage	Difference
artificial intelligence	2.32%	100.00%	97.68%
data	12.91%	45.37%	32.46%
machine learning	2.05%	32.50%	30.45%
ml	0.47%	14.01%	13.54%
python	9.50%	22.21%	12.71%
cloud	5.34%	17.20%	11.86%
design	18.22%	28.96%	10.74%
big data	1.03%	10.63%	9.60%
innovation	4.96%	13.03%	8.07%
iot	1.75%	8.69%	6.95%

Table 4.14 is sorted by highest difference between the skills mentioned in all job ads in the data and the ones that mentions artificial intelligence. AI itself is mentioned in 2.32% of all job ads, forming the baseline (100.00%) for comparison in calculation.

Data skills appear in 12.91% of all job ads, but when filtered to AI-related ads, this figure rises to 45.37%, indicating a 32.46% increase. Similarly, machine learning is noted in 2.05% of all ads but jumps to 32.50% within AI-specific ads, showing a significant 30.45% difference. The term "ML" (machine learning) appears in 0.47% of all ads but 14.01% of AI-related ones, reflecting a 13.54% increase. Python is mentioned in 9.50% of all job ads but increases to 22.21% in AI-specific postings, a 12.71% difference.

Cloud computing skills are cited in 5.34% of all ads, rising to 17.20% for AI-related roles, indicating an 11.86% increase. Design skills, while mentioned in 18.22% of all job ads, are highlighted in 28.96% of AI ads, showing a 10.74% difference. Big data is noted in 1.03% of all job ads but appears in 10.63% of AI-related ads, reflecting a 9.60% increase. Innovation is mentioned in 4.96% of all ads but 13.03% of AI-specific ads, indicating an 8.07% difference. Finally, IoT (Internet of Things) appears in 1.75% of all job ads but increases to 8.69% in AI-related postings, showing a 6.95% difference.

The prominence of data-related skills, such as data analysis and machine learning, underscores the central role that data plays in AI development. The presence of IoT in AI job ads might reflect an increasing convergence between these areas of expertise.

4.2.5 Traits mentioned in job adverts

Table 4.15: Top traits asked for in the adverts

Trait	Occurrences	Percentage
driven	34700	26.4%
kommunikativ	23067	17.6%
nyfikenhet	22290	17.0%
social	16002	12.2%
flexibel	15805	12.0%
självgående	15412	11.7%
strukturerad	14322	10.9%
ansvarstagande	13862	10.6%
lagspelare	12742	9.7%
analytisk	12498	9.5%

The analysis of job advertisements reveals the most sought-after traits for candidates across various roles (table 4.15). The most frequently mentioned trait is being "driven," appearing in 26.4% of job ads. This suggests that employers highly value individuals who are motivated and have a strong sense of initiative.

The second most common trait is "kommunikativ" (communicative), found in 17.6% of the ads. This indicates the importance of effective communication skills in the workplace, highlighting the need for employees who can convey ideas clearly and collaborate well with others.

"Nyfikenhet" (curiosity) ranks third, mentioned in 17.0% of job ads. This trait underscores the value placed on individuals who are eager to learn and explore new ideas, which is critical in dynamic and innovative fields.

Other notable traits include being "social" (12.2%), "flexibel" (flexible) (12.0%), and "självgående" (self-sufficient) (11.7%). These traits point to the importance of interpersonal skills, adaptability, and the ability to work independently.

Table 4.16: AI traits change

Trait	Total Percentage	AI Percentage	Difference
förändringsbenägen	0.20%	0.81%	0.60%
open minded	0.23%	0.83%	0.59%
framåtanda	0.34%	0.83%	0.48%
kreativ	5.33%	5.78%	0.45%
strategisk	0.65%	1.07%	0.43%
passionerad	0.68%	1.06%	0.38%
handlingskraftig	0.47%	0.83%	0.36%
problemlösande	1.47%	1.75%	0.28%
entusiastisk	0.21%	0.48%	0.27%
doer	0.37%	0.63%	0.26%

The trait "förändringsbenägen" (change-oriented) shows the most significant difference, being mentioned in 0.81% of AI job ads compared to 0.20% in general ads, indicating a 0.60% increase (table 4.16). Compared to skills the traits are not as changeable when comparing AI related adverts with the total amount of advert data. The traits mentioned more do however suggest that adaptability and a willingness to embrace change are crucial for AI roles.

5 Discussion

This chapter is the analysis of the quantitative data from the job advertisements and the qualitative data from the interviews. The aim of this chapter is to understand how listed skills and traits for the ISD job advertisements relate to the hard skills, soft skills and AI tools sought for by firms.

5.1 Q1: How do ISD managers view the effects of AI on the required skills of IS developers?

This section discusses the responses from the interview respondents. It lays out what skills they are interested in seeing in developers and why they may be interested in these skills. It then continues by analyzing how these responding managers view the effects of AI on the skills needed by developers.

5.1.1 Theme 1: Required skills for IS developers

5.1.1.1 ISD and Software Engineering Teams

From the perspective of ISD, Hassan and Mathiassen (2018) presents their view on how the building of a system is done, where teams have to work together to align systems with certain goals. R2 has a similar sentiment of systems development as being a team activity where people have to work together. R1 describes how teams can independently organize their work. Along these lines, Licorish and MacDonell (2017) talks about the ability to structure themselves and solve issues requiring intense communication. Similarly, respondents describe using Agile processes where teams communicate and interact regularly with each other in an intense manner (R2; R4). The process is closely involved and local teams working with Scrum roles are intimately involved (R4). They find ways to deal with the work ahead of them together (R2). There can also be communications directly with customers (R2).

R2 describes good social skills as a vital prerequisite to be able to work within their firm as its organizational structure is built up to take advantage of informal networks such as social connections to thrive. At the same time there is a need to communicate the activities within this informal organizational structure to the formal organization (R2). This is important for them as working with the group is vital to solving complex issues in developing. Often needing complex and heterogeneous skill sets to resolve issues. On working within a team with diverse background Tiwana and McLean (2005), IS developers with heterogeneous backgrounds can have prejudice about other roles that has to be overcome in order to integrate the diverse competencies of these roles. A similar manner of thinking differently, according to R7, has wider implications than just dealing with prejudice within the team as they say that there are different ideas of the same system from different departments designing the same product from different points of view which leads to difficulty in integrating developers collective ability.

5.1.1.2 Roles and skill levels in development

On working through diversity of backgrounds something that R4 iterates, there are a multitude of roles involved in development not only Developers. Both R4 and R5 say that developers interact with UX. While R7 and R5 explains some Scrum related roles that a developer has to interact with. There is also an example which is given by R7 where communication is performed with several parties although a notable aspect is that responsibility where seniors interact with consumers while juniors only communicate more internally with the team and team-adjacent parties such as business analysts and UX.

Developers can be required to do different sets of tasks in the firm and therefore require different specializations. R6 and R2 explain that their firm has many different sub roles a developer can be in. Then there is the level of seniority, R3 mentions that senior developers may be needed for different things within the firm, so it might not be as clear as if the firm needs a senior developer but a senior that can handle maintaining operations related tasks or is more of a specialist within a certain subsection of tasks. In context with this, clarity of tasks is important to developers as Rezvani and Khosravi (2019) discuss developers having to take on a plethora of diverse tasks. R4 also suggests that IS developers can be required to do a plethora of tasks. Some firms such as that of R5 required skills of IS developers with an expectancy to be broader to perform a diverse set of tasks to at least a minimum level of satisfaction. On clarity Windeler, Maruping and Venkatesh (2017) also expresses that a wider spectrum of tasks can be managed through the prerequisite of developers having clear leadership, what a role is and what is expected from a developer in this role helps to control stress.

To continue on the line of seniors are expected to have more depth and responsibilities. It is also expected by both respondents R4 and R5 that seniors should possess a deeper insight into the profession. R4 believes that seniors should be able to communicate their understanding of their profession well. R2 thinks that seniors need to have the wisdom to stand by their assertions and decisions. There is a certain level of skill expected from seniors but not the same for juniors. This is as R5 and R7 due to more soft skills such as leadership being needed in senior skill sets. R7 believes that senior developers should have social responsibility for leading in different ways and to be able to communicate well with stakeholders. The literature expresses that leadership is not expected in new graduates (Akman & Turhan, 2018; Aasheim, Williams & Butler, 2009). In general, Neufeld and Haggarty (2001) believes junior developers lack the right skills to be competitive on the market. R5 and R7 view of the situation for juniors is that they are in a larger surplus on the job market due to similarity of skills between aspirants.

5.1.1.3 Skills

Skills are central to developers' valuability, there are several different types of skills in two major sections. Todd, McKeen and Gallupe (1995) presents specifically technical skills and soft skills are needed for developers. Akman and Turhan (2018) explains that both hard and soft skills matter to developers. The integration of hard and soft skills is a recurring theme in both the interviews and prior research. Respondents R2 and R5 highlight the necessity of combining technical proficiency with interpersonal skills to create a balanced and effective workforce. This is consistent with findings by Akman and Turhan (2018), who emphasize that both types of skills are crucial for developers.

There are some indications such as from R3, R4 and R6 that all state that they value soft skills highly and more strictly than hard skills as soft skills are needed to work with others. R3, R4 and R1 believe that fitting into the social context is important. R3 thinks soft skills are more critical than hard skills due to social ability not being changeable according to them. In the views of R6 and Aasheim, Williams and Butler (2009) teamwork is necessary to construct systems. In a similar manner Neufeld and Haggerty (2001) explain that the team members need certain soft skills to be able to perform teamwork, such as collaboration and commitment. R6 argues that the ability of developers to follow and work jointly on a code base in a modular manner is important to be effective. They say the ability to follow standards of doing things and not to produce case per case solutions is seen as an important issue to the project. From an ISD design perspective Benbya and McKeley (2006) argues that keeping to a compostable structure modularity allows for controlling complexity giving efficiency in system adaptation to business requirements and limiting overhead in doing these changes.

5.1.1.4 Hard skills

Hard skills are seen as a baseline of what potential employees need to know to be viable candidates (R5). This aligns with prior research, such as the work by Todd, McKeen, and Gallupe (1995), which underscores the importance of technical skills in the IS domain. R1 states that programming knowledge is essential. R1, R2 and R5 as well as Montandon et al. (2021) and Lee and Mirchandani (2010) view programming as an important skill. Lee and Mirchandani (2010) presents a picture of a shifting baseline for requirements. While Montandon et al. (2021) observed that libraries and frameworks have grown in importance. This is in line with Lee and Mirchandani (2010) who says that web technologies have gained in prominence. Montandon et al. (2021) describes a growth in the complexity of skills needed. Lee and Mirchandani (2010) speaks of IT trends and changes of focus for a grown complexity of IT. R5 and R6 describe expectations of developers to have a broader skill set that allows them to perform tasks outside of typical developer skills, they want skills within using platforms and IT operations tooling knowledge as well.

R3 describes that similar skills make it easier to learn or work with adjacent skills sets. Armstrong and Hardgrave (2007) mirrors this by their mindshift view where technical skills are easier to understand when principals are more similar to each other. R4 follows this line of logic as they want more specific hard skills to be present if they can, such as knowing specific languages or frameworks well. They put value in business knowledge, if candidates have experience with the business’s operations. To them this is pertinent to scenarios of internal recruitment which gives a pragmatic evaluation to their choice between the two skill sets.

5.1.1.5 Soft skills

Soft skills aspects are seen as essential to development. Some abilities developers should have according to R2 is to think logically, solve problems and be able to manage pressure. People have different views of working with the system, these can be described as high level or low level (R1). Holistic thinking is also important according to R2 as activities cannot be understood in a vacuum. A variation of skills are needed depending on what the context is, so different compositions of people are pertinent (R1). An aspect that R4 presents is the importance of working with the others in the team (R4). According to Akman and Turhan (2018) team members are an integral building block of the team. It is seen as a serious lack in soft skills as it is hard to imbue it into people if they do not already have social ability preexistent (R4). The ability to fit into the social context of a team, effective communication, and collaboration are deemed crucial. This perspective is supported by Aasheim, Williams, and Butler (2009), who argue that teamwork is fundamental to successful system development. Similarly, Neufeld and Haggerty (2001) highlight the necessity of collaboration and commitment within teams, indicating that social skills are indispensable for IS developers. In regards to communicative ability, R4 states that gaining support from different stakeholders is important (R4). Supported by Galster et al. (2023) who argues for the ability to communicate effectively to gain support and understanding from stakeholders. The need for these soft skills was also underscored by Aasheim, Williams, and Butler (2009), who noted the necessity for interpersonal skills, particularly in entry-level positions.

Social skills and positive demeanor are important, R5 the ability to handle different aspects involved in development is important, such as dealing with customers, cooperating with the team, being able to take critique on code, to keep track of things and to be dependable and nice to people. Rezvani and Khosravi (2019) would agree to this as they also mention that emotional intelligence and trust are important aspects to building an efficient ISD team with reliability. To R2 in their firm the ability to form relationships is seen as important and these informal social bonds are viewed as vital to solve issues with the help of these connections.

Open and honest communication about thoughts and opinions on issues pertaining to project related issues are appreciated (R3; R4). Although, honesty is not viewed as a changeable trait in people (Aasheim, Williams & Butler, 2009).

5.1.2 Theme 2: Effect of AI on ISD work

5.1.2.1 AI maturity

The maturity of AI tool integration varies depending on the firm, R7 is just in the very beginning, R4 has started by using AI tools in software testing while R5 are using a larger set of AI powered assistance tools. R5 is looking to further expand their capacity even more in regards to AI. Some assistance tools they use range from Github Copilot to Microsoft 365 Copilot and more.

The path towards deeper integration varies between the different respondents. In R7's firm AI assistants are mostly integrated in other existing tools while R2 is just starting to use such AI tools in a pilot project and the greatest and most eager integration comes from R5 and R6. Hesitancy is a concern of R5's customers who are hesitant to use these tools while R7 themselves will wait to integrate these tools in their processes. Contrasting this hesitancy with what Gupta et al. (2023) suggest about ChatGPT which can in some cases produce biased answers leading to consequences of legal rights and security characteristics.

5.1.2.2 Challenges with AI-tools

On the aspect of security is another challenge. There are three different perspectives shown here, R5's and R6's firm show a greater understanding of how AI Assistants are used in the firm, the strengths and weaknesses of it. While R7 has a fear that users do not know how to use the tools in a proper manner, due to handling and security concerns. In contrast with respondents R1 and R2 who have started testing and are midway between R5 & R6 and R7 in their insights of the issues involved in integrating AI tools. The approach of R1 to mitigate risk is to only allow a few selected specialists to use AI assistants. This is not in line with Jarrahi (2018) who argues for making relevant staff familiar with AI in use in the organization so that they know how to best use them to allow for increased common performance. The way R6 deals with insecurities in their work is by requiring analysis and understanding the code before adding to the codebase. Other issues they want to avoid are legal challenges. R1, R2, R5 and R6 voice their collective fear of adding IP protected code into their codebases.

Yet another challenge posed by AI tools on integrating them into the firm is the responsibility developers have to take for the AI produced code. R1, R2 and R7 all believe that the developer himself needs to take responsibility for the code produced through code generating tools. Therefore Fan et al. (2023) presents that evaluation techniques are important to deal with issues such as hallucinations that generate biased outputs. In line with this R2 talks about the belief that a way of dealing with AI outputs is team analysis of results. Jarrahi (2018) believes AI is suitable for routine tasks but not for wider holistic decisions and long term solutions. Cabrero-Daniel et al. (2024) trusting the outputs is considered non advisable as it is not suited for precise wider scope decisions. That in relation to R1 believing that understanding could be so poor that it generates something but that it does not exactly understand what the operator wants. They are afraid that this will cause juniors to use it without critical thinking. As such they prefer senior developers as they have the ability to handle this better through understanding.

5.1.2.3 Effects of AI on skills

Xue et al. (2022) argues that to reskill or upskill the workforce will be needed to keep skills relevant. R6 reflects this notion by stating that the workforce will have to adapt by explaining that IS developers have always needed to do this and that it is not exclusive to the emergence of AI based tools. R1, R2, R4, R5 and R6 all believe that there is a need for the developer to be able to judge generated outputs of the AI tools. Grønsund and Aanestad (2020) humans can more easily handle scopes that are outside of the AI's purview of its data. R2 means that it is critical thinking about the outputs that is important. According to R1 analyzing the code will require more skills. Gupta et al. (2023) presents the dangers of tools using ChatGPT with its hallucinations and how it can be utilized maliciously for exposure to cyber threats. R4 means that the AI assistant just makes information more available that then needs to be checked.

While R7 believes that understanding technology is important to build systems. Exploring what the AI tools potential is is important and interested IS developers are the best at that (R2). While R5 has observed a large upwards trend in the effectiveness from AI assistant augmenting development. In line with this Fügener et al. (2021) proposes that humans and AI create a greater whole together. R4 describes that they gain a deeper understanding of the code during testing than when they exclusively manually review it, AI tools augment their abilities. Similar complementation is advocated by Jain et al. (2021) where the AI human support in strengthening human abilities. Bucaioni et al. (2024) presents the view that ChatGPT is not as efficient with more complex tasks as programmers and therefore not a complete replacement. With a similar view on this R4 believes that the development will be broadly about reviewing code although more specific use cases will need more of a human hand to develop more precise business logic.

5.1.2.4 AI Future

There are different views of AI tools usage between respondents on how they view the human-machine balance. The future of AI supported development in R1's opinion will be specification to fit a certain use instead of coding. They believe the fit of the product to its purpose will become more of the focus. R2 agrees with this assessment. R5 believes higher efficiency frees up more time to reason around what is to be done together with the customers. R7 also agrees that technology will get less focus but means that soft skills derived from knowing how to code such as problem solving may be transferable. They say that the focus will be more on delivering value in the form of solutions to problems. R4 continues on the line that the future as more analytically oriented, the developers will act as a controller for the AI tool. Some of the literature talks about human-machine collaboration where the human keeps the AI on track to do its job (Grønsund & Aanestad, 2020). R2 believes in the possibility that an emergence of new developer roles is ahead where developers will start doing other things with new titles.

Xue et al. (2022) brings the concept of the deskilling effect where the barrier to entry is defined by lower skills needed for the same task as before. While R2 is fearful of how the deskilling effect of the tools will lead down the road of less innovation in work processes creating less novel things. Fügener et al. (2021) talks about this reliance in a similar way where they also show concern about innovativeness.

The perspective of the deskilling effect of AI tools on programming is R7 that of soft skills becoming more relevant in return. R1 and R2 have a belief that the effects will benefit juniors so far as it allows them to do more from the start. R2 also expresses some concerns for juniors on their ability to judge the content generated. R5 posits that the tools will make juniors lose their standing due to being redundant in relation to seniors.

Projecting what is to come, R5 presents the deskilling effect of natural language skills needed in development projects and its larger effect on the needs for deskilling AI tools. R6's outlook on the future is that learning to use the tools will allow for more exploitation of their beneficial sides.

5.2 Q2: What skills are associated with AI in ISD job advertisements?

This section discusses the results of the quantitative dataset. The aim is to discuss the results of this study and how the skills needed for ISD jobs are associated with AI.

5.2.1 Technical skills

It is evident that proficiency in traditional programming languages remains foundational, with a particular emphasis on object-oriented programming and scripting languages. However, there is a clear trend towards a more comprehensive skill set that encompasses both platform-specific knowledge and broader IT operations tooling. This trend towards a broader and more integrated technical skill set supports the arguments made by Montandon et al. (2021), who highlighted the growing specificity and diversity of technical skills demanded in the IT sector. The emphasis on a variety of tools reflects the industry's shift towards more holistic development practices, echoing the dynamic nature of the IT landscape described by Lee and Mirchandani (2010).

Job advertisements consistently emphasize the necessity for developers to be adept at using a variety of tools and technologies integral to modern development processes. Tools such as Jenkins, Azure DevOps, GitHub, Docker, Kubernetes, and Terraform are frequently mentioned, reflecting the industry's shift towards DevOps practices.

This shift underscores the importance of developers not only being skilled in coding but also in managing and automating deployment processes using these tools. Additionally, the integration of cloud platforms like GCP, Azure, and AWS into the development workflow indicates a need for developers to have expertise in cloud computing. The introduction of cloud platforms and the emphasis on DevOps practices align with the trends identified by Niederman et al. (2016) and Grønsund & Aanestad (2020), who noted the increasing complexity and integration of technical environments in ISD.

Furthermore, the demand for specialized skills in emerging technologies such as artificial intelligence and machine learning is highlighted. The inclusion of AI skills points to the growing importance of developers being able to work with advanced algorithms and data analysis techniques. AI's integration into various aspects of system development necessitates these new skills, as noted by Acemoglu et al. (2022).

While the need for a broad range of technical skills is clear, the balance between depth and breadth remains an important issue. Armstrong and Hardgrave (2007) argue that transitioning between similar but different programming paradigms requires a significant cognitive shift, which can be challenging for developers. There may be diminishing returns if the depth of expertise in specific areas is sacrificed. Mardis et al. (2017) highlighted the increasing importance of technical competencies such as system integration and architecture.

Additionally, the emphasis on AI and machine learning introduces potential deskilling concerns, as some respondents fear that reliance on AI tools could reduce the opportunity for developers to innovate and deepen their technical expertise. This sentiment resonates with the concerns raised by Ford et al. (2021) about the potential negative impacts of AI on job complexity and developer skill levels.

5.2.2 Occupations

The data indicates a pronounced demand for "systemutvecklare" (systems developers), which comprise over half (51.07%) of the total job adverts, followed by "mjukvaruutvecklare" (software developers) at 18.65%. The substantial proportion of job adverts for systems and software developers suggests a market heavily focused on the technical aspects of ISD. However, the presence of other roles such as "projektledare" (project manager) at 10.21%, "backend-utvecklare" (backend developer) at 5.52%, and "frontendutvecklare" (frontend developer) at 5.48% points to a diverse range of expertise required to support the development lifecycle. These roles are integral in ensuring that projects are managed efficiently and that both the server-side and client-side components of applications are robustly developed.

Furthermore, the top skills associated with these common occupations reflect the specific technical and non-technical competencies demanded by employers. The dual emphasis on language skills and technical expertise highlights the importance of communication and teamwork in addition to technical proficiency. Notably, the role of software engineers stands out with a significant emphasis on design (38.7%) and agile methodologies (20.3%), indicating the need for creative problem-solving and adaptive project management skills in these positions.

Benbya and McKelvey (2006) discuss the changeable nature of software systems, requiring developers to adapt. The high demand for systems and software developers identified in the results reflects this need for adaptability and continuous development of complex systems . This is further supported by Riemenschneider and Armstrong (2021), who describe workers within ISD as operating in dynamic and demanding environments. The predominance of developer roles in the job market underscores their central role in managing this complexity.

Prior research by Todd, McKeen, and Gallupe (1995) and Montandon et al. (2021) also highlighted the increasing importance of both technical and soft skills for IS developers. The results of this study, showing significant demand for technical skills such as proficiency in Java and agile methodologies, corroborate these findings . This indicates that while technical proficiency remains crucial, there is also a growing emphasis on methodologies that facilitate adaptability and collaboration within development teams.

Moreover, the results reveal a nuanced skill requirement across different roles within ISD, such as backend and frontend developers, project managers, and fullstack developers. This diversity in required skills aligns with the broad competencies framework proposed by Assyne, Ghanbari, and Pulkkinen (2022).

5.2.3 Skills associated with artificial intelligence

The data shows a significant increase in job advertisements mentioning AI, highlighting a rising demand for AI-related skills. This growth reflects the broader integration of AI technologies across various industries and the increasing recognition of AI's potential to drive innovation and efficiency.

The detailed analysis of job advertisements reveals that AI is frequently associated with several key skills. Data skills are the most prevalent, appearing in 45.37% of AI-related job postings. This emphasizes the critical role of data management and analysis in AI projects, as the ability to handle and interpret large datasets is foundational to developing effective AI solutions. Machine learning, another cornerstone of AI, is mentioned in 32.50% of the adverts, underscoring its importance in creating algorithms that enable machines to learn from and make decisions based on data.

Design skills are also prominently featured, appearing in 28.96% of the AI-related advertisements. This suggests that the development of AI systems is not solely a technical challenge but also involves significant considerations of user experience and interface design. The need to create intuitive and accessible AI-driven applications necessitates a blend of technical and creative skills, highlighting the interdisciplinary nature of AI development.

Programming languages like Python and Java are frequently mentioned, with Python appearing in 22.21% and Java in 18.73% of AI-related job ads. Python's popularity can be attributed to its extensive libraries and frameworks that facilitate AI and machine learning development. Java, known for its robustness and scalability, remains relevant, particularly in enterprise environments where integration with existing systems is crucial.

Moreover, the prominence of cloud computing skills (17.20%) reflects the growing trend of deploying AI solutions on cloud platforms, which offer the computational power and scalability needed for AI tasks. This shift towards cloud-based AI solutions is indicative of the broader digital transformation trends influencing many sectors.

The discussion of these skills in job advertisements aligns with the broader trends observed in the literature. The increasing emphasis on data and machine learning skills mirrors the findings of Xue et al. (2022), who noted that AI integration often necessitates reskilling and upskilling to adapt to new roles and responsibilities. The mention of design skills aligns with the observations of Niederman et al. (2016), who highlighted the growing importance of user-friendly interfaces as technology matures and becomes more integrated into applications.

Todd, McKeen, and Gallupe (1995) highlight the increasing importance of soft skills alongside technical skills . This is corroborated by the results showing a substantial demand for design skills in AI-related job ads, suggesting a need for a blend of technical and creative skills to develop user-friendly AI applications. This interdisciplinary requirement aligns with Klendauer et al. (2012), who emphasize the broad competencies needed for software engineers, including communication and behavioral skills.

One of the key findings in section 4.2.4 about skills associated with artificial intelligence is the prominence of cloud computing skills, reflecting the trend towards cloud-based AI solutions. The growing emphasis on cloud skills suggests that organizations are increasingly leveraging cloud platforms to deploy scalable AI solutions, a trend that has been accelerated by the broader digital transformation across industries.

While the prior research emphasizes the need for a variety of technical skills over time, with some technologies becoming less relevant (e.g., the decline of the C programming language as noted by Lee and Mirchandani, 2010) , the current findings suggest a robust demand for established programming languages like Python and Java. This indicates that while new technologies emerge, some foundational technical skills remain consistently valuable.

5.2.4 Traits mentioned in job adverts

The predominant trait mentioned is being "driven," appearing in 26.4% of job ads. This high frequency suggests that employers prioritize candidates who exhibit strong motivation and a proactive attitude. Such individuals are likely perceived as capable of taking initiative and contributing to the company's goals effectively, which is crucial in dynamic and competitive work environments.

The second most common trait is "kommunikativ" (communicative), found in 17.6% of the ads. This underscores the importance of effective communication skills in the workplace which echoes the sentiments of Klendauer et al. (2012). Who argue that effective communication is crucial not only for the technical execution of tasks but also for the collaborative nature of modern software development environments. Employers value individuals who can clearly convey ideas, collaborate with team members, and interact with clients and stakeholders efficiently. In a professional setting, the ability to communicate well is essential for teamwork, project management, and problem-solving.

"Nyfikenhet" (curiosity) ranks third, mentioned in 17.0% of job ads. Curiosity indicates a candidate's eagerness to learn and explore new ideas, which is particularly critical in fields that require constant innovation and adaptation to new technologies and methodologies. Employers seek curious individuals who can drive the company forward by continually improving and seeking out new opportunities.

Other notable traits include being "social" (12.2%), "flexibel" (flexible) (12.0%), and "självgående" (self-sufficient) (11.7%). These traits highlight the value placed on interpersonal skills, adaptability, and independence. Social skills are crucial for maintaining a positive work environment and facilitating effective teamwork. Flexibility is important for adapting to changing circumstances and demands, while self-sufficiency indicates that a candidate can work independently without requiring constant supervision.

Additionally, the data shows specific traits that have become more emphasized in AI-related job adverts. The trait "förändringsbenägen" (change-oriented) shows a significant increase, being mentioned in 0.81% of AI job ads compared to 0.20% in general ads. This suggests that adaptability and a willingness to embrace change are particularly valued in roles involving AI. Similar trends are observed for traits such as "open-minded" and "framåtanda" (forward-thinking), which are slightly more prominent in AI job ads.

This sector requires not only technical expertise but also a heightened ability to adapt and innovate, as described by Alekseeva et al. (2021). The integration of AI into ISD roles underscores the need for developers who can navigate and leverage complex AI tools effectively, aligning with the insights provided by Niederman et al. (2016) on the evolving nature of technological competencies.

5.3 Q3: How are the required skills for IS developers affected by AI?

This chapter explores the impact of AI on the skills required for IS developers, combining insights from both interviews with industry managers and analysis of job advertisements.

Table 5.1: Comparing interviews with job ads

Theme	Interviews	Job Ads
Technical Skills	AI perceived to increase demand for specialized technical skills	AI-related skills (machine learning, data science) more prevalent in recent ads
	Broader skill set expectations including platforms and IT operations	Common mentions of specific programming languages and frameworks such as Python
Soft Skills	Need for adaptability and continuous learning emphasized by managers	Traits such as curiosity, flexibility, and change-oriented mentioned more frequently
	Critical thinking and analytical skills essential for evaluating AI outputs	High demand for communication, teamwork, and problem-solving skills
	Importance of cultural fit and adaptability to company culture	Traits like 'communicative', 'flexible', and 'self-sufficient' are commonly highlighted
General Reflections	Managers note the need for balancing AI tools with human creativity and decision-making	Job ads reflect a balanced demand for both AI-specific skills and traditional development skills
	AI tools are seen as augmenting rather than replacing human roles, especially in complex problem-solving	Emphasis on the ability to integrate AI tools within existing workflows and environments
	Ability to handle complexity and work well in teams is crucial	Adaptability and willingness to embrace change are emphasized, especially in AI-related roles

A recurring theme in the interviews is the need to balance the use of AI tools with human creativity and decision-making. Managers perceive AI as an augmentation rather than a replacement for human roles, particularly in complex problem-solving tasks. This perspective is supported by job ads that reflect a balanced demand for both AI-specific and traditional development skills. There is a notable emphasis on the ability to integrate AI tools within existing workflows, highlighting the interdisciplinary nature of ISD roles.

The interviewed ISD managers highlighted several ways in which AI is reshaping the landscape, with a notable emphasis on the increased efficiency and productivity AI tools bring to development processes. R7 and R5 mentioned that AI tools enable developers to accomplish more with less, potentially reducing the demand for new graduates as one senior developer equipped with AI tools can handle tasks that previously required multiple individuals.

Both data sources emphasize the importance of soft skills, though with some differences in focus. Interviews revealed that managers value critical thinking, adaptability, and continuous learning, particularly for evaluating AI outputs and integrating AI tools effectively. This is consistent with job ads that highlight traits such as curiosity, flexibility, and problem-solving abilities. Communication and teamwork are also frequently mentioned in job ads, aligning with managers' views on the importance of social fit and collaborative skills. While interview respondents emphasize the importance of soft skills and adaptability, the job advertisement data shows a stronger focus on technical skills, particularly in AI-related roles. This discrepancy suggests that while employers value soft skills, the immediate demand in job postings may prioritize technical competencies.

Moreover, AI tools like code assistants are perceived to have a dual impact. On one hand, they can help junior developers by providing support and enabling them to start earlier in their careers, as noted by R1 and R2. On the other hand, R5 expressed concern that the skill levels of new graduates might become redundant, making it harder for them to secure jobs. This suggests a shift in the job market dynamics, emphasizing the need for continuous learning and adaptation to maintain relevance in the industry. An over-reliance on code assistants might also lead to a decline in the development of foundational technical skills among developers, particularly junior ones. As AI increasingly automates routine coding tasks, there is a risk that developers may not acquire a deep understanding of programming concepts, which could hinder their ability to innovate or troubleshoot complex issues that AI cannot address.

Additionally, the potential deskilling effect of AI tools on programming skills, mentioned by some interviewees, contrasts with the job advertisement data's emphasis on advanced technical skills such as machine learning and cloud computing. This contradiction highlights the evolving landscape of ISD roles where AI tools could potentially simplify certain tasks, yet simultaneously, there is a demand for highly specialized technical knowledge to develop and manage these tools effectively.

While some interview respondents downplay the importance of certain technical skills due to rapid technological changes. However, job advertisement data shows a consistent demand for foundational technical skills like Java and SQL, suggesting that while adaptability is important, a strong technical foundation remains crucial. Other ISD managers concurred with this, highlighting that traditional programming skills remain foundational. The job ads data indicates a growing demand for AI-related skills, reflecting the broader industry trend towards AI integration. The number of job advertisements mentioning AI has increased significantly over the years, with a notable rise in skills such as data management, machine learning, and design. This aligns with the interview findings that emphasize the importance of these skills in the context of AI-enhanced ISD work.

Respondents highlighted several ways in which AI is developed, with a notable emphasis on the increased efficiency and productivity AI tools bring to ISD processes. R7 and R5 mentioned that AI tools enable developers to accomplish more with less, potentially reducing the demand for new graduates as one senior developer equipped with AI tools can handle tasks that previously required multiple individuals.

6 Conclusion

This chapter concludes the master thesis. It concludes with a summary of the findings, gives a view of general reflections and a statement of interests for future research.

This study has aimed to explore the evolving landscape of skills required for IS developers in the context of the increasing integration of AI. Through a mixed-method approach, combining quantitative analysis of job advertisements with qualitative insights from interviews, the study reveals a shift in the demand for both technical and soft skills. AI technologies, while automating routine tasks and reducing the emphasis on manual coding, have increased the need for more analytical, integrative, and AI-related competencies. Additionally, there is a notable rise in the importance of soft skills, such as adaptability, communication, and problem-solving, reflecting the evolving role of IS developers.

6.1 Answering the research questions

Q1: How do ISD managers view the effects of AI on the required skills of IS developers?

ISD managers perceive AI as both an enabler and a disruptor in the realm of technical skills. The automation capabilities provided by AI tools are expected to reduce the amount of manual coding, shifting the focus towards more analytical and integrative tasks. Managers emphasize that while AI tools can automate routine coding tasks, a deep understanding of programming concepts is essential to effectively leverage these tools and troubleshoot complex issues. However, there is a concern that reliance on AI might lead to a 'deskilling' effect, particularly among junior developers, who may not develop this depth of understanding traditionally required in the field.

A recurring theme in the interviews is the need to balance AI tools with human creativity and decision-making. Managers perceive AI as an augmentation that enhances human roles, particularly in complex problem-solving scenarios. This perspective aligns with job advertisements that reflect a balanced demand for both AI-specific and traditional development skills.

Looking forward, ISD managers anticipate the emergence of new developer roles and the continuous evolution of required skills. The integration of AI is expected to drive a broader set of competencies, blending technical and soft skills to adapt to new technological innovations.

Q2: What skills are associated with AI in ISD job advertisements?

The analysis of job advertisements show changes to the asked for skills and their associated with AI in the Information Systems Development (ISD) sector. The increasing integration of AI technologies has led to a significant shift in the demand for both technical and soft skills.

The data underscores the prominence of several key technical skills associated with AI in job advertisements. Data management skills are the most frequently mentioned. This highlights the critical role of data handling, analysis, and interpretation in AI projects. The prevalence of machine learning underscores its importance in developing algorithms that enable machines to learn from and make decisions based on data. Programming skills remain foundational, with Python and Java being the most commonly cited languages.

In addition to technical competencies, the demand for soft skills is increasingly emphasized. Traits such as adaptability, curiosity, and a willingness to embrace change are crucial for roles involving AI, as these roles often require continuous learning and flexibility in the face of rapid technological advancements. Job advertisements frequently mentioned traits like "communicative," "flexible," and "self-sufficient," highlighting the importance of effective communication, teamwork, and independent problem-solving abilities in AI-related positions.

Q3: How are the required skills for IS developers affected by AI?

AI has increased the demand for specialized technical skills among IS developers. Proficiency in machine learning and data science is now more critical than ever, as these technologies form the backbone of AI-driven applications. Developers must be adept at handling large datasets, understanding complex algorithms, and implementing AI models effectively. Traditional programming languages like Python and Java remain essential, but there is a growing need for expertise in frameworks and tools specifically designed for AI.

Adaptability and continuous learning are emphasized, as the rapid evolution of AI technologies requires developers to stay current with new developments. Critical thinking and problem-solving are paramount, especially for evaluating AI outputs and integrating these technologies into existing systems. Communication and teamwork are increasingly important, as developers must collaborate across multidisciplinary teams to implement AI solutions effectively.

For junior developers, AI tools like code assistants can provide valuable support, enabling them to contribute effectively earlier in their careers. However, there is a concern that over-reliance on AI could lead to a deskilling effect, where foundational technical skills might not be as robust. Conversely, senior developers benefit from AI tools that enhance their productivity and allow them to tackle more complex tasks requiring a blend of technical and strategic skills.

6.2 General reflections

The study found that AI is perceived as an augmentation rather than a replacement for human roles, particularly in complex problem-solving tasks. Both job advertisements and interviews reflect a balanced demand for AI-specific skills and traditional development skills. This balance indicates that while AI tools enhance efficiency and productivity, human creativity and decision-making remain indispensable. Furthermore, the ability to integrate AI tools within existing workflows and environments is crucial, highlighting the interdisciplinary nature of ISD roles. While traditional programming skills remain foundational, the emphasis on data management, machine learning, and cloud computing reflects the evolving landscape of technical competencies.

The long-term implications of AI integration on the workforce should also be considered. As AI tools continue to evolve, they could potentially reshape the job market by reducing the demand for certain roles while creating new ones that require different skill sets. This shift necessitates a reevaluation of educational and training programs to ensure that the future workforce is equipped with the skills needed to thrive in an AI-enhanced environment. Companies may also need to adopt more flexible workforce strategies to adapt to the changing demands of the industry.

6.3 Future Research

While this study has provided valuable insights into the evolving skills required for IS developers in the age of AI, there are several areas where future research can address existing gaps. One limitation of the current research is the focus on the Swedish job market, which may not fully capture global trends and variations in skill requirements. Future studies should consider a broader geographical area to provide a more comprehensive understanding of demands for new skills.

Another area for future research is the integration of other data sources. While this study relied heavily on job advertisements and interviews with ISD managers, incorporating data from companies or conducting case studies could enhance the validity and applicability of the findings. This approach would provide a more nuanced understanding of how AI tools are impacting daily work and the skills that are most beneficial in ISD work going forward.

Appendix 1: Interview guide

Table A1.1, Interview guide

Introduction: ● General introduction ● Explain the research question ● Ask for permission to record ● Explain the research subject ● What is your role in the company? ● What tasks and areas does a developer work with within your organization? ● What other roles are in your ISD team? ● Can you describe your ISD process?	**Introduktion:** ● Generell introduktion ● Förklara forskningsfrågan ● Fråga om tillåtelse att spela in ● Förklara forskningsämnet ● Vad är din roll i företaget? ● Vilka arbetsuppgifter och områden arbetar en utvecklare med inom er organisation? ● Vilka andra roller finns i ert ISD team? ● Kan du beskriva er ISD-process?
Theme 1: Required skills for IS developers ● How does recruitment of developers work? ● How do you define the skills which are written in job descriptions? ○ Which stakeholders are involved in defining the selection of these skills? ● Which hard skills aret important for IS developers? ● Is the need for certain specific technical skills a problem when recruiting new developers? ○ Are there any other important skills? ● What characteristics, or soft skills, are most important for IS developers? ● How much do competences linked to cooperation and teamwork factor into the employment decision? ○ How do they compare to other skills you consider? ● How do you view the difference of skill levels among people seeking developer-work? ● How would you describe the difference in skill level between entry level and other employees?	**Tema 1: Sökta IS-utvecklar färdigheter** ● Hur fungerar rekrytering av utvecklare? ● Hur definieras färdigheterna som skrivs i jobbannonser? ○ Vilka stakeholders är med och definierar dessa färdigheter? ● Vilka tekniska färdigheter är viktigast för IS utvecklare? ● Är behovet av vissa specifika tekniska färdigheter ett problem när ni rekryterar nya utvecklare? ○ Finns det några andra viktiga färdigheter? ● Vilka soft skills är viktigast för IS utvecklare? ● Hur mycket väger kompetenser kopplade till samarbete och lagarbete in i anställningsbeslutet? ○ Hur jämförbara är de med andra färdigheter som ni överväger? ● Hur ser du på skillnaden i kompetensnivåer bland människor som söker utvecklararbete? ● Hur skulle du beskriva skillnaden i kompetensnivå mellan nybörjare och andra anställda?
Theme 2: Effect of AI on ISD work ● How mature is the current AI integration in your firm and in the development team? ● How do you see the development of ML and AI has affected ISD work?	**Tema 2. Effekter av AI på ISD arbete** ● Hur mogen är integrationen av AI i ert företag och i utvecklarteamet? ● Hur ser du utvecklingen av maskininlärning och AI har påverkat arbetet med ISD? ● Vilka nya färdigheter behövs för att

- What new skills are needed to adapt to the development of ML and AI? - What hard skills do you need for evaluating AI responses? - Are some skills less needed given this development? - How are the importance of communication skills and soft skills affected by AI tools? - Do you see any problems with integrating or developing AI? - Are there any certain skills needed to address those problems? - What is needed to handle the risk for bias in AI-technology? - Has there been any shift in the need for different types of skills? - How does AI affect junior developers compared to senior developers?	hantera utvecklingen av ML och AI? - Vilka tekniska färdigheter (hard skills) behöver ni för att utvärdera svar från AI-verktyg? - Är vissa färdigheter mindre nödvändiga som följd av utvecklingen? - Hur påverkar utvecklingen av AI-verktyg vikten av soft skills? - Ser du några problem med att integrera eller utveckla AI? - Finns det några specifika färdigheter som behövs för att hantera dessa problem? - Vad behövs för att hantera risken för fördomar eller bias i AI-teknologi? - Har det skett något skifte i behovet av olika typer av färdigheter? - Hur påverkar AI juniora utvecklare jämfört med seniora utvecklare?
Closing questions: - What trends do you think will affect the skills in demand for ISD in the near future? - Do you think there are any other aspects worth mentioning?	**Avslutande frågor:** - Vilka trender tror du påverkar behovet av olika färdigheter i ISD i den nära framtiden? - Finns det några andra aspekter som du tror är värda att nämna?
Conclusion: Thank the interviewee	**Avslutning:** Tacka för intervjun

Appendix 2: Thematic codes

Table A2.1: Thematic codes

Thematic Codes	Notes about the code
skills	A general code for skills related topics.
hard skills	A code relating to technical or extrinsic tools skills.
soft skills	For social skills or personal traits.
skills combination	The combination of soft and hard skills sets.
skill balance	balance of soft and hard skill sets.
will to learn	The will to learn new things.
problem solving	The ability to problem solve.
skill-gap	The skills that the worker has and the needed skill set.
skill transferability	The ability to use one skill in a broader sense, how specific the skill is.
architecture	The systems architectural ability of the worker.
complexity	Ability to deal with complexity.
interaction	Ability to interact with different parties.
teamwork	Ability to work on tasks with the team.
team fit	The workers ability to fit into a team context.
design	Systems design ability.
introspection/self reflection	The ability to understand the experiences of oneself.
confidence	To be confident of oneself and one's assertions.
demeanor	How is the worker and what is the mood displayed by them.
honesty	To be honest to others in relation to work.
social intelligence	The ability to understand others.
teams composition	The worker as a component of the team.
emotional intelligence	The ability to understand others on an emotional level.
business knowledge	Knowledge related to a firm, how processes work etc.
roles	The different roles involved in development or tangential to developing a system.
cross roles	Working between usual role lines.

junior	Entry level skill levels.
senior	Later levels of superior skills. Related to longer experience.
object oriented	A paradigm of software development.
social skills	Ability to socialize with others within a work setting.
innovativeness	The ability to create and innovate.
reasoning	The ability to
mathematics	The mathematical ability of a worker.
outgoing	If the worker is social.
curious	If the worker is interested in new things.
critical thinking	The ability to reason around and critically place something in relation to something else.
analytical	The ability to analyze something methodically.
handle pressure/stress	The ability to handle some state of strain and tension.
driven	Driven to perform a task
open minded	Being able to process new thoughts.
holistic thinking	Thinking about things from a higher perspective.
detail thinking	Thinking about things from a detailed perspective.
collaboration	Being able to work with other related parties.
self organizing	Being able to organize oneself or inside the group
scarcity	The lack of something within a circumstance, a skill in the context. The skill on the market.
time manage	The ability to manage time, be in time and do thing reasonably with time as a factor.
business skills	The ability to put the business in center frame for how to develop the system.
security	Cyber security and information security related skill sets.
AI security risks	The security risks represented by AI.
communication	The ability to communicate with other parties.
software security	The security reasoning around a certain topic.
trends	Trends within software engineering.
AI risks	The risks represented by AI.

AI data protection	Factors related to the security of data and how to protect it from exposure.
programming	The ability to program and code in different languages and frameworks.
leadership	To lead other team members in the task to construct development activities.
responsibility	Being responsible.
AI responsibility/evaluation	The evaluation of outputs and how to use the AI in different use cases.
learning to use AI	The need to learn how to use AI.
diligence	The worker is being careful about things.
AI's understanding of the user	The ability of the AI to understand the user of it.
deskilling effect	An effect related to needing lower skills levels to perform the same or similar tasks.
AI assistant	The AI in its form is able to be directly interacted with.
AI enhancements	The AI enhance human ability and skills
ISD methodology (agile etc.)	The methodology per the work in the ISD is structured and performed.
ISD	The activity of developing an Information System.
AI integration	The level or interest in integrating AI into the organization and its processes.
skill level	The level of skill of a worker.
AI maturity	To the extent that AI tools have been integrated into the organization.
socio-technical systems	A system is made up of the technical parts and the social parts that shape its form and changes.
AI and developer's role	how is the developers role affected by AI
AI legal	Legal aspects to AI.
AI responsibility of code	There is still responsibility for the code.
AI effects	Direct effects of AI change on the developer.
AI challenges	Things that are challenging about the integration of AI into the business context.

AI future	The future of AI.

Appendix 3: Technical skills

Table A3.1: Full list of programming languages

Skill	Count	Percentage
java	34138	15.6%
javascript	29433	13.5%
c#	29425	13.5%
c++	21763	9.9%
python	21341	9.8%
sql	17478	8.0%
css	15031	6.9%
html	12649	5.8%
typescript	8661	4.0%
php	6452	2.9%
xml	3197	1.5%
asp.net	3025	1.4%
kotlin	2153	1.0%
swift	2118	1.0%
scala	1744	0.8%
perl	1454	0.7%
bash	1347	0.6%
basic	1337	0.6%
objective-c	1287	0.6%
react native	1244	0.6%
ml	1064	0.5%
ruby	940	0.4%
ajax	937	0.4%
cobol	603	0.3%
shell	559	0.3%
erlang	551	0.3%

asp	537	0.2%
labview	534	0.2%
vhdl	480	0.2%
xslt	435	0.2%
opengl	381	0.2%
delphi	367	0.2%
ruby on rails	311	0.1%
rust	255	0.1%
ada	244	0.1%
xsd	238	0.1%
assembler	236	0.1%
abap	201	0.1%
clojure	189	0.1%
elm	186	0.1%
visual basic	176	0.1%
xsl	161	0.1%
xaml	159	0.1%
verilog	129	0.1%
cuda	108	0.0%
scheme	104	0.0%
lua	92	0.0%
haskell	91	0.0%
opencl	89	0.0%
rpg	84	0.0%
fortran	83	0.0%
xhtml	78	0.0%
ado.net	70	0.0%
java enterprise edition	67	0.0%
sgml	51	0.0%
pascal	33	0.0%

tcl/tk	27	0.0%
pl/1	26	0.0%
rexx	24	0.0%
wml	19	0.0%
visual basic.net	18	0.0%
apl	15	0.0%
lisp	14	0.0%
actionscript	11	0.0%
clojurescript	9	0.0%
lingo	9	0.0%
eiffel	8	0.0%
dhtml	7	0.0%
smalltalk	6	0.0%
awk	6	0.0%
prolog	5	0.0%
coldfusion	5	0.0%
java standard edition	3	0.0%

Table A3.2: Full list of development tools

Skill	**Count**	**Percentage**
git	14874	6.8%
scrum	13652	6.2%
node	8689	4.0%
jenkins	4936	2.3%
jira	4122	1.9%
kanban	3570	1.6%
eclipse	1834	0.8%
agila arbetsmetoder	1239	0.6%
unified modeling language	1175	0.5%

active directory	1034	0.5%
bitbucket	875	0.4%
teamcity	574	0.3%
intellij	482	0.2%
android studio	371	0.2%
xcode	289	0.1%
bamboo	154	0.1%
sqlite	130	0.1%
vagrant	107	0.0%
bower	101	0.0%
hudson	83	0.0%
emacs	33	0.0%
testlink	31	0.0%
testrail	17	0.0%
windows powershell	14	0.0%
adobe golive	14	0.0%
typo3	11	0.0%
sed	9	0.0%
adobe dreamweaver	4	0.0%
frontpage	2	0.0%
pico	1	0.0%

Table A3.3, Operating system

Skill	**Count**	**Percentage**
linux	12008	5.5%
android	7144	3.3%
ios	5065	2.3%
unix	2212	1.0%
windows server	1334	0.6%
operativsystem	1167	0.5%

rtos	677	0.3%
ubuntu	435	0.2%
jcl	170	0.1%
gnu	163	0.1%
vms	140	0.1%
ose	119	0.1%
vxworks	113	0.1%
dos	90	0.0%
solaris	60	0.0%
mac os x	41	0.0%
mvs	20	0.0%
vse	1	0.0%

Table A3.4: Application platforms

Skill	**Count**	**Percentage**
docker	7818	3.6%
sap	2462	1.1%
apache kafka	1721	0.8%
windows server	1334	0.6%
iis	865	0.4%
apache tomcat	828	0.4%
ibm websphere	319	0.1%
google cloud platform	193	0.1%
weblogic server	97	0.0%
windows azure	41	0.0%
ibm domino	4	0.0%
salesforce cloud	3	0.0%

Appendix 4: Example code

```
import json
import os
from collections import defaultdict
from datetime import datetime
import pandas as pd

# Define the list of occupations to check
valid_occupations = [
	"systemutvecklare", "mjukvaruutvecklare", "projektledare", "backend-utvecklare",
"frontendutvecklare",
	"civilingenjör", "lösningsarkitekt", "it-arkitekt", "javautvecklare", "software engineer",
"it-projektledare",
	".net-utvecklare", "fullstack-utvecklare", "affärskonsult", "applikationsutvecklare",
"webbutvecklare", "devops",
	"systemanalytiker", "systemutredare", "applikationskonsult", "verksamhetskonsult",
"systemarkitekt", "kravanalytiker",
	"ingenjör", "produktägare"
]

# Define the range of years to process
years = range(2016, 2023 + 1)

# Initialize counters
skill_counter_by_occupation = defaultdict(lambda: defaultdict(int))
total_skills_by_occupation = defaultdict(int)

# Process each file for the specified years
for year in years:
	file_path = f'formated.sys_lines/{year}.output_file.jsonl'
	if not os.path.exists(file_path):
	print(f"File {file_path} does not exist. Skipping.")
	continue

	with open(file_path, 'r', encoding='utf-8') as file:
	for line in file:
	data = json.loads(line.strip())
	publication_date = data.get('publication_date', '')
	try:
	pub_date = datetime.strptime(publication_date, "%Y-%m-%dT%H:%M:%S")

	# Extract and process occupation lists
	occupation_lists = data.get('keywords_enriched_occupation', [])
	skill_lists = data.get('keywords_enriched_skill', [])

	if any(occupation.lower() in valid_occupations for occupation in occupation_lists):

	for occupation in occupation_lists:
	occupation_lower = occupation.strip().lower()
```

```
        if occupation_lower in valid_occupations:
                for skill_list in skill_lists:
                if isinstance(skill_list, str):
                items = [item.strip().lower() for item in skill_list.split(',')]
                for item in items:
                # Count skills by occupation
                skill_counter_by_occupation[occupation_lower][item] += 1
                total_skills_by_occupation[occupation_lower] += 1

        except ValueError:
        continue # Skip entries with invalid date formats

# Prepare data for the Excel file
data_for_excel = []

# Get the top 10 occupations based on the number of lines
top_occupations = [occupation for occupation, _ in
sorted(total_skills_by_occupation.items(), key=lambda x: x[1], reverse=True)[:10]]

# Create a dictionary to store the top skills for each occupation
top_skills_by_occupation = {}

# For each of the top 10 occupations, get the top skills sorted by percentage
for occupation in top_occupations:
        total_skills = total_skills_by_occupation[occupation]
        skills_with_percentages = [(skill, (count / total_skills) * 100) for skill, count in
skill_counter_by_occupation[occupation].items()]
        # Sort skills by percentage in descending order
        sorted_skills = sorted(skills_with_percentages, key=lambda x: x[1], reverse=True)
        top_skills = sorted_skills[:10]

        top_skills_with_percentages = [f"{skill} ({percentage:.1f}%)" for skill, percentage in
top_skills]

        top_skills_by_occupation[occupation] = top_skills_with_percentages

# Prepare data for the DataFrame
data_for_excel = []
max_skills_length = max(len(skills) for skills in top_skills_by_occupation.values())

# Create the rows for the DataFrame
for i in range(max_skills_length):
        row = {}
        for occupation in top_occupations:
        skills_with_percentages = top_skills_by_occupation.get(occupation, [])
        if i < len(skills_with_percentages):
        row[occupation] = skills_with_percentages[i]
        else:
        row[occupation] = ''
        data_for_excel.append(row)

df = pd.DataFrame(data_for_excel)
```

```
# Save the data to an Excel file with a heatmap
output_file = 'output_skills_by_occupation_16.xlsx'
with pd.ExcelWriter(output_file, engine='xlsxwriter') as writer:
        df.to_excel(writer, sheet_name='Skills Analysis', index=False)

        # Access the XlsxWriter workbook and worksheet
        workbook = writer.book
        worksheet = writer.sheets['Skills Analysis']

        # Set the column width
        for col_num, col in enumerate(df.columns):
        worksheet.set_column(col_num, col_num, 20) # Adjust the width as necessary

        # Extract all percentage values to calculate the max percentage
        max_percentage = df.applymap(
        lambda x: float(x.split('(')[-1].strip('%)')) if '(' in x else 0
        ).values.max()

        # Define a format for the heatmap based on the extracted percentages
        for col_num, col in enumerate(df.columns):
        for row_num, value in enumerate(df[col]):
        if value and '(' in value:
        percentage = float(value.split('(')[-1].strip('%)'))
        color = workbook.add_format({'bg_color': '#ff5a5a'}) # Default red for low values
        if percentage > max_percentage * 0.66:
        color = workbook.add_format({'bg_color': '#a4e471'}) # Green for high values
        elif percentage > max_percentage * 0.33:
        color = workbook.add_format({'bg_color': '#f8f884'}) # Yellow for mid values
        worksheet.write(row_num + 1, col_num, value, color)


print(f"Data has been successfully written to {output_file}")
```

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