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Competence in the Era of Digital Automation: Implications for Knowledge Workers – A Literature Review

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Research full-length paper

Abstract

Digital automation based on technologies that learn, reason, and act is changing work life. This will inevitably and specifically have implications for knowledge workers and their interplay with digital technologies. In this paper, we report from a review of IS literature on the implications of digital technology for knowledge work and knowledge workers' competence. We take the knowledge worker's perspective and provide an overview of research and knowledge in the field. The aim of this article is to analyse and relevantly understand the implications of digital automation on work and professions. The contribution is twofold. First, the paper provides an overview of previous research and knowledge on digital automation and knowledge work. Second, it contributes to conceptualising and understanding the challenges and opportunities that digital automation brings to human competence and knowledge work.

Keywords*:* *digital automation, knowledge work, knowledge worker, professional competence, skills*

1 Introduction

"I did laugh off the idea of AI replacing writers or affecting my job until it did," narrated Dean Meadowcroft, a former copywriter in a small marketing department, reflecting on the profound impact artificial intelligence (AI) has had on his profession. Initially introduced to augment the efficiency of his team, AI fell short of expectations, producing content lacking in individuality and requiring significant human oversight to ensure originality. Despite initial drawbacks, AI eventually outpaced human copywriters, completing tasks in a fraction of the time. Dean Meadowcroft and his team were laid off approximately four months after the AI implementation, leading Dean to suspect they had been replaced by the now adequately trained AI (Rose, 2023, June 15). Stories and anecdotes like this tell us something about the transformation of work accelerated by digital automation (e.g., Arregui Pabollet et al., 2019; European Commission, 2019b). By digital automation, we refer to automation enabled by technologies such as AI and machine learning, generative AI, chatbots and cognitive process automation to carry out work previously done by humans (see, e.g., Benbya 2021; Lacity & Willcocks, 2021; Johansson et al., 2020; Ciarli et., al 2022).

Reconfiguration of work, propelled by digital automation, has become a transformative force altering work dynamics (Arregui Pabollet et al., 2019). Digital automation transcends substituting unqualified tasks to include complex decisions and customer engagement. Digital automation technologies are now utilised for tasks ranging from the mundane to the complex. Such digital automation has complex and unexpected implications for work and workplaces (Mayer et al., 2020). While digital automation can lead to replacing or deskilling specific groups of knowledge workers, it can also augment professionals to perform previously impossible tasks (see, e.g., Benbya et al., 2021; Coombs et al., 2020; Davenport & Kirby, 2015). This clearly has implications for the competence of knowledge workers and their interplay with "digital competence."

In this review, we consider knowledge workers who represent employees who apply theoretical and analytical knowledge acquired through formal education to make judgments competently and perform qualified tasks (see, e.g., Drucker, 1969; Cortada, 1998). Drawing on Acemoglu and Autor (2010), we also define skills as the ability to use practical knowledge and know-how to complete work tasks successfully, including work-related problem-solving. Competence is traditionally defined as the interaction between individuals and their work tasks, focusing not merely on knowledge and skills alone but on the specific knowledge and skills needed to execute a particular job or task effectively (McClelland, 1973).

Implications of digital automation have led to some concerns. In Sweden, nearly one in five people, specifically 18 per cent, currently utilise AI tools in their workplace. Despite this, there is some apprehension regarding the technology, with 27 per cent feeling they need to significantly alter their skill sets due to AI (Voister, 2023). Research suggests that in many sectors, such as language and retail, the need for human involvement in tasks will likely decrease due to digital automation (see, e.g., Grace et al., 2018). In addition, it requires digital literacy, i.e., the ability to perform work effectively in a digital setting (Nguyen et al., 2020). It also highlights the growing importance of advanced skills and formal education in the workforce (Hession & Rifkin, 1996). In short, as tasks become automated, the value of cognitive, social, and emotional skills increases (Davenport, 2016) and imposes a redefinition of knowledge workers' competence needs (Autor, 2015; Brynjolfsson & McAfee, 2014).

Despite a growing body of knowledge on the implications of different kinds of digital automation, empirical research on digital automation's implications for knowledge workers in private white-collar work is still limited, especially from the knowledge worker's perspective. There is also a lack of investigations into how tasks change once digital automation has been implemented in knowledge work (McGuinness et al., 2019; Acemoglu & Restrepo, 2017; Coombs et al., 2020). Moreover, audits and evaluations of automation initiatives from knowledge workers' perspectives are explicitly called for (Aleksandre Asatiani, 2022; Lacity and Wilcocks, 2021). Therefore, questions to be answered by the literature in this review regarding knowledge workers' competence we ask according to Information Systems (IS) literature:

i) *What are the implications of digital automation on knowledge worker's competence in knowledge work?*

ii) *What are the most investigated implications of digital automation on knowledge workers' competence, and how have they been investigated?*

iii) *What does the literature recommend/indicate for future research?*

The contribution is twofold. First, we provide an overview of previous research and knowledge on digital automation and knowledge work. Second, the paper contributes to understanding the general implications, sector-specific and implications for professions brought to knowledge work by digital automation. The rest of this paper is structured as follows: section two covers the background of related literature, followed by our method section in section three. Section four discusses the main results of our review, followed by a discussion of our limitations and future research agenda in section five.

2. Background

Digital automation is nothing new. It has been discussed extensively, especially regarding workplace implementation (Venkatesh et al., 2003; Lauterbach & Mueller, 2014; Tsai & Compeau, 2017; Baldauf et al., 2021). Scholars have suggested different terms for using digital technology to automate tasks, such as computerisation (Kling, 1996), virtualisation (Brynjolfsson & McAfee, 2014), digital innovation (Kohli & Melville, 2018), and digital transformation (Osmundsen, 2020). However, these terms fall short of cogently describing the recent breakthroughs in intelligent technology and the potential for replacing human labour in knowledge work. In our view, they do not capture the transformative nature of current AI advancements.

In information systems research, digital automation and its implications for work have gained significant interest. Previous studies (e.g., Bessen, 2020; Susskind & Susskind, 2022) point to decreased routine positions and reduced weekly hours in these roles (Frey & Osborne, 2013; Susskind, 2020). Moreover, digital automation has prompted shifts in the job market, triggering responses ranging from optimism about innovation to anxieties about job displacement (Kumar et al., 2023; Levels et al., 2019). Researchers present two views on automation's impact on jobs: skill-biased technical change (SBTC) and job polarisation (Gustavsson et al., 2018). The SBTC perspective suggests technological advancements favour higher-educated workers in "high-skill" jobs over "middle-skill" and "low-skill" positions (Autor et al., 2008; Fonseca et al., 2018). However, some scholars argue that SBTC studies lack direct examination of employee skills and technology use, especially from their perspective (Gordon Benzell et al., 2019; Biagi & Federico, 2018).

Information Systems literature explores the implications of technology interaction on IT identity and professional competence (Orlikowski & Baroudi, 1988; Brooks et al., 2011; Stein et al., 2013; Strich et al., 2021). As work environments become automated, workers must integrate new technologies into their professional identities (Carter & Grover, 2015). The OECD (2019) highlights a rising demand for digital skills, critical thinking, effective communication, responsibility, and adaptability. Research efforts focus on understanding the implications of automation on white-collar professionals (Strich et al., 2021; Staaby et al., 2021; Peeters & Plomp, 2022). Thus, it's essential to comprehend how digital automation of knowledge workers' tasks occurs and its implications on workers' competence from their perspective in information systems.

2.1 Human Competence

Competence can be understood as the interaction between individuals and their work tasks, focusing not merely on knowledge and skills alone but on the specific knowledge and skills needed to execute a particular job or task effectively (McClelland, 1973). In analysing discussions around competence and how it relates to knowledge work, we examine how it is represented in professional practice. Three primary perspectives emerge based on the work of Sandberg and Pinnington (2009). Firstly, competence is a *prerequisite*, evidenced by the training and education needed to qualify for practice in particular professions. Equally, Teodorescu (2006) suggests that the *traits* and *skills* of successful individuals can be emulated by those who are "less successful." Secondly, competence is also viewed as an *outcome* associated with meeting established performance standards. On this note, Teodorescu and Binder (2004) identify incompetence as the result of insufficient guidance and feedback, emphasising the importance of detailed performance evaluations that include clear objectives and benchmarks. Lastly, competence is described as the *ability* to effectively perform specific job tasks (knowledge work), a concept Gherardi (2000) terms as a practical accomplishment (Sandberg & Pinnington, 2009).

It is apparent that competence and practice are intertwined rather than distinct; they can collectively influence how knowledge workers perceive their roles, approach their tasks, and determine which qualities to apply in specific situations—be it knowledge, skills, or attributes (Sandberg, 2000). Our literature review centres on the third interpretation of competence related to job performance (the practice of doing) in knowledge work, encompassing knowledge, skills, abilities, and traits or attitudes, allowing us to leverage research across various perspectives in IS see Figure 1.

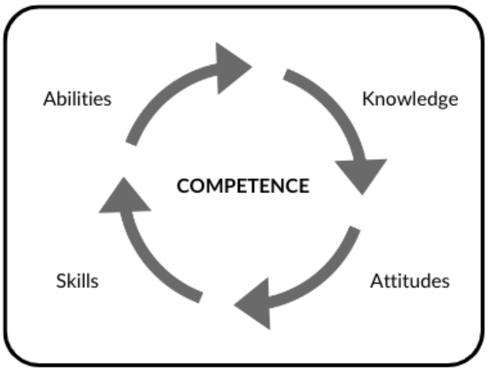

Figure 1: Competence based on (McClelland, 1973; Teodorescu, 2006; Sandberg & Pinnington, 2009; Shalalei, 2021)

In the past, research has established a substantive link between professional conduct and competence. Billett et al. (2014, pp. 29-56) define professional competence as the synergistic integration of knowledge, skills, and attitudes, which are manifested effectively in practical contexts. Moreover, competence embodies an individual's engagement with their professional identity, answering the pivotal questions of *"Who am I within my profession?"* and *"How do I enact my professional role?"* (Chreim et al., 2007; Craig et al., 2019; Nelson & Irwin, 2014; Reay et al., 2017). In IS research, human competence has been recognised as a central area impacting IS-related interactions among individuals, organisations, and society (Wiesche et al., 2020). Concerning knowledge work, Lindgren et al. (2003) argue that competence descriptions do not demonstrate whether knowledge workers apply competence in accomplishing knowledge work. They further highlight that competence descriptions are not rooted in knowledge work practice. At best, they indicate prerequisites for accomplishing a certain work task. Shalalei (2021) emphasises worker competence as the capability or potential exercised in accomplishing work tasks. As digital automation is implemented in the workplace, competence will change due to the continuous interactions that technology and humans encounter as they work hand in hand and as technology advances. This recognises the relational association between humans and technology and emphasises the effort and "work" involved in managing these interactions (Baptista et al., 2020). Therefore, in this review, we ask, *"What are the implications of digital automation on knowledge worker's competence in knowledge work?"*

2.2 Knowledge work and knowledge workers

Over the past fifty years, since Peter Drucker introduced the concept of "knowledge workers", their proportion in the workforce has consistently increased, along with various technological tools designed to enhance their productivity (Davenport, 2011). Knowledge work, a term introduced by Drucker in the late 1950s, emerged from his anticipation of a significant transformation in the nature of human labour. He predicted a growing need for types of work distinguished primarily by their emphasis on *thinking* as the main task, setting them apart from traditional forms of work (Reinhardt et al., 2011). "Knowledge work is "the situated practice of applying knowledge within an operational context to produce knowledgeable, creative, intellectual, and non-routine work" (Newell, 2015, p. 3; Coombs et al., 2020). This practice perspective, proposed by Newell (2015) and building on the ideas of Cook and Brown (1999), refers to knowledge as the result of work in localised situations inherently linked to these practices.

This perspective aligns with earlier scholars, who imply that knowledge serves as the primary input for the work, the principal method of executing the work, and the main result of the work (Davenport & Prusack, 1998). According to Wagner and Prester (2019), knowledge work goes beyond the work of white-collar professionals, such as lawyers, accountants, and managers, but also includes contemporary occupations, such as software developers, marketers, and designers. Service work can be described as the act of utilising personal resources, such as knowledge, to benefit oneself or others (Barrett et al., 2015). Coombs et al. (2020) include diverse jobs, including retail, security, office cleaning, and more knowledge-intensive work such as consulting. Therefore, in our review of IS literature within the context of digital automation and its implications on knowledge workers' work, when we say knowledge work, we mean what other scholars call white-collar professions and service work that includes (white-collar) office and administrative work.

Knowledge work has experienced changes over the years since its conception. This has mainly been due to the introduction of different types of technology that have only advanced over the years; see Table 1 below, showing the key technologies used in various knowledge work professions in relation to different time periods.

Table 1. Author's illustration of knowledge work evolution

Period	**Key technologies**	**Examples of knowledge work professions**
Third Industrial Revolution (1950s-1970s)	-Mainframe computers, Early PCs	- Data Entry Clerks, Accountants
The PC Revolution (1980s)	-Personal Computers, Internet	- Software Developers, Financial Analysts, Administrative assistants
The Internet Era (1990s)	-World Wide Web, Email, Mobile communications	- IT Professionals, Digital Marketers, Bank tellers
Mobile and cloud computing (2000s)	-Smartphones, Cloud platforms, SaaS	- Remote Workers, Cloud Computing specialists
AI and automation (2010s - present)	-Artificial Intelligence, Machine Learning, Big Data, Robotics, IoT	- Data Scientists, AI Specialists, Business Analysts, Consultants

Table 1. The evolution of knowledge work according to the authors (based on readings from Benanav, 2020; Barley, 2020; Sako, 2020; Autor, 2015; Brynjolfsson & McAfee, 2014; Kling, 1996)

The IS research community has taken a keen interest in knowledge work, especially since technology began to be included in the work environment of knowledge workers. For example, scholars have investigated matters to deal with the professional status of knowledge workers in the labour market (Autor et al., 2001), the improvement of knowledge work processes (Davenport, 2011), the future of knowledge workers (Frey & Osborne, 2013) and knowledge management (Newell, 2015). The IS field has also gained much interest from researchers who have investigated different focus areas, which include consequences for discontinuing knowledge work (Kahila et al., 2018), what knowledge workers stand to gain from automation (Lacity & Willcocks, 2015), the implementation of automation as distributed cognition in knowledge work (Asatiani et al., 2019) and digital platforms for knowledge work (Wagner & Prester, 2019). Some authors highlight what digital automation does for the knowledge worker; for example, they emphasise the augmentation of knowledge work where machines are added as key resources in knowledge work practice (Raisch & Krakowski, 2021). Despite the numerous valuable contributions made to the body of knowledge generally and specifically to information systems, there still lies a void in understanding how digital automation changes knowledge workers' work from the perspective of the knowledge workers themselves.

3. Method

To review previous research on digital automation and work, we explored the literature with research questions to guide us, as recommended by Webster and Watson (2002). Our literature review aimed to understand how digital automation has been represented in IS literature and how its implications on knowledge workers' competence have been investigated, including what this indicates for future research. The following questions drove it:

i) What are the implications of digital automation on knowledge worker's competence in knowledge work?

ii) What are the most investigated implications of digital automation on knowledge workers' competence, and how have they been investigated?

iii) *What does the literature recommend/indicate for future research?*

3.1 Search strategy and process

A systematic search was conducted using scientific databases, including but not limited to Web of Science, Science Direct, and Scopus, to ensure all relevant studies were found. We focused on conference papers and journals. Renowned sources like the AIS eLibrary, a reliable database for top IS conferences, were also referred to. Given the diverse nature of digital automation and its varied terminology, a comprehensive strategy was essential. The search terms included "automation," "white-collar sector," "digital automation," "artificial intelligence," "employee competence," "employee skills," and "knowledge worker." These general terms were used for two reasons: to keep the research focused on specific questions and because papers on the topic lack uniform terms regarding the implications of automation on knowledge worker skills. The inclusion of "*" after certain words aimed to capture variations, while quotation marks ("”) targeted specific terms. Boolean operators (AND, OR) were used to refine searches. The senior scholar list of premier journals was also searched to ensure rigour and relevance. The search strings used for each database can be found in Table 2 and have been used in the context of information systems. The selection process involved an initial screening of titles, keywords, and abstracts to assess relevance. Afterwards, selected studies underwent a thorough full-text review to check for eligibility. This was followed by a final analysis, which included studies meeting the inclusion criteria; see a detailed breakdown of the process in Table 2 below:

Table 2. Process of selection of papers

Databases	*Web of Science*	*Science Direct*	*Scopus*	*Senior scholar list of premier journals*
Search String	("automation" OR "digital automation" OR "artificial intelligence" AND ("employee skill competence" OR "skills development" OR "white-collar" OR "knowledge worker implications" OR "private sector" OR "competence")			
Criteria Filters	Title-Abstract-Keywords	Title-Abstract-Keywords	Title-Abstract-Keywords Peer-reviewed	Title-Abstract-Keywords
Initial Results	Total retrieved (n= 798)			
Refinement	Removal of papers that use the term automation or digital automation for non-related concepts			
Results after refinement	-After duplicates removal - 350 -After studies not written in English - 200			
Inclusion Criteria	-Studies conducted on digital automation in private sector knowledge work within the last ten years. - Research focusing on the implications of digital automation on knowledge workers' competence and their work			
Exclusion criteria	- Studies not in the IS field -Simulation studies.			

	-Editorials. -Studies with no focus on digital automation or automation in the context of knowledge workers -Non-peer-reviewed scientific publications (editorials, books, book chapters, articles).
Results after applying criteria	- after title-abstract-scan: 200 - after full-text retrieval:17 -after forward- backward-search: 25

Table 2: Search and selection process of the sample of articles used in this literature review

This table shows a summary of the research process. Our first sample retrieved 798 papers, and after several steps using our inclusion and exclusion criteria, we remained with 17 papers. When we carried out a forward and backward search, we found some papers that complimented our review and added them to the sample to leave us with 25 final papers for analysis. The sample articles were selected based on the three main research questions and some extra details like the context, level of analysis, study approach, and discipline they referenced. The main finding of each paper was used to decide which research question it fits into. If a paper had important findings related to more than one research question, it was sorted into all the relevant categories. Paré et al. (2015) state that setting rules for which studies to include or exclude in a review is important. This helps researchers remove studies that don't answer the main research questions. However, ethical considerations regarding this review are not required since we are looking at already published literature.

4. Results

This section discusses the findings of our IS literature analysis concerning our three research questions. We unveiled many kinds of implications from the various authors in our sample. Our findings are summarised after the discussion to give a comprehensive view. Due to the diverse nature of our findings, we have categorised them into three main groups, as shown in Table 3 below.

Table 3. Table showing the articles selected

	Authors	**Implication Description**					
		General Implications		*Sector Specific Implications*		*Implications on professions*	
		Enhanced productivity	Ethics and employee response	Skill requirement changes	Work dynamics shifts	Job role changes	Competence evolution
1	Coombs et al. (2020)	✓		✓	✓	✓	
2	Jiyong Park & Jongho Kim (2022)	✓		✓	✓	✓	
3	Denagama Vitharanage et al., (2020)	✓			✓	✓	

4	Seiffer et al. (2021)	✓	✓	✓	✓	✓	✓
5	Asatiani et al. (2020)		✓	✓	✓		✓
6	Johansson et al., (2020)	✓	✓	✓		✓	✓
7	Waizenegger and Techatassanasoontorn, (2022)		✓	✓		✓	✓
8	Maria Sako, (2023)	✓	✓	✓	✓	✓	✓
9	Venermo et al., (2022)		✓	✓		✓	
10	Rinta-Kahila et al., (2018)	✓	✓	✓		✓	
11	Hadidi & Klein, (2024)		✓			✓	
12	Sejahtera et al., (2018)	✓	✓	✓			✓
13	Pinski & Benlian, (2023)	✓	✓	✓	✓	✓	
14	Kortum et al., (2022)	✓		✓		✓	
15	Viale & Zouari, (2020)		✓			✓	
17	Ranerup & Henriksen, (2020)	✓	✓			✓	✓
18	Kohli & Melville, (2018)	✓	✓				✓
19	Mendling et al., (2018)	✓	✓	✓	✓	✓	✓
20	Meyer von Wolff et al., (2020)	✓			✓		
21	Staaby et al., 2021	✓	✓				✓
2**2**	Lacity & Willcocks, (2021)	✓	✓	✓	✓		✓
23	Eikebrokk and Olsen (2020)	✓		✓			
24	Meyer von Wolff et al., (2021)	✓	✓	✓			
25	Ranerup & Henriksen, (2020)	✓					

Table 3: Summary of sampled papers

The table above shows our sample's main findings: enhanced productivity is the most discussed implication in the literature, while competence evolution is the least investigated.

Research in IS on the implications of digital automation on knowledge workers' competence has taken diverse perspectives, presenting the community with valuable suggestions for approaches to research, future research areas, and types of analysis. Much of the literature in our sample focused on different literature reviews that discuss various implications, which we have classified into three main categories: *general, sector-specific, and implications for professionals*.

General Implications

These are the broad, overarching implications that apply to various contexts and fields regardless of specific job roles or industries. In our study, **anxiety** and **insecurity** are the prominent responses generally expressed by knowledge workers. The fear of being replaced or losing a job has been described by several studies in our sample (see, e.g., Asatiani et al., 2020; Meyer von Wolff et al., 2021; Waizenegger and Techatassanasoontorn 2020; Eikebrokk and Olsen 2020; Staaby et al. 2021). These responses are motivated by the change in work when employees experience changes in how they do their work. Staaby et al. (2021) report that employees expressed concerns about job loss due to changes in their work tasks, for example. These employees' (knowledge workers) experiences may manifest in feelings of isolation as they struggle to justify the value of their work. Such expressions raise ethical concerns about how employees find meaning in their work and feel like valuable contributors to their organisations (Johansson et al.,2020; Staaby et al., 2021). As a result, some negative responses have emerged, with employees presenting acceptance issues and reluctance to complete tasks due to their fears of replacement and ambiguous responsibilities, bringing in issues of trust in the technology and, in some cases, management decisions (Waizenegger and Techatassanasoontorn 2020; Meyer von Wolff et al., 2021; Staaby et al., 2021). On the other hand, some responses portray positive implications for and from knowledge workers. For example, knowledge workers express that technologies like chatbots enhance their work abilities by aiding with repetitive tasks and enhancing productivity. This has also been represented as a reduction in workload to concentrate on other complex tasks like data analysis and decision-making (Waizenegger and Techatassanasoontorn, 2020; Meyer von Wolff et al., 2019; Viale & Zouari, 2020; Asatiani et al., 2020; Denagama Vitharanage et al., 2020).

Sector-specific Implications

These are targeted effects that implicate aspects of work or specific job functions. Concerning sector-specific implications, the implications that several researchers have extensively discussed are re-skilling, deskilling, and upskilling to fulfil the new job roles that emerge because of automating knowledge workers' tasks (Venermo et al., 2022; Pinski & Benlian, 2023; Asatiani et al., 2020; Johansson et al., 2020; Kortum et al., 2022; Rinta-Kahila et al.,2018). Digital automation aids in the resource optimisation of knowledge workers, creating room for different work models like hybrid work and remote work in the professional services sector especially (Hadidi & Klein, 2024; Jiyong Park & Jongho Kim, 2022; Seiffer et al., 2021; Maria Sako, 2023). Organisations have expressed how automating knowledge workers' tasks gives them a competitive advantage in the sector and increases their reliability because of their ability to deliver their deliverables efficiently, on time, and accurately (Denagama Vitharanage et al., 2020). Asatiani et al. (2020) advise organisations to consider three perspectives when implementing automation in knowledge work: allocating tasks between humans and automation, reducing the risks of deskilling, and managing collective knowledge shared between humans and automation.

Implications for professionals

These implications directly affect specific professions and the knowledge workers in this case. They are tailored to the unique characteristics and requirements of those fields. The need to learn additional skills is viewed as having two benefits on the task front for the knowledge worker and skill-wise giving employees some motivation to work (Asatiani et al. 2020; Johansson et al. 2020; Waizenegger and Techatassanasoontorn 2020) and that they can frame their work better with the new skills attained (Staaby et al., 2021). However, these benefits or positive responses can only be attained depending on the knowledge workers' attitude toward changes to their work processes. Digital automation implicates the job outcomes of knowledge workers. While some scholars report positive outcomes, as discussed earlier under "sector-specific implications," a study by Staaby et al. (2021) highlights a decrease in job meaningfulness. The study found that automation of routine tasks increased employees' workloads, often with some repetitive tasks, making it difficult for them to justify the value of their work. Task disaggregation or bundling is another implication that has not been discussed in detail. New tasks will be created by AI, but how these tasks will be bundled into jobs, new or existing, remains uncertain (Sako, 2023). There is also distributed cognition to consider in cases where knowledge workers like managers must closely examine their operations at the level of individual activities and tasks to understand their characteristics and determine whether they should be assigned to humans or automated systems (Asatiani et al., 2020). To echo this, Eikebrokk and Olsen (2020) state that employees must learn to generate value in new ways as they take on tasks that cannot be automated. One way of creating value has been through cross-team collaboration on tasks (Johansson et al. 2020; Staaby et al. 2021). Pinski and Benlian, (2023) discuss that this creates an environment of continuous learning in the case where knowledge workers need to acquire new technical skills, for example, developing competencies to judge what it means for an AI application in a specific field (e.g., medicine or business) not to be functionally transparent (e.g., legal and ethical implications or effects on humans interacting with AI). In their study to investigate the consequences of removing automation from the workplace, Kahila et al. (2018) mention automation complacency and latent deskilling as implications that are represented when knowledge workers display strong trust in their systems and feel that they execute their jobs reliably, without making mistakes. This can impact their critical thinking and lead to unrealistic expectations of automation. For example, this would be very risky for accountants who usually handle various related but distinct tasks, requiring them to maintain a broad set of skills.

Table 4. Implications description

	Implication Category	**Description**	**Examples**
1	*General implications*	- These are broad, overarching implications that apply to various contexts and fields regardless of specific job roles or industries.	- ethical challenges, productivity changes, new work models, technical skill changes, job displacement, fear, curiosity
2	*Sector-specific implications*	-These are targeted effects that implicate aspects of work or specific job functions.	- work task changes, reskilling, deskilling, technological dependence,
3	*Implications for professionals*	- These implications directly affect specific professions and knowledge workers in this case. They are tailored to the unique characteristics and requirements of those fields.	- competence changes, skillset evolution, job threats, work-life balance, continuous learning and adaptability, skill degradation, automation complacency and latent deskilling

Table 4: Table showing the summary of implications classification according to the authors.

The table above shows a summary of the implications that were revealed by our sample.

Literature reviews and empirical studies were the most prominent approaches used to investigate the implications of digital automation on knowledge workers' competence. Researchers emphasise the need for *interdisciplinary approaches* to enhance knowledge workers' competence in digital automation, integrating insights from computer science, sociology, and business management (Coombs et al., 2020; Mendling et al., 2018). They argue that interdisciplinary approaches give a comprehensive view of what is happening within a particular research phenomenon. There are also calls for *human-centric empirical research.* For example, Waizenegger & Techatassanasoontorn (2022), Johansson et al. (2020), and Sejahtera et al. (2018) all emphasise that empirical studies will help gather data on the real-world impacts of automation technologies, highlighting the importance of investigating how knowledge workers can adapt to new technologies and what support they need to maintain and enhance their competence. In our findings, we noted that most studies that have been done concentrate on pointing out the implications like reskilling, the need for adaptability, and continuously learning, for example, but very *few focus on giving guidance* to how these can be achieved from the organisations or knowledge worker's perspectives (see, e.g., Venermo et al., 2022; Kortum et al., 2022; Kohli & Melville, 2018; Meyer von Wolff et al.,2019).

We also note that studies have concentrated on investigating a particular type of automation, for example, chatbots and business process machines, with more papers looking into *management-level inquiries*, which yield mostly findings about how automation enhances productivity and promotes efficiency in organisations (Mendling et al., 2018; Viale & Zouari, 2020; Ranerup & Henriksen, 2020; Meyer von Wolff et al., 2021). This leaves a void in inquiries at the *knowledge worker level* because while aiming for increased digital automation promises cost savings, it confines our thinking to the parameters of the work currently being accomplished. Studies have also attempted to analyse using knowledge workers, taking various perspectives like the *psychological and social impacts* of chatbot use (Meyer von Wolff et al., 2021; Seiffer et al., 2021;), others have raised ethical implications concerning knowledge workers when automation is implemented in their work tasks, while this is valuable for the community, few inquiries have thoroughly addressed these implications and give recommendation on how to ensure these implications are dealt with or even resolved (Waizenegger & Techatassanasoontorn, 2022; Johansson et al., 2020; Jiyong Park & Jongho Kim 2022; Coombs et al. 2020). Another point to note is that a few detailed investigations have been done into how competencies or tasks in a particular profession have changed. Jiyong Park and Jongho Kim (2022) attempted to analyse automatable occupations in the US labour force to explain how tasks would generally change. They highlight that the often-overlooked reality is that technology directly affects the demand for specific skills and *calls for a data-driven approach to measuring task automation.* There are calls asking for inquiries into how the redesign of human tasks is done, keeping in mind that technology can substitute and complement human tasks (Coombs et al., 2020).

Our review shows that digital automation augments human intelligence for some tasks, boosting demand for professions where these tasks are performed. This duality underscores the importance of understanding which tasks are more susceptible to automation and which can complement it. The literature lacks comprehensive studies on how human work tasks are redesigned to accommodate digital automation, how job skill requirements change, and how workers respond to these changes. We also note that there are also calls for longitudinal studies to critically analyse the changes occurring in different professions.

5. Discussion

5.1 Implications

Our first research question investigated the implications of digital automation on human competence in knowledge work that have been studied in the literature. Our second research question sought to explore the most investigated implications of digital automation on knowledge workers' competence and how they have been investigated. To answer these, when we compared our findings to previous research, we identified some frequently discussed implications in our sample, such as job losses, reskilling, deskilling, enhanced productivity, and improved accuracy (see, e.g., Mendling et al., 2018; Meyer von Wolff et al., 2020; Johansson et al., 2020; Rinta-Kahila et al., 2018). However, because our focus was on knowledge workers' competence and how they are implicated when digital automation transforms their tasks, we see implications like changes in tasks, job roles, and skillset evolution becoming more significant implications for this review (see, e.g., Coombs et al., 2020; Asatiani et al., 2020; Maria Sako, 2023; Sejahtera et al., 2018). The existing research does not provide a clear or detailed analysis of how tasks within a specific profession will change, be disaggregated, or be aggregated. This is problematic because it could lead to an overestimation of the implications of technology on knowledge work and the worker's competence. This includes not only quantitative outcomes, such as job destruction and job creation, but also qualitative changes in work and employment, such as deskilling, up-skilling, and the development of new task profiles for existing jobs and or what others have called *"new collar work"* (Levels et al., 2019).

Some authors have discussed the *overreliance on technologies* in our sample (Hadidi & Klein, 2024; Rinta-Kahila et al., 2018). They argue that due to the constant use of digital automation and the frequent accuracy of its results, workers can develop what they term *"automation complacency."* Rinta-Kahila et al. (2018) discuss this in their work, which means that workers begin to depend on machine outputs and stop critically thinking through these results. This over-reliance on automation can lead to latent deskilling, which is unfortunate because, for human-machine collaboration to work, there must continue to be the "human-in-the-loop" in knowledge work practice not only concerning transparency but also in work ownership and responsibility to ensure any deskilling that could arise is addressed. This can be done by encouraging knowledge workers to take on new tasks to broaden their skills as machines aid their work instead of isolating themselves and allowing their attitudes towards digital automation to take a negative direction (Strich et al., 2021). Digital automation must be viewed as a *complementary tool* to humans in their work because it can enhance their capabilities if used and monitored correctly (augmentation), but not as a substitute, which is what we and other authors, argue for (Davenport and Kirby 2015; Coombs et al., 2020; Benbya et al., 2020;).

According to Davenport and Kirby (2015), augmentation means starting with what humans do today and figuring out how that work could be deepened rather than diminished by a greater use of machines. This explanation emphasises humans more than machines, complementing the resolution of ethical concerns like *autonomy in knowledge work*. When workers lose the ability to perform tasks they once did manually or think critically about their work, this increases risk in knowledge work, whose fundamental separation from other forms of work is thinking, as discussed by (Reinhardt et al., 2011). This risk has implications on their competence, begging the need to answer the question, who am I, and what do I do? This question can be answered by looking at knowledge workers' tasks, seeing the *level of materiality of the automation* added to their tasks and comparing how much change occurs in their knowledge work in practice. Jiyong Park and Jongho Kim (2022), in our sample, argue that, in some instances, higher levels of automation do not necessarily result in reduced labour demands for specific tasks. This suggests that investigations employing data-driven approaches and quantitatively measuring the degree of automation at the task level can be of more value to investigating this phenomenon, especially when specific professions are investigated from the knowledge worker's perspective. Our review calls for dynamic, data-driven approaches that reflect recent changes in human competence of knowledge work and the technological capabilities to automate various tasks at the worker's level. This includes adopting a task-level degree of digital automation to provide a comprehensive view of technological advances, changes in task content and how these implicate human competence. This has also been echoed by other scholars who state that tasks are the fundamental unit of production of knowledge work and that the future of work depends on "the mixture of new technologies and how [they change] the task content of production of knowledge work (see, e.g. Acemoglu & Restrepo, 2017; Frey & Osborne, 2017).

However, our findings also point to an interesting area that is not clearly addressed in the literature. This area deals with the competence needed to understand or handle the responsibility of the work produced by knowledge workers' interaction with the machines they use. Raisch and Krakowski (2021) mention responsibility or ownership of knowledge work and explicitly point out that humans can only take responsibility if they retain some level of involvement with and control over the relevant tasks. For example, regarding complex managerial tasks, machines usually can only provide an array of options that all relax certain real-life constraints. Managers then need to use their *intuition* and *common-sense judgment* (which usually would come from their knowledge and experience of using the machines*)* – to reconcile the machine output with reality − to make a final decision about the most desirable option (Brynjolfsson & McAfee, 2014: 92). This is why relatively routine and well-structured tasks can be automated, whereas more complex and ambiguous tasks cannot be automated but can be addressed through augmentation (Brynjolfsson & McAfee, 2014; Daugherty & Wilson, 2018; Davenport & Kirby, 2016). It is important to note that machines still have many limitations. We are in an era in which the human-machine relationship is no longer dichotomous but evolving into a machine "augmentation" of human capabilities. Rather than being adversaries, humans and machines should combine their complementary strengths, enabling mutual learning and multiplying their capabilities.

Therefore, in summary, we say augmentation is a co-evolutionary process during which humans learn from machines and machines learn from humans. This kind of interaction definitely implicates competence over time, and it is these competencies and how they change that need to be assessed in relation to digital automation implemented in the workplace, especially through the lens of the knowledge worker empirically. This lens is relevant because it places equal emphasis on both human experts and intelligent machines. Thus, it is crucial for IS scholars to revisit the study of knowledge work as intelligent machines become more common in the workplace and to assess the relevance of existing theories and methodologies for examining knowledge work practices (Gkeredakis & Pachidi, 2019).

5.2 Limitations and Future Research

Our final question was, *"What does the literature recommend/indicate for future research?".* When we synthesised findings from various studies in IS literature, several prominent themes emerged, providing a comprehensive understanding of how digital automation implicates the competence of knowledge workers. The results highlight the need for interdisciplinary approaches, robust theoretical frameworks, human-centric and empirical research, task reconfigurations, and longitudinal studies about digital automation and its implications on knowledge worker competence. We also saw the methodological challenges due to the broad nature of our phenomenon. This aligns with the discussion made by Orlikowski and Baroudi (1988), who discussed that existing empirical studies do not provide a sufficient answer to how technological developments will affect the world of work. Since then, very few responses have sufficiently answered this call. Therefore, we know that our work has some limitations. First, like any literature review, our findings may have been influenced by our selection process and the inclusion and exclusion criteria. We strictly followed established guidelines (Webster & Watson, 2002), searched four high-quality databases, and conducted comprehensive forward and backward searches. Future studies could incorporate additional databases and possibly expand the search terms based on our results to cover more research fields. As noted, the literature has several gaps, suggesting future research opportunities according to themes, as can be seen in Table 5 below.

Table 5. Future directions

Theme Area	**Questions**
Theoretical Frameworks and Methodologies	1. What theoretical frameworks are most effective for studying the impact of intelligent automation on knowledge workers' competence? 2. What methodological challenges arise when studying knowledge workers' competence in dynamic environments with intelligent automation?
Impacts of Automation on Competence	1. How does automation implicate knowledge workers' competence, satisfaction, and productivity?

	2. How are tasks being reconfigured and new tasks created due to automation, affecting knowledge workers' competence? 3. What are the long-term effects of AI and robotics on the competence and job characteristics of knowledge workers? 4. How do knowledge workers' attitudes towards automation affect their competence and the adoption of such technologies?
Skills and Competence Development	1. What new skills are required for knowledge workers to maintain competence in automated environments? 2. How can interdisciplinary approaches enhance knowledge workers' competence in intelligent automation?
Social and Professional Influences	1. How do social and professional norms influence knowledge workers' competence in adopting AI technologies?
Best Practices and Management	1. What are the best practices for managing the implementation of automation technologies to enhance knowledge workers' competence?

Table 5: Proposed future research questions and theme areas they relate to.

Digital automation transforms knowledge work by altering tasks, roles, and required skills. While it boosts productivity and accuracy, it also risks job losses, deskilling, and overreliance on technology. Maintaining a *"human-in-the-loop"* approach and encouraging continuous learning can help mitigate these risks. The concept of augmentation, where technology enhances rather than replaces human capabilities, is crucial. Future research should measure the impact of automation at the task level to better understand and improve human-machine collaboration. As intelligent machines advance and get implemented in knowledge work, it's essential to revisit existing theories to ensure effective integration and enhancement of knowledge work practices.

6. Conclusion

Digital automation, with its advanced capabilities, is significantly affecting knowledge work. Unlike traditional information technologies, it allows intelligent machines to take over tasks that previously required complex human reasoning and analysis. Consequently, this can challenge professional expertise, complicate the development of experts, reshape job roles, and introduce new methods of control and coordination. This paper lays the groundwork for advancing IS research by synthesising existing literature, identifying research gaps, and proposing a future research agenda. This paper presents critical insights from a systematic IS literature review, including an overview of implications arising from automating knowledge workers' tasks and what this means for their competence. Moreover, our findings suggest that while implications like deskilling, job displacement, and reskilling are highly researched in IS prior research, there are also some interesting perspectives and findings of implications like automation complacency and positive perspectives like viewing automation as a complimentary tool. Therefore, our study is a starting point for future research on individual-level implications. A deeper insight could help understand knowledge workers' competence changes and their consequences in digital automation implementation and bring them to light.

References

Acemoglu, D., & Autor, D. (2010, June 1). *Skills, Tasks and Technologies : Implications for Employment and Earnings*. National Bureau of Economic Research. http://www.nber.org/papers/w16082

Acemoglu, D., & Restrepo, P. (2017). Robots and Jobs : Evidence from US Labor Markets. *National Bureau of Economic Research*. https://doi.org/10.3386/w23285

Adler, P. S. (1988). Automation, Skill and the Future of Capitalism. *Berkeley Journal of Sociology*, *33*(1), 1–36. https://www.jstor.org/stable/41035388

Aleksandre Asatiani. (2022). What Can Public Sector Organizations Learn from Private Sector Experiences of Robotic Process Automation ? *Progress in IS*, 219–227. https://doi.org/10.1007/978-3-030-92644-1_12

Arghavan Shahlaei, C. (2021). Rethinking Competence : On Performing Digital Transformation. *Www.diva-Portal.org*. https://www.diva-portal.org/smash/record.jsf?pid=diva2:1612547

Arregui Pabollet, E., Bacigalupo, M., Biagi, F., Cabrera Giraldez, M., Caena, F., Castano Munoz, J., Centeno Mediavilla, C., Edwards, J., Fernández-Macías, Enrique, Gomez Gutierrez, E., Gomez Herrera, E., Inamorato dos Santos, A., Kampylis, P., Klenert, D., López-Cobo, Montserrat, Marschinski, R., Pesole, A., Punie, Y., Tolan, S., & Torrejon Perez, S. (2019). The changing nature of work and skills in the digital age. *EUR (Luxembourg. Online)*. https://doi.org/10.2760/679150

Arthur, M. B., Defillippi, R. J., & Lindsay, V. J. (2008). On Being A Knowledge Worker. *Organisational Dynamics*, *37*(4), 365–377. https://doi.org/10.1016/j.orgdyn.2008.07.005

Asatiani, A., Penttinen, E., Rinta-Kahila, T., & Salovaara, A. (2019). Organisational Implementation of Intelligent Automation as Distributed Cognition : Six Recommendations for Managers. *ICIS 2019 Proceedings*, *7*. https://aisel.aisnet.org/icis2019/practice_is_research/practice_is_research/7

Autor, D. H. (2001). Why Do Temporary Help Firms Provide Free General Skills Training? *The Quarterly Journal of Economics*, *116*(4), 1409–1448. https://doi.org/10.1162/003355301753265615

Autor, D. H. (2015). Why Are There Still So Many Jobs? The History and Future of Workplace Automation. *The Journal of Economic Perspectives*, *29*(3), 3–30. https://www.jstor.org/stable/43550118

Autor, D. H., Katz, L. F., & Kearney, M. S. (2008). Trends in U.S. Wage Inequality: Revising the Revisionists. *Review of Economics and Statistics*, *90*(2), 300–323. https://doi.org/10.1162/rest.90.2.300

Baldauf, M., Fröhlich, P., Sadeghian, S., Palanque, P., Roto, V., Ju, W., Baillie, L., & Tscheligi, M. (2021). Automation Experience at the Workplace. *Extended Abstracts of the 2021 CHI Conference on Human Factors in Computing Systems*. https://doi.org/10.1145/3411763.3441332

Baptista, J., Stein, M.-K., Klein, S., Watson-Manheim, M. B., & Lee, J. (2020). Digital work and organisational transformation: Emergent Digital/Human work configurations in modern organisations. *The Journal of Strategic Information Systems*, *29*(2), 101618. https://www.sciencedirect.com/science/article/pii/S0963868720300263

Barrett, M., Davidson, E., Prabhu, J., & Vargo, S. L. (2015). Service Innovation in the Digital Age: Key Contributions and Future Directions. *MIS Quarterly*, *39*(1), 135–154. https://www.jstor.org/stable/26628344

Baskerville, R., Myers, M., & Yoo, Y. (2020a). Digital First: The Ontological Reversal and New Challenges for Information Systems Research. *MIS Quarterly*, *44*(2), 509–523. https://doi.org/10.25300/MISQ/2020/14418

Baskerville, R., Myers, M., & Yoo, Y. (2020b). Digital First: The Ontological Reversal and New Challenges for Information Systems Research. *MIS Quarterly*, *44*(2), 509–523. https://doi.org/10.25300/MISQ/2020/14418

Benbya, H., Davenport, T., & Pachidi, S. (2020). Special Issue Editorial. Artificial Intelligence in Organisations: Current State and Future Opportunities. *MIS Quarterly Executive*, *19*(4). https://aisel.aisnet.org/misqe/vol19/iss4/4

Bergquist, M., Ljungberg, J., & Lundh-Snis, U. (2001). Practising Peer Review in Organizations: A Qualifier for Knowledge Dissemination and Legitimisation. *Journal of Information Technology*, *16*(2), 99–112. https://doi.org/10.1080/02683960110054780

Bessen, J. (2020). Automation and Jobs: When Technology Boosts Employment. *Economic Policy*, *34*(100). https://doi.org/10.1093/epolic/eiaa001

Biagi, R., & Federico. (2018). The Routine Biased Technical Change hypothesis: à critical review. *Publications Office of the European Union.* https://doi.org/10.2760/986914

Billett, S., Harteis, C., & Gruber, H. (2014). *International handbook of research in professional and practice-based learning* (pp. 29–56). Springer.

Brooks, N. G., Riemenschneider, C. K., Hardgrave, B. C., & O'Leary-Kelly, A. M. (2011). IT professional identity: needs, perceptions, and belonging. *European Journal of Information Systems*, *20*(1), 87–102. https://doi.org/10.1057/ejis.2010.48

Brynjolfsson, E., & McAfee, A. (2014). *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies*. W.W. Norton & Company.

Brynjolfsson, E., & Mitchell, T. (2017). What can machine learning do? Workforce implications. *Science*, *358*(6370), 1530–1534. https://www.jstor.org/stable/26401130

Brynjolfsson, E., Perrault, R., Shoham, Y., Clark, J., Etchemendy, J., Grosz, B., Lyons, T., Manyika, J., Mishra, S., Carlos, J., & Niebles. (2019a). *2019 annual report ar intelligence index*. https://hai.stanford.edu/sites/default/files/ai_index_2019_report.pdf

Brynjolfsson, E., Perrault, R., Shoham, Y., Clark, J., Etchemendy, J., Grosz, B., Lyons, T., Manyika, J., Mishra, S., Carlos, J., & Niebles. (2019b). *2019 annual report ar intelligence index*. https://hai.stanford.edu/sites/default/files/ai_index_2019_report.pdf

C.W. Peeters, M., & Plomp, J. (2022). For Better or for Worse: The Impact of Workplace Automation on Work Characteristics and Employee Well-Being. *Digital Transformation - towards New Frontiers and Business Opportunities*. https://doi.org/10.5772/intechopen.102980

Carter, M., & Grover, V. (2015). Me, My Self, and I(T): Conceptualizing Information Technology Identity and its Implications. *MIS Quarterly*, *39*(4), 931–957. https://doi.org/10.25300/misq/2015/39.4.9

Chreim, S., Williams, B. E. (Bernie), & Hinings, C. R. (Bob). (2007). Interlevel Influences on the Reconstruction of Professional Role Identity. *The Academy of Management Journal*, *50*(6), 1515–1539. https://www.jstor.org/stable/20159487

Ciarli, T, M. Savona, E. Steinmueller , & S Vannuccini . (2022). *The Design of Digital Automation Technologies: Implications for the Future of Work*. https://www.cesifo.org/DocDL/econpol-forum-2022-5-savona-ciarli-steinmueller-vannuccini-digital-automation.pdf

Coito, T., Viegas, J. L., Martins, M. S. E., Cunha, M. M., Figueiredo, J., Vieira, S. M., & Sousa, J. M. C. (2019). A Novel Framework for Intelligent Automation. *IFAC-PapersOnLine*, *52*(13), 1825–1830. https://doi.org/10.1016/j.ifacol.2019.11.501

Cook, S. D. N., & Brown, J. S. (1999). Bridging Epistemologies: The Generative Dance Between Organizational Knowledge and Organizational Knowing. *Organization Science*, *10*(4), 381–400. https://doi.org/10.1287/orsc.10.4.381

Coombs, C., Hislop, D., Taneva, S. K., & Barnard, S. (2020). The strategic impacts of Intelligent Automation for knowledge and service work: An interdisciplinary review. *The Journal of Strategic Information Systems*, *29*(4), 101600. Sciencedirect. https://doi.org/10.1016/j.jsis.2020.101600

Cortada, J. W. (1998). Rise of the knowledge worker. Butterworth-Heinemann.

Craig, K., Thatcher, J. B., & Grover, V. (2019). The IT Identity Threat: A Conceptual Definition and Operational Measure. *Journal of Management Information Systems*, *36*(1), 259–288. https://doi.org/10.1080/07421222.2018.1550561

Dahlin, E. (2019). Are Robots Stealing Our Jobs? *Socius: Sociological Research for a Dynamic World*, *5*(5), 1–14. https://doi.org/10.1177/2378023119846249

Davenport, & Prusack. (1998). *(PDF) Working Knowledge: How Organisations Manage What They Know*. ResearchGate. https://www.researchgate.net/publication/229099904_Working_Knowledge_How_Organizations_Manage_What_They_Know

Davenport, T. (2011, February 11). *Rethinking knowledge work: A strategic approach | McKinsey*. Www.mckinsey.com. https://www.mckinsey.com/capabilities/people-and-organizational-performance/our-insights/rethinking-knowledge-work-a-strategic-approach

Davenport, T. (2016). *Only Humans Need Apply: Winners and Losers in the Age of Smart Machines*. https://leadersexcellence.com/wp-content/uploads/dlm_uploads/2016/08/Davenport-Leaders-Excellence-presentation.pdf

Davenport, T. H. (2005). *Thinking for a living how to get better performance and results from knowledge workers*. Harvard Business School Press.

Davenport, T. H., & Kirby, J. (2015, June 1). *Beyond Automation*. Harvard Business Review. https://hbr.org/2015/06/beyond-automation

Denagama Vitharanage, I., Bandara, W., Syed, R., & Toman, D. (2020). An Empirically Supported Conceptualisation Of Robotic Process Automation (RPA) Benefits. *ECIS 2020 Research-In-Progress Papers*, *58*(58). https://aisel.aisnet.org/ecis2020_rip/58

Drucker, P. F. (1985). *Innovation and entrepreneurship: practice and principles*. Harper & Row.

Drucker, P. F. (1999). Knowledge-Worker Productivity: The Biggest Challenge. *California Management Review*, *41*(2), 79–94.

Dulebohn, J. H., & Johnson, R. D. (2013). Human resource metrics and decision support: A classification framework. *Human Resource Management Review*, *23*(1), 71–83. https://doi.org/10.1016/j.hrmr.2012.06.005

Eikebrokk, T., & Olsen, D. (2020). Towards a Process Theory of IS Business Value Co-creation. Insights from enterprise systems adoption in an SME cluster. *Scandinavian Journal of Information Systems*, *32*(2). https://aisel.aisnet.org/sjis/vol32/iss2/8

Engel, C., Ebel, P., & Leimeister, J. M. (2022). Cognitive automation. *Electronic Markets*, *32*(1), 339–350. https://doi.org/10.1007/s12525-021-00519-7

European Commission. (2019a, September 24). *How is technological revolution changing the world of work and skills in the EU?* Joint-Research-Centre.ec.europa.eu. https://joint-research-centre.ec.europa.eu/jrc-news-and-updates/how-technological-revolution-changing-world-work-and-skills-eu-2019-09-24_en

European Commission. (2019b, September 24). *How is technological revolution changing the world of work and skills in the EU?* Joint-Research-Centre.ec.europa.eu. https://joint-research-centre.ec.europa.eu/jrc-news-and-updates/how-technological-revolution-changing-world-work-and-skills-eu-2019-09-24_en

European Commission. (2022, December 13). *Changing nature of work | knowledge for policy*. Knowledge4policy.ec.europa.eu. https://knowledge4policy.ec.europa.eu/foresight/changing-nature-work_en

Faraj, S., Pachidi, S., & Sayegh, K. (2018). Working and organising in the age of the learning algorithm. *Information and Organization*, *28*(1), 62–70. https://doi.org/10.1016/j.infoandorg.2018.02.005

Faunce, W. A., Hardin, E., & Jacobson, E. H. (1962). Automation and the Employee. *The ANNALS of the American Academy of Political and Social Science*, *340*(1), 60–68. https://doi.org/10.1177/000271626234000109

Fonseca, T., Lima, F., & Pereira, S. C. (2018). Job polarisation, technological change and routinisation: Evidence for Portugal. *Labour Economics*, *51*(51), 317–339. https://doi.org/10.1016/j.labeco.2018.02.003

Frey, C. B., & Osborne, M. A. (2013). The Future of employment: How Susceptible Are Jobs to computerisation? *Technological Forecasting and Social Change*, *114*(1), 254–280. https://www.sciencedirect.com/science/article/abs/pii/S0040162516302244

Frey, C. B., & Osborne, M. A. (2017). The Future of employment: How Susceptible Are Jobs to computerisation? *Technological Forecasting and Social Change*, *114*(1), 254–280. https://doi.org/10.1016/j.techfore.2016.08.019

Gherardi, S. (2000). Practice-Based Theorising on Learning and Knowing in Organisations. *Organisation*, *7*(2), 211–223. https://doi.org/10.1177/135050840072001

Gkeredakis, E. (Manos), & Pachidi, S. (2019). Studying and Theorizing Knowledge Work in the Age of Intelligent Machines. *ICIS 2019 Proceedings*. https://aisel.aisnet.org/icis2019/pdws/pdws/6

Gordon Benzell, S., Brynjolfsson, E., Maccrory, F., & Westerman, G. (2019). *Identifying the Multiple Skills in Skill-Biased Technical Change*. https://ide.mit.edu/wp-content/uploads/2019/08/Identifying-the-Multiple-Skills-in-SBTC-8-2-19.pdf

Grace, K., Salvatier, J., Dafoe, A., Zhang, B., & Evans, O. (2018). When Will AI Exceed Human Performance? Evidence from AI Experts. *Journal of Artificial Intelligence Research*, *62*(62), 729–754. https://doi.org/10.1613/jair.1.11222

Gustavsson, E., Bhiladvala, S., & Larsson, C. (2018). The Automatisation and Its Impact on the Swedish Labour Market: A Qualitative Study on How Automatisation within the Retail Market Contributes to the Job Polarisation in Sweden. In *hj.diva-portal.org*. https://urn.kb.se/resolve?urn=urn:nbn:se:hj:diva-40002

Hadidi, R., & Klein, B. (2024). The Future of Work, Physical Location of Workers, Technological Issues and Implications. *Journal of the Midwest Association for Information Systems (JMWAIS)*, *2024*(1). https://doi.org/10.17705/3jmwa.000085

Harnegie, M. P. (2013). SciVerse Science Direct. *Journal of the Medical Library Association: JMLA*, *101*(2), 165. https://doi.org/10.3163/1536-5050.101.2.020

Hession, C. H., & Rifkin, J. (1996). Review of The End of Work: The Decline of the Global Labor Force and the Dawn of the Post-Market Era. *Review of Social Economy*, *54*(3), 391–393. https://www.jstor.org/stable/29769862

Hopp, W. J., Iravani, S. M. R., & Liu, F. (2009). Managing White-Collar Work: An Operations-Oriented Survey. *Production and Operations Management*, *18*(1), 1–32. https://doi.org/10.1111/j.1937-5956.2009.01002.x

Jan, Z., Ahamed, F., Mayer, W., Patel, N., Grossmann, G., Stumptner, M., & Kuusk, A. (2023). Artificial intelligence for industry 4.0: Systematic review of applications, challenges, and opportunities. *Expert Systems with Applications*, *216*(216), 119456. https://doi.org/10.1016/j.eswa.2022.119456

Jiyong Park, & Jongho Kim. (2022). A Data-Driven Exploration of the Race between Human Labor and Machines in the 21st Century. *Communications of the ACM*, *65*(5), 79–87. https://doi.org/10.1145/3488376

Johansson, B., Engberg, S., Lindgren, I., & Sördal, T. (2020). Impacts of RPA on employees' skill variety. *AMCIS 2020 Proceedings*, *9*. https://aisel.aisnet.org/amcis2020/cognitive_in_is/cognitive_in_is/9

Kahila , T. R., Penttinen , E., Salovaara , A., & Soliman , W. (2018). *AIS Electronic Library (AISeL) - Hawaii International Conference on System Sciences 2018 (HICSS-51): Consequences of Discontinuing Knowledge Work Automation - Surfacing of Deskilling Effects and Methods of Recovery*. Aisnet.org. https://aisel.aisnet.org/hicss-51/os/dark_side/2/

Kling, R. (1996). *Computerisation and controversy: value conflicts and social choices*. Academic Press.

Kohli, R., & Melville, N. P. (2018). Digital innovation: A review and synthesis. *Information Systems Journal*, *29*(1), 200–223. https://doi.org/10.1111/isj.12193

Kortum, H., Rebstadt, J., & Thomas, O. (2022). Dissection of AI Job Advertisements: A Text Mining-based Analysis of Employee Skills in the Disciplines Computer Vision and Natural Language Processing. In *scholarspace.manoa.hawaii.edu*. Proceedings of the 55th Hawaii International Conference on System Sciences. https://hdl.handle.net/10125/79973

Kumar, R., Gupta, M., & Nischay. (2023). Impact of White-Collar Automation on Work. *NEU Journal for Artificial Intelligence and Internet of Things*, *2*(4). https://dergi.neu.edu.tr/index.php/aiit/article/view/812/373

Lacity, M. C., & Willcocks, L. (2015, June 19). *What Knowledge Workers Stand to Gain from Automation*. Harvard Business Review. https://hbr.org/2015/06/what-knowledge-workers-stand-to-gain-from-automation

Lacity, M., & Willcocks, L. (2021). Becoming Strategic with Intelligent Automation. *MIS Quarterly Executive*, *20*(2). https://aisel.aisnet.org/misqe/vol20/iss2/7

Lacity, M., Willcocks, L., & Gozman, D. (2021). Influencing information systems practice: The action principles approach applied to robotic process and cognitive automation. *Journal of Information Technology*, 026839622199077. https://doi.org/10.1177/0268396221990778

Lauterbach, J., & Mueller, B. (2014). Adopt, Adapt, Enact or Use? *IFIP Advances in Information and Communication Technology*, *446*, 8–29. https://doi.org/10.1007/978-3-662-45708-5_2

Levels, M., Somers, M., & Fregin, M.-C. (2019). Scenarios for the impact of intelligent automation on work. In *Maastricht University*. ROA. https://cris.maastrichtuniversity.nl/en/publications/49a4837b-051e-4c8e-8c25-1fa2e48b72ce

Lindgren, R., Stenmark, D., & Ljungberg, J. (2003). Rethinking competence systems for knowledge-based organisations. *European Journal of Information Systems*, *12*(1), 18–29. https://doi.org/10.1057/palgrave.ejis.3000442

Mani, P., S. Neelakandan, Abbas Mardani, Sudhanshu Maurya, N. Arulkumar, & K. Thangaraj. (2023). Eagle Strategy Arithmetic Optimisation Algorithm with Optimal Deep Convolutional Forest Based FinTech Application for Hyper-automation. *Enterprise Information Systems*, *17*(10). https://doi.org/10.1080/17517575.2023.2188123

Mayer, A.-S., Strich, F., & Fiedler, M. (2020). Unintended Consequences of Introducing AI Systems for Decision Making. *MIS Quarterly Executive*, *19*(4). https://aisel.aisnet.org/misqe/vol19/iss4/6

McClelland, D. C. (1973). Testing for competence rather than for "intelligence." *American Psychologist*, *28*(1), 1–14. https://doi.org/10.1037/h0034092

Mendling, J., Decker, G., Hull, R., Reijers, H. A., & Weber, I. (2018). How do Machine Learning, Robotic Process Automation, and Blockchains Affect the Human Factor in Business Process Management? *Communications of the Association for Information Systems*, *43*, 297–320. https://doi.org/10.17705/1cais.04319

Meyer von Wolff, R., Hobert, S., & Schumann, M. (2019). How May I Help You ? – State of the Art and Open Research Questions for Chatbots at the Digital Workplace. *Hawaii International Conference on System Sciences 2019 (HICSS-52)*, *2*(2). https://aisel.aisnet.org/hicss-52/cl/ai_and_cognitive_assistants/2/

Meyer von Wolff, R., Hobert, S., & Schumann, M. (2021). Sorry, I Can't Understand You ! – Influencing Factors and Challenges of Chatbots at Digital Workplaces. *Wirtschaftsinformatik 2021 Proceedings*, *4*. https://aisel.aisnet.org/wi2021/QDesign/Track10/4

Morandini, S., Fraboni, F., De Angelis, M., Puzzo, G., Giusino, D., & Pietrantoni, L. (2023). The Impact of Artificial Intelligence on Workers' Skills: Upskilling and Reskilling in Organisations. *Informing Science: The International Journal of an Emerging Transdiscipline*, *26*, 39–68. https://doi.org/10.28945/5078

Nelson, A. J., & Irwin, J. (2014). "Defining What We Do—All Over Again": Occupational Identity, Technological Change, and the Librarian/Internet-Search Relationship. *Academy of Management Journal*, *57*(3), 892–928. https://doi.org/10.5465/amj.2012.0201

Newell, S. (2015). Managing Knowledge and Managing Knowledge Work: What we know and what the future holds. *Journal of Information Technology*, *30*(1), 1–17. https://doi.org/10.1057/jit.2014.12

Newell, S., & Al, E. (2009). *Managing knowledge work*. Palgrave Macmillan, Cop.

Nguyen, A., Hong, Y., & Gardner, L. (2020). A Taxonomy of Digital Learning Activities for Digital Inclusion. *ECIS 2020 Research Papers*. https://aisel.aisnet.org/ecis2020_rp/135

OECD. (2019). *An OECD Learning Framework 2030*. OECD.

OECD. (2023). Defining and classifying AI in the workplace. *OECD Social, Employment and Migration Working Papers*. https://doi.org/10.1787/59e89d7f-en

Orlikowski, W. J., & Baroudi, J. J. (1988). The information systems profession: myth or reality? *Office Technology and People*, *4*(1), 13–30. https://doi.org/10.1108/eb022652

Orlikowski, W. J., & Scott, S. V. (2014). Exploring Material-Discursive Practices. *Journal of Management Studies*, *52*(5), 697–705. https://doi.org/10.1111/joms.12114

Osmundsen, K. (2020). Competences for Digital Transformation: Insights from the Norwegian Energy Sector. *Hawaii International Conference on System Sciences 2020 (HICSS-53)*. https://aisel.aisnet.org/hicss-53/in/digital_transformation/5/

Panel for the Future of Science and Technology. (2021). *Digital automation and the future of work*.
https://www.europarl.europa.eu/RegData/etudes/STUD/2021/656311/EPRS_STU(2021)656311_EN.pdf

Parasuraman, R., Sheridan, T. B., & Wickens, C. D. (2000). A model for types and levels of human interaction with automation. *IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans*, *30*(3), 286–297. https://doi.org/10.1109/3468.844354

Paré, G., Trudel, M.-C., Jaana, M., & Kitsiou, S. (2015). Synthesising information systems knowledge: A typology of literature reviews. *Information & Management*, *52*(2), 183–199. https://www.sciencedirect.com/science/article/abs/pii/S0378720614001116

Perez, J. (2023, April 12). *How Automation Drives Business Growth and Efficiency*. Harvard Business Review. https://hbr.org/sponsored/2023/04/how-automation-drives-business-growth-and-efficiency

Pinski, M., & Benlian, A. (2023). AI Literacy - Towards Measuring Human Competency in Artificial Intelligence. *Hawaii International Conference on System Sciences 2023 (HICSS-56)*, *3*. https://aisel.aisnet.org/hicss-56/cl/ai_and_future_work/3

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

Ranerup, A., & Henriksen, H. Z. (2020). Digital Discretion: Unpacking Human and Technological Agency in Automated Decision Making in Sweden's Social Services. *Social Science Computer Review*, *40*(2), 089443932098043. https://doi.org/10.1177/0894439320980434

Reay, T., Goodrick, E., Waldorff, S. B., & Casebeer, A. (2017). Getting Leopards to Change Their Spots: Co-Creating a New Professional Role Identity. *The Academy of Management Journal*, *60*(3), 1043–1070. https://www.jstor.org/stable/26398603

Reinhardt, W., Schmidt, B., Sloep, P., & Drachsler, H. (2011). Knowledge Worker Roles and Actions-Results of Two Empirical Studies. *Knowledge and Process Management*, *18*(3), 150–174. https://doi.org/10.1002/kpm.378

Richardson, S. (2020). Cognitive automation: A new era of knowledge work? *Business Information Review*, *37*(4), 182–189. https://doi.org/10.1177/0266382120974601

Rinta-Kahila, T., Penttinen, E., Salovaara, A., & Soliman, W. (2018). Consequences of Discontinuing Knowledge Work Automation - Surfacing of Deskilling Effects and Methods of Recovery. In *scholarspace.manoa.hawaii.edu*. Proceedings of the 51st Hawaii International Conference on System Sciences. http://hdl.handle.net/10125/50543

Rose, I. (2023, June 15). The workers already replaced by artificial intelligence. *BBC News*. https://www.bbc.com/news/business-65906521
Sako, M. (2020). Artificial intelligence and the future of professional work. *Communications of the ACM*, *63*(4), 25–27. https://doi.org/10.1145/3382743
Sandberg, J. (2000). Understanding human competence at work: an interpretative approach. *Academy of Management Journal*, *43*(1), 9–25. https://doi.org/10.2307/1556383
Sandberg, J., & Pinnington, A. H. (2009). Professional Competence as Ways of Being: An Existential Ontological Perspective. *Journal of Management Studies*, *46*(7), 1138–1170. https://doi.org/10.1111/j.1467-6486.2009.00845.x
Seidel, S., Berente, N., Lindberg, A., Lyytinen, K., & Nickerson, J. V. (2018). Autonomous tools and design. *Communications of the ACM*, *62*(1), 50–57. https://doi.org/10.1145/3210753
Sejahtera, F., Wang, W., Indulska, M., & Sadiq, S. (2018). Enablers And Inhibitors Of Effective Use Of Big Data: Insights From A Case Study. *PACIS 2018 Proceedings*, *27*. https://aisel.aisnet.org/pacis2018/27
Staaby, A., Hansen, K., & Grønli, T.-M. (2021). Automation of Routine Work: A Case Study of Employees' Experiences of Work Meaningfulness. *Proceedings of the Annual Hawaii International Conference on System Sciences*, *54*. https://doi.org/10.24251/hicss.2021.018
Stein, M.-K., Galliers, R. D., & Markus, M. L. (2013). Towards An Understanding of Identity and Technology in the Workplace. *Journal of Information Technology*, *28*(3), 167–182. https://doi.org/10.1057/jit.2012.32
Strich, F., Mayer, A.-S., & Fiedler, M. (2021). What Do I Do in a World of Artificial Intelligence? Investigating the Impact of Substitutive Decision-Making AI Systems on Employees' Professional Role Identity. *Journal of the Association for Information Systems*, *22*(2), 304–324. https://doi.org/10.17705/1jais.00663
Susskind, D. (2020). *A world without work : technology, automation, and how we should respond*. Metropolitan Books/Henry Holt And Company.
Susskind, R., & Susskind, D. (2022). *FUTURE OF THE PROFESSIONS : how technology will transform the work of human experts, updated... edition.* Oxford Univ Press.
Teodorescu, T. (2006). Competence versus competency: What is the difference? *Performance Improvement*, *45*(10), 27–30. https://doi.org/10.1002/pfi.4930451027
Teodorescu, T. M., & Binder, C. (2004). Getting to the bottom line competence is what matters. *Performance Improvement*, *43*(8), 8–12. https://doi.org/10.1002/pfi.4140430805
Tsai, H. (Phoebe), & Compeau, D. (2017). Change-Related Communication and Employees' Responses During the Anticipation Stage of IT-Enabled Organizational Transformation. *ACM SIGMIS Database: The DATABASE for Advances in Information Systems*, *48*(4), 30–50. https://doi.org/10.1145/3158421.3158425
Venermo, K., Lampi, A., Salo, M., & Henri Pirkkalainen. (2022). Employees' Challenges And Needs For Reskilling When Working With Software Robots. *Mcis 2022 Proceedings*, *24*. Https://Aisel.Aisnet.Org/Mcis2022/24/
Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User Acceptance of Information technology: toward a Unified View. *MIS Quarterly*, *27*(3), 425–478. JStor. https://doi.org/10.2307/30036540
Viale, L., & Zouari, D. (2020). Impact of digitalisation on procurement: the case of robotic process automation. *Supply Chain Forum: An International Journal*, *21*(3), 1–11. https://doi.org/10.1080/16258312.2020.1776089
Voister. (2023, October 26). *Tre av tio behöver kompetensutveckling på grund av AI*. Voister. https://voister.se/artikel/2023/10/tre-av-tio-behover-kompetensutveckling-pa-grund-av-ai
Wagner, G., & Prester, J. (2019). Information Systems Research on Digital Platforms for Knowledge Work: A Scoping Review. *ICIS 2019 Proceedings*, *2*. https://aisel.aisnet.org/icis2019/future_of_work/future_work/2

Waizenegger, L., & Techatassanasoontorn, A. (2020). "You have no idea how much we love Casper" – Developing configurations of employees' RPA implementation experiences. *ACIS 2020 Proceedings*. https://aisel.aisnet.org/acis2020/21

Waschull, S., Bokhorst, J. A. C., Wortmann, J. C., & Molleman, E. (2022). The redesign of blue- and white-collar work triggered by digitalisation: Collar matters. *Computers & Industrial Engineering*, *165*(165), 107910. https://doi.org/10.1016/j.cie.2021.107910

Webster, J., & Watson, R. T. (2002). Analysing the Past to Prepare for the Future: Writing a Literature Review. *MIS Quarterly*, *26*(2), 13–23. https://www.jstor.org/stable/4132319

Wiesche,M, Damien , J., Thatcher, J., Gu, B., & Krcmar, H. (2019, June 18). *MIS Quarterly*. MIS Quarterly. https://www.misqresearchcurations.org/blog/2019/6/17/it-workforce

Wilson, H. J., & Daugherty, P. R. (2018, July). *Collaborative Intelligence: Humans and AI Are Joining Forces*. Harvard Business Review. https://hbr.org/2018/07/collaborative-intelligence-humans-and-ai-are-joining-forces

Wolfswinkel, J. F., Furtmueller, E., & Wilderom, C. P. M. (2013). *Using Grounded Theory as a Method for Rigorously Reviewing Literature*. ResearchGate. https://www.researchgate.net/publication/255856903_Using_Grounded_Theory_as_a_Method_for_Rigorously_Reviewing_Literature

World Economic Forum. (2023, April 30). *The Future of Jobs Report 2023*. World Economic Forum. https://www.weforum.org/publications/the-future-of-jobs-report-2023/

Yao, Z., Lum, Y., Johnston, A., Mejia-Mendoza, L. M., Zhou, X., Wen, Y., Aspuru-Guzik, A., Sargent, E. H., & Seh, Z. W. (2022). Machine learning for a sustainable energy future. *Nature Reviews Materials*, *8*(3), 202–215. https://doi.org/10.1038/s41578-022-00490-5