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Digital Automation Of Knowledge Work – A Literature Review On Implications For Work Environment

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DIGITAL AUTOMATION OF KNOWLEDGE WORK – A LITERATURE REVIEW ON IMPLICATIONS FOR WORK ENVIRONMENT

Research paper

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Abstract

The implications of digital automation for knowledge work have sparked intense discussions in society and amongst scholars. This paper provides an overview of information systems (IS) literature on digital automation, knowledge work and work environment implications. We explore digital automation's implications through a systematic literature review, identifying 179 papers of which 18 were selected as core research studies relevant by inclusion criteria. We provide an overview of IS literature relating to digital automation of knowledge work and the implications for work environment. We show how digital automation is represented and outline positive and negative implications for knowledge workers and organizations. The literature review concludes by pointing out research opportunities that are particularly relevant in progressing IS research on digital automation.

Keywords: Digital automation, Knowledge work, Work environment, Research opportunities.

1 Introduction

Digital automation, powered by AI, is rapidly transforming the work environment of knowledge workers (Benbya et al., 2020; Cole et al., 2021). Like any automation, digital automation is used to carry out work previously done by humans, but also to complement or augment human work (see e.g. Benbya et al., 2024; Lacity & Willcocks, 2021). By digital automation we mean automation enabled by digital technologies such as robotic and cognitive process automation, artificial intelligence, machine learning, and large language models. While digitalization previously has dealt with automation of well-structured and repetitive tasks, todays automation technologies have reached a point where knowledge work (decision-making, problems-solving, artistic work, etc.) is subjected to automation (see e.g. Benbya et al., 2024; Wang & Siau, 2019). Asked 2015 about their beliefs about progress in AI, machine learning researchers predicted that AI will outperform humans in many activities in the next ten years (Grace et al., 2018). This development undoubtedly opens for new opportunities for knowledge work (Al Halbusi et al., 2023), yet it also brings risks and challenges. In this paper we pay particular attention to the implications for the work environment of knowledge workers.

The most pressing implication of digital automation of knowledge work is the risk of job displacement. According to the World Economic Forum (2023 p. 32) knowledge workers are "expected to suffer the greatest reduction in employment" because of digital automation. Other implications relate to critical issues such as transparency, trust, ethical considerations, security, and changed work conditions (see e.g. Tambe et al., 2019; Monod et al., 2024). Some researchers recount digital automation as an opportunity for knowledge workers to get rid of boring tasks, saving time for creative activities such as knowledge creation (see e.g. Benbya et al., 2024; Davenport & Kirby, 2016, p. 7; Spencer, 2018). Yet others suggest that digital automation create new jobs, boost productivity, improve living

standards and benefit novices or less skilled workers (see e.g. Benbya et al., 2024). A McKinsey Global Institute (2018) report indicates that almost half of the global jobs have the potential to be replaced by AI. No doubt, digital automation can lead to job displacement, inequality of wealth (Wang & Siau, 2019) or even create a class of humans who may be not only unemployed, but also unemployable (Harari, 2016). It has also been suggested that intelligent machines will reshape the labour market, leaving people without jobs and displacing them with ever-more advanced machines (see Benanav, 2020 p.2; Lee et al., 2023).

Obviously, digital automation has implications for knowledge work (Cole et al., 2021; Benbya et al., 2024; Guggenberger et al., 2023). Less obvious, however, is how digital automation implicate the work environment of knowledge workers (Coombs et al., 2020). As discussions and debates continue in society and academia, research on digital automation progress. Despite this, we are still lacking sufficient knowledge on implications of digital automation on knowledge work and work environment (Battina, 2020; Coombs, 2020; Rinta-Kahila et al., 2023). This paper contributes to the growing body of research by providing an overview of IS literature on digital automation and implications thereof. We reviewed the IS literature guided by the following questions*: How is digital automation represented? What does the IS literature say about the implications of digital automation for work environment? What research opportunities have been identified for the future research?*

The contribution is threefold. First, we provide an overview of previous research on digital automation and knowledge work. Second, the paper contributes to the understanding of how digital automation implicate knowledge work and the work environment. Third, we provide a summary of opportunities for future IS research. The remaining part of this paper is structured as follows. Section 2 presents a background of digital automation, knowledge work, and work environment. In Section 3, the method for the literature review is outlined. Section 4 focuses on the analysis and the results of our review. Finally, section 5 is devoted to the discussion and conclusion.

2 Background

2.1 Automation and its evolution into Digital Automation of work

Scholars have used a variety of terms to label the application of computer technologies that automate work tasks. Some commonly used terms include computerization, virtualization and automation. (Coombs et al., 2020). The term automation was coined in 1947 by Ford Motor Company Vice President Delmar S. Harder (Noble, 1984). At the time, it referred to the usage of electromechanical, hydraulic, and pneumatic machinery to automate work tasks (Cole et al., 2021). Today, the National Academy of Sciences (2017) defines automation as "the technique, method, or system of operating or controlling a process by highly automatic means, as by electronic devices, reducing human intervention to a minimum."

Focusing on automation of knowledge work, in this paper we use the definition by Parasuraman and Riley (1997), where automation is framed as the act of delegating tasks, traditionally performed by human workers, to computers. In this vein *digital automation* is the application of digital technologies to streamline, replace, complement, or augment tasks previously performed by workers. The goal of digital automation is to streamline and optimize workflows, increase efficiency, and reduce the need for manual effort in repetitive or routine activities, yet more cognitive tasks (Cole et al., 2021). Digital automation represents a transformative digital solution that integrates advanced automation technologies to enhance cognitive, decision-making, and analytical capabilities, thereby streamlining and simplifying complex and repetitive tasks (Ghobakhloo et al., 2023).

Returning to the origins of automation, we find that automation of work is not a new phenomenon (see Figure 1 below). Organization's desire to automate work tasks has a long history, and fears about its effect on human life have existed for a long (AlHalbusi et al., 2023; Benanav, 2020; Cole, 2021). Be-

ginning in 1784, automation has evolved through four industrial revolutions (Wang & Siau, 2019), presented in Figure 1. The first industrial revolution began with the invention of the steam engine, laying the foundation for today's modern production systems (Machkour & Abriane, 2020). It allows the mechanization of production and increases productivity (Sako, 2020). The second industrial revolution brought mass production to life using electric power, enhancing job automation. This was followed by the third industrial revolution, which further advanced automated production by introducing electronics and information technology (Machkour & Abriane, 2020).

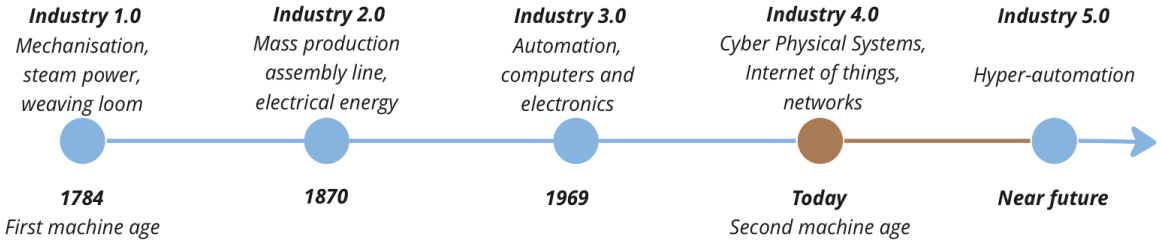

Figure 1. Automation timeline (Based on Benanav, 2020; Cole, 2021; Fast-Berglund, 2018; Noble, 1984; Raisch & Krakowski, 2021; Sostero, 2020).

While the first two industrial revolutions transformed human physical work into machine-based tasks through mechanization, the third industrial revolution introduced the computerization of tasks requiring human intellect (Barley, 2020). This computerization era extended automation across a broad spectrum of knowledge work, affecting clerical, technical, and professional roles (Sako, 2020). Enabling automation technologies now include AI and machine learning and the integration of technologies like the Internet of Things, big data, robotics, virtual reality, 3-D printing, and quantum computing, the fourth industrial revolution has arrived (Wang & Siau, 2019). Brynjolfsson and McAfee (2016) have called the fourth industrial revolution "the second machine age". Digital automation came with the development of automation technologies aimed at, fully or partially, replacing or complement worker skills with machine input for specific tasks (Sostero, 2020). In summary, the main difference between 21st-century automation from 20th-century automation is the use of intelligent digital technologies (Coombs et al., 2020; Davenport and Kirby, 2015).

The academic discussion around AI and automation gained significant momentum in the late 1990s and early 2000s when AI emerged as a serious technology with the potential to enhance automation systems in the workplace. Research began exploring the integration of AI, especially in robotics and intelligent systems, laying the groundwork for what is now referred to as digital automation, also known in the literature as intelligent or cognitive automation (Amonett, 2022; Nilsson, 1998; Thrun et al., 2005). With its advanced cognitive capabilities, digital automation is poised to become a major focus of scholarly debate in the coming years (Lee et al., 2023). In sum, digital automation has sparked discussions and concerns about e.g. job displacement, human redundancy, replacement of employee skills, digital skill gaps, the work environment, workers resistance, and security issues (Ghobakhloo et al., 2023; Gkeredakis, & Pachidi, 2019). Yet, several researchers (see e.g. Güner et al., 2022; Monod et al., 2024) point out positive implications of digital automation such as efficiency, accuracy, objectivity and improved work environment (Al Halbusi et al., 2023; Ghobakhloo et al., 2023).

2.2 Work environment automation and knowledge work

In this paper, when we discuss digital automation and implications thereof, our focus is on the digital work environment of knowledge workers. The term work environment refers to the surrounding conditions in which an employee operates (e.g. physical surroundings, ergonomics and organizational cul-

ture) that affect the psychological well-being and productivity of the employees (Chan et al., 2014). By digital work environment we mean the system of digital resources that an employee uses, or is affected by, when performing work tasks (see Johansson et al., 2018, p. 10). The term knowledge worker was originally coined by Peter Drucker (1959) to describe the role of a growing percentage of employees in business - *The manual worker is yesterday—and all we can fight on that front is a rearguard action. The basic, capital resource, the fundamental investment, but also the cost center of a developed economy, is the knowledge worker who puts to work what he has learned in systematic education, that is, concepts, ideas, and theories, rather than the man who puts to work manual skill or muscle* (Drucker, 1973, p. 28). From literature we can deduce that a knowledge worker is a person who deal with a type of work which involves intellectual, creative, and non-routine tasks that utilize and generate knowledge (Coombs et al., 2020; Dalkir, 2011; Hislop et al., 2018). Knowledge work require a higher level of education and including a wide range of professions, such as information and communication, consulting, pharmacology, management, and other professions that are primarily performed in an office or other administrative setting (Davenport, & Kirby, 2016; Kuusisto & Meyer, 2003). Knowledge worker is a broad term which includes many professions. In this paper our focus is knowledge workers in management and clerical positions typically working in an office setting, performing administrative, managerial, decision-making, analytical and creative tasks. This is sometimes referred to as white-collar work (Bain & Price, 1972).

2.3 Digital automation and implications for the work environment

There are both positive and negative views among scholars towards digital automation and its implications on the knowledge work environment. Some articles pay attention to mainly positive implications focusing on the benefits of automation, and despite obvious tensions, building positive perspectives for the future, where automation technologies bring efficiency, accuracy and objectivity (Abdul et al., 2020; Güner et al., 2022; Willcocks, 2020). Digital automation leads to new knowledge generation or improving creativity (Davenport & Kirby, 2016; Spencer, 2018), bringing new opportunities (Al Halbusi et al., 2023) and creating new jobs, boosting productivity, improving living standards (Cole et al., 2021; Manyika et al., 2017; Willcocks, 2020), saving time, improving work processes, and facilitating the development of new products and services (Kshetri, 2020), as well as benefiting novices and less skilled workers (Benbya et al., 2024).

Conversely, some articles discuss the negative implications of digital automation such as losing jobs and workers redundancy (Benanav, 2020, p.2; Lee et al., 2023). Human life quality depends on their work, and its disappearance would lead to a societal crisis (Manyika et al., 2017). The skills and knowledge of some workers can be reduced (Lee et al., 2023). Digital automation can lead to job insecurity and elevation of stress as well as psychological outcomes among employees (Lee et al., 2023). According to Spencer (2023), historically technologies were used to extend the duration of work and intensify its pace. Some scholars argue that automation technologies help to reduce human biases in working processes (for example, in HR), making them fairer. Still, Van den Broek et al. (2021) and Jackson (2021) argue that intelligent technologies are biased as their algorithms are built on biased data. The biased or irrelevant data led to serious errors and consequences for work processes (Van den Broek et al., 2021). Besides those two perspectives, another point of view argues for augmentation and collaborative employee-machine work. According to this perspective, digital automation will be more effective if it augments (rather than replaces) workers (Davenport et al., 2020). Digital automation improves work performance if workers are involved in a process too (Coombs et al., 2020). Also, automation must be considered a tool that helps workers complete their tasks effectively, rather than a co-worker who can make its own decisions (Monod et al., 2024).

3 Method

A systematic literature review is an explicit and reproducible method for identifying, evaluating, and synthesizing existing research literature in a specific field (Collins et al., 2021) It facilitates gathering relevant research fitting predefined criteria to address a specific research question (Kitchenham, 2004). Utilizing clear and systematic procedures, minimizes bias in searching, identifying, appraising, synthesizing, analyzing, and summarizing studies (Mengist et al., 2020).

This literature review is informed by the guidelines by Okolo (2015), which are beneficial for researchers across various disciplines. Following the guidelines helps to construct validity where an author is supposed to achieve the right measures for a concept under investigation (Petersen et al., 2015). Okolo (2015) prescribes a process divided into four steps - planning, selection, extraction, and execution. Each step includes a sub-step (see Figure 2) and discussed in detail further in this section.

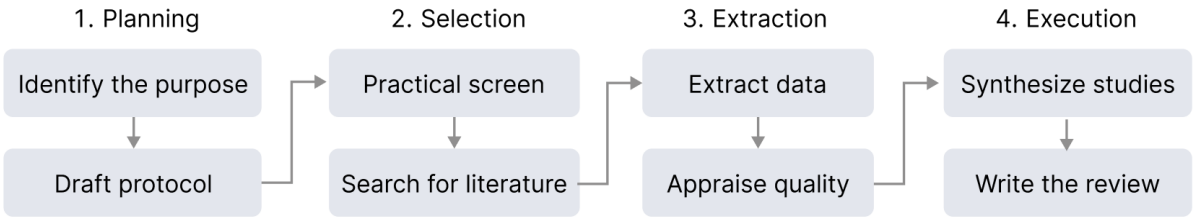

Figure 2. A systematic guide to literature review development (Okoli, 2015).

Our literature review was guided by the following questions: *How is digital automation represented? What does the IS literature say about the implications of digital automation for work environment? What research opportunities have been identified for the future research?*

Before conducting the literature review a review protocol was outlined (see Table 1 below). It details the procedures to be followed in the review process: databases, key words, string as well as exclusion and inclusion criteria and outlining searching limitations.

As a first step to fill the protocol the following databases were chosen: Scopus, Science Direct and Web of Science. These databases are broadly used by researchers due to their extensive scope of sources and convenient searching system (Tober, 2011). Also, IS journals and conferences were scanned separately to not miss any relevant research in this field (see Appendix 1). To support literature gathering process, the specific keywords were identified based on research questions. These keywords helped to create search strings for the digital library's search tools (Mengist et al., 2020).

We started by a pilot search to refine the suitable searching keywords, ensuring our search results were limited to the most relevant articles (Mengist et al., 2020). During that process, we tried different strings and various combinations of keywords (See Appendix 1). Doing so we got a result with a big number of duplications. That is why it was decided to use Boolean operators like AND or OR (or combinations), to minimize duplications (Abrar et al., 2020). Then the final search string was developed (see Table 1).

SLR protocol	Description
Database	Science direct, Scopus, Web of science, IS journals and conferences
Key words	Digital automation, work environment, RPA, AI, future of work, knowledge work
Search string	“Automation and work environment”, “RPA and work environment”, “AI and knowledge work”, “AI and work environment”
Final search string	("digital automation" OR "automation technology" OR "artificial intelligence" OR "robotic process automation") AND ("knowledge work" OR "professional services" OR "future of work" OR "workforce transformation”)
Inclusion criteria	Search topic must include following elements: automation or automation technologies in a context of work environment and white-collar jobs. Period: 2018- February2024, Research papers in a field of IS
Exclusion criteria	Books, review papers, web sources, papers concentrated on in-depth description of the technology functions from technical perspective, technical and engineering papers. Studies with no focus on automation implications. Duplicate articles.
Limitations	English language only

Table1. Literature review protocol.

The journals which do not provide an opportunity to search with the help of long string was scanned using shorter strings and key words (see Appendix 1). A keyword strategy was applied to nine IS journals and three IS conferences (rest was scanned manually, as the keyword searching option was not available).

The search across three databases and IS journals and conferences yielded 4384 total number of articles. After non relevant by title articles and duplications were removed, 179 studies were left (see Appendix 1). The overview of the selection and screening process used in this SLR is presented in Figure 3 with 4 steps of the searching process and number of included and excluded articles.

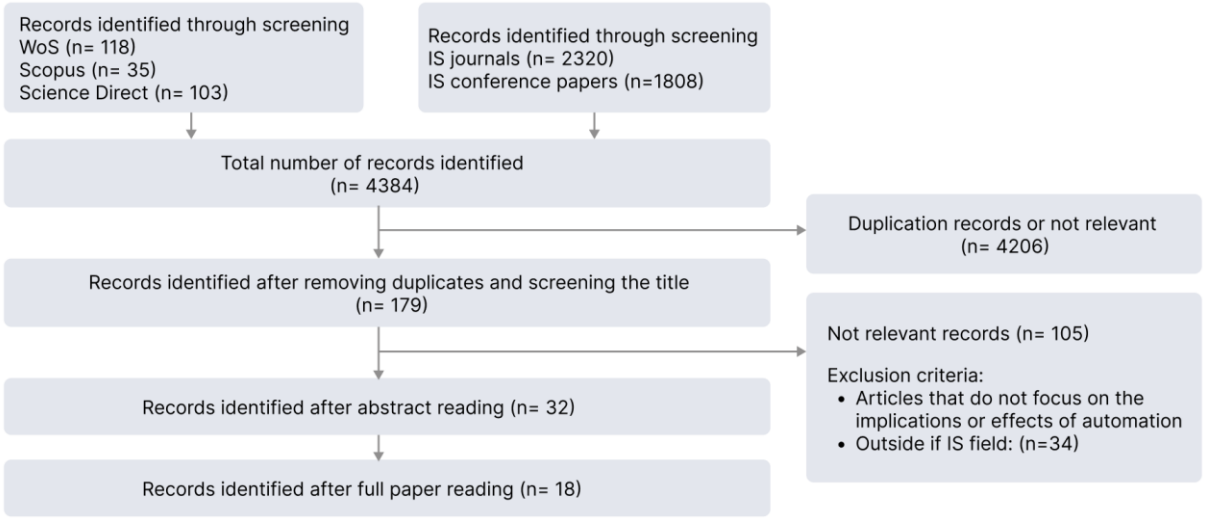

Figure 3. Paper selection process.

At the next round, we judged articles by abstract relevance. All articles which do not focus on automation implications and not in a field of IS were removed. After the full-text reading round, we got 18 final articles. At this point we exclude all articles which did not concentrate on automation implications, overfocusing on technical part of the problem and not suitable to answer research questions. Articles were suitable for inclusion in this SLR if they presented empirical data on digital automation or automation technologies (such as AI, ML, RPA), automation implications or non-empirical studies if

they can help to answer the research questions. The applied inclusion and exclusion criteria presented in Table 1 above.

4 Analysis and results

4.1 Analysis of the primary literature

This section presents the analysis of the 18 primary papers, based on the research questions listed previously. The results represent the state of digital automation in IS literature, digital automation implications (positive and negative), identified research potential opportunities.

To organize our results, we compiled Table 2 below that includes 18 primary papers with the article's citation, type of paper, and knowledge work that each paper focuses on. This table effectively summarizes the selected papers and provides a coding system for the papers, simplifying the analysis process for further review.

Code	Paper	Type of paper	Knowledge work
P1	Gelinas et al., (2022)	Literature review	Management
P2	Baum et al., (2023)	Empirical study	
P3	Guler & Cahalane (2022)	Empirical study	
P4	Abdul et al., (2020)	Empirical study	
P5	van den Broek et al., (2019)	Empirical study	
P6	Güner., (2020)	Literature review	
P7	Willems & Hafermalz (2021)	Empirical study	
P8	Kinowska & Sienkiewicz (2023)	Empirical study	
P9	Monod et al., (2024)	Empirical study	
P10	Rinta-Kahila et al., (2023)	Empirical study	Accounting
P11	Seethamraju & Hecimovic (2020)	Empirical study	
P12	Strich et al., (2021)	Empirical study	Consulting
P13	Savoli & Bhatt (2023)	Empirical study	Knowledge and service work
P14	Kunz et al., (2022)	Empirical study	
P15	Coombs et al., (2020)	Literature review	
P16	Venermo et al., (2022)	Empirical study	Work in general
P17	Yu et al., (2023)	Empirical study	
P18	Willcocks (2020)	Statistical analysis	

Table 2. Final list of articles with codes.

Table 2 shows that most primary papers are empirical studies (n=14), two are literature reviews, and one is statistical analysis. Most primary articles focus on management work (n=9). Two articles address accounting work, and one article focuses on consultants. Next three articles investigate customer service and knowledge work, and the final three articles examine the implications of automation on the work environment generally. Analysing this outcome, we observe a tendency in IS literature to focus more on management work when investigating automation and automation technologies.

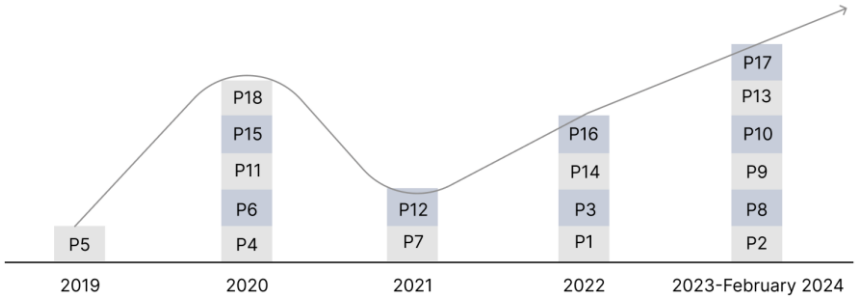

Figure 4. Publication trend.

Figure 4 shows the trend of recent and relevant publications (from 2019 to February 2024) in the IS field. The table shows an uptrend in the subject, indicating the interest of academics and researchers. There is only one relevant article in 2019 identified. The number of publications has steadily increased in 2020 (n = 5), then went down in 2021 (n=2), however, since 2021, number of relevant articles continue growing (2022 n=4, 2023-Feb 2024 n=6). Based on the recent trend, we may conclude, that more publications on work environment and knowledge work automation are expected in the coming years.

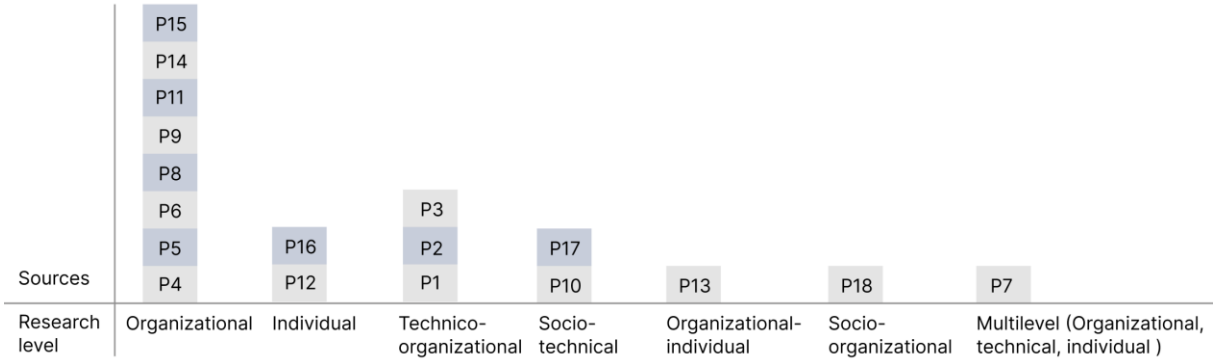

Figure 5. Levels of the research

The primary literature was also analysed on research level criteria (see Figure 5). The analysis revealed that eight out of eighteen primary papers investigate work automation implications at the organizational level, while only two focus on the individual level. The remaining papers explore automation of work at mixed levels. Figure 5 highlights the tendency of IS literature to predominantly investigate work automation at the organizational level.

4.2 Results

4.2.1 How is digital automation represented?

The analysis of primary literature revealed that most papers discussing digital automation and knowledge work use various other terms, including automation technologies (see Figure 6). This led to the conclusion that the term "digital automation" is not commonly used in the analysed IS literature. However, the concept of digital automation is broad and encompasses several related sub-terms that describe different aspects of automation, which are presented in the literature and represent key characteristics of automation.

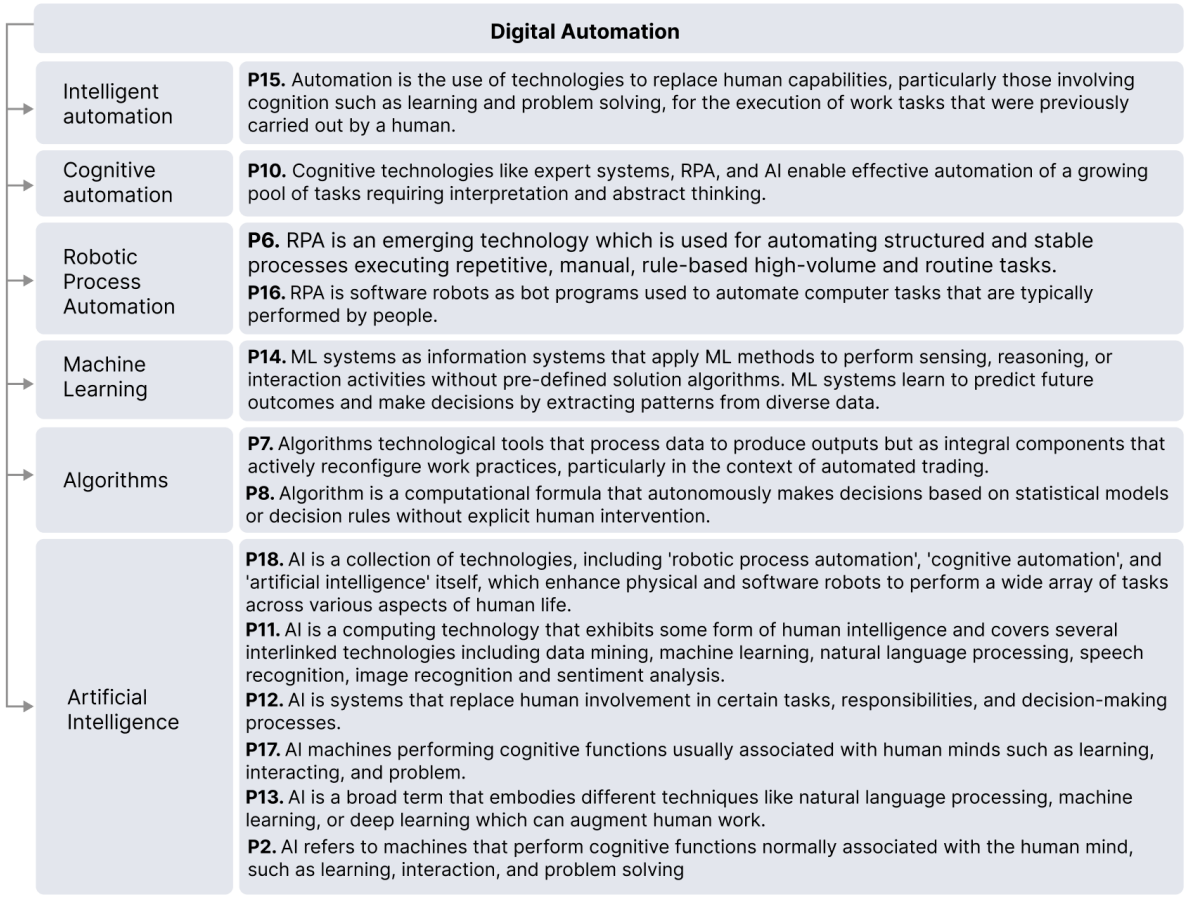

Figure 6. Digital automation as an umbrella term.

As it shown in Figure 6, sex out of eighteen papers discusses artificial Intelligence, describing situation with automation of knowledge work. Two papers discuses RPA. Two papers discuses algorithms and one paper Machine Learning. The closest to "digital automation" are terms such as Intelligent and Cognitive automation highlighted only in one paper each. When summarizing the scoped definitions, extracted from the primary literature, it becomes clear that all of them describe processes of digital automation, where technologies aim to replace, complement, or augment cognitive tasks previously carried out by human workers.

4.2.2 What does the IS literature say about the implications of digital automation for work environment?

The analyses of the primary literature helped to identify implications of digital automation on work environment from both organizational and worker perspectives, encompassing discussions on both positive and negative implications.

The analysis identifies four main groups of implications: "negative for workers," "positive for workers," "negative for organizations," and "positive for organizations" (see Table 3 below). The table reveals that "negative for workers" and "positive for organizations" groups are two groups that includes biggest number of implications mentioned in papers. Group "Positive for workers" has the lowest number of implications.

Negative									
	Implications	Sources							
For workers	Human exclusion and unemployment	P6	P7	P9	P12	P14	P15	P17	P18
	Skills gap/reskilling	P4	P6	P7	P10	P12	P15	P16	P18
	Losing autonomy	P3	P7	P8	P9	P15	P12	P17	
	Fear, insecurity, stress	P3	P6	P10	P13	P15	P17		
	Changing work structure	P4	P11	P14	P17				
	Make work more complex	P3	P10	P16					
	Work tasks redistribution	P4	P14	P16					
For organizations	Ethical concerns	P6	P8	P9	P14	P15	P18		
	Lack of technology transparency	P2	P8	P11	P12	P14			
	Technological errors	P7	P14	P16					
	Low quality of work outcome	P3	P13	P17					
	Data quality dependence	P3	P11						
	Expectations mismatch	P2	P7						
	Need for new roles	P3							

Positive								
	Implications	Sources						
For workers	Making work more attractive	P6	P9	P13	P14	P16	P17	P18
	Upskilling	P1	P5	P11	P12			
	Better general well-being	P1	P17					
	Satisfaction in work	P13						
For organizations	Accuracy	P3	P6	P10	P11	P14	P15	P16
	Save time	P4	P7	P9	P13	P14	P15	P17
	Efficiency and productivity	P3	P7	P9	P11	P14	P17	P18
	Reduce inequality, biases	P1	P5	P11				
	Save costs	P11	P16	P17				
	Creating new tasks /work	P9	P18					
	Risks reduction	P11	P14					
	Improve communication	P1						

Table 3. Automation implications identified in core literature.

Negative for workers is the largest group, that includes seven implications. Most mentioned implications here are *human exclusion and unemployment* and *skills gap and reskilling* that discussed in eight out of eighteen papers. Of the entire list of the identified implications, *fear of losing* work and *worker redundancy* as well as *reskilling issue* are the most discussed. Next most mentioned implication in this group is the issue of *workers losing their autonomy* because of smart technologies, becoming too dependent on algorithmic outputs. Seven out of eighteen papers highlining this issue as important to consider. Less discussed implications in this group are connected to automation that *creating more complex work structure* and *work tasks redistribution*. Those implications highlighted only in three papers, making them less relevant.

Negative for organizations is the next group that includes seven implications. The most mentioned of them is *ethical concerns* which comes with digital automation implementation, including social questions, issues related to privacy, surveillance, and biases. Six out of eighteen papers highlighting this implication as important for discussion. *Lack of technology transparency* mentioned in five papers as the implication that brings lack of trust to technology and making it difficult to follow the reason behind its decision-making process, due to "black box"- nature. *Need for new roles* in organization after automation implementation mentioned only in one paper, which make this implication less discussed in this group.

Positive for workers is the smallest group, that includes only four implications with the most relevant of them where the automation *making work more attractive* for workers. Seven out of eighteen papers mentioned this as a positive point. Four papers writing about upskilling enabled by automation as workers constantly learning new things. Two papers writing about workers well-being what becomes better due to automation new functions that helps to complete tasks faster. One paper saying that automation and AI can bring satisfaction of work because the AI helps workers to succeed.

Positive for organizations group is another large group consisting of eight implications. The most discussed implications here are *accuracy, efficiency, and productivity* to work processes and environment as well as *time saving*. Each of those three implications discussed in seven articles. Less relevant but still positive implications in this group are *creating new tasks/works* that do not exist today (n=2), automation *reduces the risks*, as it can fast and accurate identify them and prevent (n=2) and automation *improve communication* as technology can revolutionize how employees work and engage (n=1).

4.2.3 What potential opportunities have been identified for the future research?

The analysis identified nine potential research directions for future research: investigating professional role identity from workers perspective, conducting long-term automation studies, examining automation integration strategies, generating empirical data, exploring the role of context in automation and the work environment, studying automation-human-worker collaboration, addressing ethical issues, assessing automation's impact on organizations, and understanding changes in business process strategies. These directions are summarized and presented in Table 4 below, which illustrates the broad diversity of potential future research areas.

In addition, our analysis helped to identify the most highlighted direction in the literature: *professional role identity from worker's perspective.* Thirteen out of eighteen papers propose this direction as important for future research. This direction includes need for investigation of how automation and AI can enhance quality and efficiency of workers. Need of continuous workers adaptation and professional learning to keep pace with rapid technological advancements. Investigation of new activities generation and reallocation of tasks between workers. Need to dive deeper into the future employment and the required education. Worker's engagement and satisfaction of their new work conditions as well as skill erosion and digital skills requirements must be in research focus. It is also critical to investigate how workers respond towards challenges connected to automation, their general well-being and self-identity.

Less mentioned potential direction for future research is *business process changes.*

Themes	Description	Sources
Professional role identity, workers perspective	Workers adaptation, new activities and the reallocation of tasks between workers, future employment and the education needed, engagement, employee satisfaction and respond towards changes, skill erosion, digital skills requirements, well-being	P1 P3 P4 P7 P8 P10 P11 P12 P13 P14 P15 P16 P17
Continues study	Long-term effects on organizations, effect the work and what changes are happening, integration evolving technology impact and dynamics over time	P3 P5 P6 P7 P8 P9 P12 P13
Automation integration strategies	Effectiveness, limitations, decision making impact, augmentation, determination of task and level to automate	P2 P3 P4 P7 P9 P15 P17
Lack of empirical data	Factors influencing the adoption and implementation, automation effect organizations and workers, social and technological interactions	P3 P6 P7 P9 P11 P17
The role of context in automation	Company size affects, industry type, regulations and client readiness, human aspect, diverse cultural and economic backgrounds	P2 P4 P8 P11 P12 P15
Automation - human-worker collaboration/ interplay	Dynamics, used strategies, decision-making processes, human complexity effect, technology and work routine capability, collaboration or interaction	P6 P7 P9 P10 P12 P15
Ethical issues	What is ethics in Ai, ethical implications on algorithms, potential biases in AI-driven recruitment, transparency, surveillance, trust	P3 P5 P7 P9 P15
Automation impact in organizations	Work practice, organizational structure, performance, inclusion and onboarding	P1 P4 P7 P14 P15
Business process changes	Changes in business processes, optimal business models development, changes in activity composition, allocation, and sequence within business processes	P11 P14 P17

Table 4. *Research opportunities identified in primary literature.*

Table 4 provides a comprehensive overview of potential research directions extracted from primary literature. These directions are listed in order of frequency from most to least mentioned, offering a clear perspective on their relative relevance in the field.

5 Discussion and conclusions

This section summarizes the findings of our literature review highlighting the critical areas that IS research on digital automation and work environment has focused on to date and key findings from this papers analysis. The overall goal of this literature review is to answer the research questions to find out how digital automation is represented in IS literature, identify implications of digital automation for work environment and potential opportunities for the future research. The reviewed literature is limited to English-language publications in Information Systems, covering literature from the past five years up to February 2024.

Thus, this section will discuss relevant and critical insights we found from the literature, starting with the digital automation representation, continuing with most relevant digital automation implications and worker perspective in automation study, and finalizing with future research opportunities. By using a systematic literature review, we identified, classified, and analysed 179 papers on digital automation implications on work environment within knowledge work context. Of these, 18 were identified as primary papers, after a rigorous filtering process.

5.1 Representation of digital automation

Our findings shows that the term "digital automation" is not widely used in the IS literature. Many papers focusing on related concepts such as artificial intelligence, robotic process automation, and machine learning (see e.g., Güner & Juell-Skielse, 2020; Kinowska & Sienkiewicz, 2023; Kunz et al., 2022; Yu, 2023). In our discussion on the implications of digital automation comprehensively, we included papers that address various automation technologies in our search process. Out of eighteen primary papers, sixteen focus on a single technology investigating work automation, while two primary papers explore cognitive and intelligent automation.

Figure 6 (presented in section 4.2.1) illustrates our understanding of digital automation, presenting it as an umbrella term that encompasses various digital automation technologies. This visualization helps to summarize and contextualize the diverse technologies aimed at streamlining, replacing, complementing, or augmenting tasks traditionally performed by workers under one term.

Our background research, detailed in Section 2, highlights the lack of clear representation and definition of digital automation in the IS literature. As a starting point, we adopted Parasuraman and Riley's (1997) definition, which frames automation as the delegation of tasks traditionally performed by human workers to computers. With the ongoing development and utilization of new digital technologies for work automation, we propose framing digital automation as the application of these technologies to streamline, replace, complement, or augment tasks previously performed by workers (Sostero, 2020).

The results of our analysis show that the proposed in section 2 definition of digital automation, as well as the lack of its representation in IS literature, aligns with the current state of the field. Digital automation is essentially a summary of various digital technologies aimed at optimizing tasks performed by workers. This gap in the literature underscores the need for more comprehensive studies and discussions to fully understand and integrate digital automation into the broader context of IS research.

5.2 Digital automation implications. Positive for organization and negative for workers

There are several implications were identified from the primary papers, showing that digital automation will implicate work environment from different perspectives. Positive and negative views towards automation (presented in section 2.3) helped to identify positive and negative implications existence. For example, Davenport and Kirby (2016) talks about a new knowledge generation and improving creativity in work. Cole et al. (2021) stats that digital automation will create new jobs and improve living standards. But job losing and human redundancy can be a big problem raised by automation (Benanav, 2020) as well as ethical issues, insecurity, and elevation of stress (Lee et al., 2023). Our analysis confirms that while some implications of automation can be beneficial, others can negatively impact the work environment.

However, the background study did not identify an extensive overview or existence of the implication's classification. Our results, however, provides a thorough summary and assesses whether positive or negative implications are more prominent. To organize the summarized implications, we categorized them into four groups: "negative for workers," "positive for workers," "negative for organizations," and "positive for organizations" (refer to Table 3, section 4.2.2). Through this classification, we observe two predominant groups: "positive for organizations" and "negative for workers." Group with positive implications for organizations is the group with biggest number of implications, which most often highlighted in papers. That summary brings us to the conclusion, that digital automation plays generally a positive role for the work environment in organizational level. For example, it helps to improve work accuracy and productivity, save time and costs as well as creates new tasks and reduces the risks, inequality and biases (see e.g., Abdul et al., 2020; Guler & Cahalane, 2022; Monod et al., 2024).

It should be noted that some positive implications for organizations can have negative effects on workers. For example, Güner et al. (2020) states that automating tasks through RPA can lead to significant cost savings for organizations by reducing the need for human intervention in routine tasks. While this benefits organizations, it negatively impacts workers, as many are at risk of losing their jobs. Similarly, Coombs et al. (2020) discuss how automation can improve work processes, yet workers may experience a lack of autonomy, increasing their stress levels. Automation also changes the nature of work, often resulting in a mismatch between worker's existing skills and those required for new roles. This necessitates extensive retraining and education (Coombs et al., 2020), which can be positive for organizations as their workforce's competencies and skills are growing (Gelinas, 2022), but negative for workers who must invest time in further education (Willcocks, 2020). Additionally, while algorithms enhancing efficiency and helping workers complete tasks faster and more effectively, they can also lead to the erosion or loss of skills among workers (Willems & Hafermalz, 2021).

The results also show that digital automation generally negatively implicates workers. This is evident as the group with negative implications for workers in the results is the second largest, while the group with positive implications for workers is the smallest among the identified implications (refer to Table 3, section 4.2.2).

Our findings also highlight important issues regarding the research level and perspective in primary papers. Most primary papers are focusing on the organizational level and perspective. Specifically, eight out of eighteen studies describe implications for organizations and, when addressing workers' situations, do so within an organizational context. For example, Güner et al. (2020) and Seethamraju and Hecimovic (2020) state that automation can lead to significant cost savings for organizations, allowing human workers to perform more valuable tasks. Coombs et al. (2020) note that automation technologies provide greater precision and enhance worker performance for organizations. Monod et al. (2024) report that AI in organizations leads to more personalized and effective customer service. Van den Broek et al. (2019) discuss the standardization of work processes and the reduction of biases

due to algorithms. Abdul et al. (2020) highlight improvements in work processes, as automotive technologies help workers save time. Kinowska and Sienkiewicz (2023) explore the effects of algorithms on workplace well-being from an organizational perspective. Finally, Kunz et al. (2022) discuss process quality improvements, as workers, freed from routine tasks, can contribute more valuable work to the organization.

In addition, the review of primary papers points out the lack of employee perspective in IS research focusing on digital automation implications. Only two primary papers are focusing on worker perspective. For example, Venermo et al. (2022) investigated the challenges as well as the new skills needed for workers when working with software robots. Strich (2021) investigated worker's professional role identity and how workers identify themselves after automation implementation. However, the worker's respective is much broader and need to be addressed more.

The background study did not provide us with information on importance of the research level and perspective. After analysing the primary papers, it can be concluded that the level of research may influence the interpretation of implications and view towards digital automation.

5.3 Future research opportunities

This paper provides a structured understanding of the digital automation implications on work environment within knowledge work context. This was achieved by identifying 18 primary papers out of 179 related papers over a five-year period (20018 – February 2024) and analysed them with respect to (1) definitions of digital automation and its implication on work environment, (2) focus on specific work, (3) frequency of publication by year, (5) research level and perspective. As we have concluded AI-powered digital automation is a relatively new phenomenon that has not yet been thoroughly researched. In this paper we have identified nine directions for future research opportunities. All encompass a range of issues, from worker self-identification and ethics to changes in organizational to business strategies (see Table 4, section 4.2.3).

Addressing any of the identified research directions can provide valuable insights into the understanding of the digital automation implications on knowledge work environment. However, the most relevant direction, highlighted by many authors is professional role identity and workers respective. This finding aligns with our result of research level, which point out a lack of worker's perspective in IS research and research on individual level. In addition, our review suggests that there is a need to study digital automation and work environment continuously. Thus, we find it crucial to collect more empirical material on the long-term effects on organizations, on knowledge workers and the work environment. In short, there is a need for empirical research with a focus on worker perspective on individual level.

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APPENDIX 1

The first round of literature gathering.

Resource	Strings	Number of articles	Relevant by title and abstract	Duplicates	Result
IS Conference papers					
ICIS	("digital automation" OR "automation technology" OR "artificial intelligence" OR "robotic process automation") AND ("knowledge work" OR "professional services" OR "future of work" OR "workforce transformation") - Boolean Operators	660	20		20
ECIS		425	20		20
AMCIS		326	17		17
PACIS		393	17		17
HICSS	Manuel search through content	-	4		4
MCIS	Manuel search through content	-	2		1
IS journals					
European journal of information system	Automation and work environment	75	0		0
	RPA and work environment	1	1		
	AI and knowledge work	27	0		
	AI and work environment	137			
	Boolean Operators	0	0		
MIS Quarterly	Search through key words not available	1	1		1
Skandinavian jornal of information systems	Automation and work environment	20	0		0
	RPA and work environment	0	0		
	AI and knowledge work	1	0		
	AI and work environment	23	0		
	Boolean Operators	25	0		
Information & Management	Automation and work environment	65	1		1
	RPA and work environment	3	1	1	
	AI and knowledge work	1			
	AI and work environment	60	1	1	
	Boolean Operators	0			
information and Organization	Automation and work environment	15	2		2
	RPA and work environment	0			
	AI and knowledge work	1	1	1	
	AI and work environment	2	2	2	
	Boolean Operators	0			
Information systems journal	Automation and work environment	38	0		0
	RPA and work environment	7	0		
	AI and knowledge work	0	0		
	AI and work environment				
	Boolean Operators	73	0		
Information system research	Automation and work environment	91	1		5
	RPA and work environment	13	0		
	AI and knowledge work	79	1	1	

	AI and work environment	302	1		
	Boolean Operators	75	3		
Journal of the AIS	Automation and work environment	176	3		4
	RPA and work environment	3	1	1	
	AI and knowledge work	5	1		
	AI and work environment	119	3	3	
	Boolean Operators	68	3	3	
Journal of information technology	Automation and work environment	62	3		4
	RPA and work environment	9	3	3	
	AI and knowledge work	5	0		
	AI and work environment	51	3	3	
	Boolean Operators	13	4	3	
Journal of MIS	Automation and work environment	68	0		1
	RPA and work environment	0	0		
	AI and knowledge work	3	0		
	AI and work environment	202	1		
	Boolean Operators	1	1	1	
Journal of strategic information systems	Automation and work environment	24	3		3
	RPA and work environment	1	1	1	
	AI and knowledge work	2	1	1	
	AI and work environment	17	3	3	
	Boolean Operators	113	3	3	
Information technology & people	Search through key words not available	3	3		3
Communications of the ACM	Automation and work environment	3	3		12
	RPA and work environment	12	7		
	AI and knowledge work	11	1		
	AI and work environment	9	1	1	
	Boolean Operators	13	1		
Decision support system	Automation and work environment	57	0		0
	RPA and work environment	3	0		
	AI and knowledge work	1	0		
	AI and work environment	71	0		
	Boolean Operators	60	0		
Databases					
Science direct	Boolean Operators	103	31		31
Scopus		35	28		28
Web of science		118	20		20
N duplications removed manually	110				
N Final articles after 1st round	179				