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The future of work of academics in the age of Artificial Intelligence: State-of-the-art and a research roadmap

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ABSTRACT

The Future of Work (FoW) has garnered significant attention among scholars and practitioners, with the advent of Artificial Intelligence (AI) playing an important role in shaping this discourse. Despite the common perception that intelligent machines pose a threat to workers in routine roles, AI technologies are increasingly being utilized for advanced tasks carried out by knowledge workers. Drawing on state-of-the-art research and real-life examples we develop an integrated framework to explore the future of academic work. Our focus is on academics, an essential yet under-researched group of knowledge workers, and we discuss their work in relation to AI across space, time, and task dimensions. Our analysis reveals that the usage of AI technologies can have implications for the research, teaching, and service activities of academics and thereby also for the creation, acquisition, dissemination, and application of knowledge. Based on our framework we develop scenarios and propose a future research roadmap.

1. Introduction

The current developments in Artificial Intelligence (AI) have important consequences for higher education (workers), as research shows that AI is applied in a variety of ways to automate and augment the work of academics (Bearman et al., 2022). AI refers to a set of technologies that have the ability to interpret data and learn from it to achieve specific objectives through adaptation (Kaplan & Haenlein, 2019), based on imitating natural intelligence through sensing and perceiving the environment (Russell & Norvig, 2022).

The Future of Work (FoW) literature has attracted growing academic attention, especially since the expanding digitalization and the resultant widespread use of exponential technologies such as AI (Boyd & Huettinger, 2019). The FoW generally refers to the anticipation of (future) changes in work(places) due to technological and societal advancements. In this paper, we follow the FoW perspective to specifically study the work of academics, because research has shown that AI has the potential to fundamentally change higher education (Bearman et al., 2022; Zawacki-Richter et al., 2019).

The FoW literature has predominantly focused on the threat to workers, because of an expected replacement of routine jobs by (intelligent) machines (e.g., Brynjolfsson & McAfee, 2014; Frey & Osborne, 2017). Nevertheless, historical analysis shows that, although negative effects on jobs were often expected, in reality, these intelligent technologies also lead to new tasks or even jobs (Autor, 2015; Frank et al., 2019), where workers are augmented instead of replaced (Pettersen, 2018; Raisch & Krakowski, 2021). For

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those reasons, the contemporary debate focuses on the automation and augmentation of highly educated and skilled professionals, such as academics.

Academics are an important group of knowledge workers, whose primary task is the generation of knowledge (e.g., Drucker, 1994). Knowledge work can be characterized by the use of information technology, highly-educated personnel, and non-routine tasks (Pyöriä, 2005; von Richthofen et al., 2022). It is vital to understand the unique job demands, attitudes, and behaviors of knowledge workers, as opposed to traditional workers, given the expanding importance of the knowledge economy and the widespread use of advanced technologies (Dekas et al., 2013). Indeed, Gartner consulting company estimated that the worldwide number of knowledge workers reached one billion in 2019 (Roth, 2019). It is crucial to better comprehend what the permanent structures including space, time, and tasks of their work are altering (Minbaeva, 2020).

As AI applications seem to impact knowledge work(places) more than previous technologies have done (Faraj et al., 2018), we claim that more attention should be devoted to how the use of AI is likely to alter the space, time, and tasks of academics. This is important because AI applications are currently already impacting teaching, but also changing academic research, and thereby potentially influencing academic careers and raising important ethical concerns. We address this by adopting a knowledge work perspective and integrating it with the FoW literature. Therefore, we aim to answer the following research question: "What is the FoW of academics in the age of AI?" Academics are a specific category of knowledge workers whose primary activities involve acquiring, creating, distributing, and applying knowledge.

Overall, professionals such as consultants, accountants, engineers, and academics are frequently mentioned categories of knowledge workers that are now also affected and even threatened by AI technology (Meltzer, 2014; Susskind & Susskind, 2022). Thus, hitherto, the FoW of academics has received only limited attention in the literature (e.g., Kezar & Holcombe, 2015; Peres et al., 2023). Moreover, although some studies have examined technologies for teaching and research individually, to the best of our knowledge, no research has focused specifically on different dimensions of the FoW of academics. Therefore, in this paper, integrating FoW dimensions with knowledge work, we explore and demonstrate how (different) AI applications influence (1) where (space), (2) when (time), (3) and what (work/tasks) of the main activities of academic knowledge workers such as doing research, teaching, and providing academic services (Rapert et al., 2002) – which in turn aids our understanding of how knowledge workers and AI could co-exist in the future workplaces.

To do so, we first introduce the FoW literature after which we discuss the concepts of knowledge work(ers), with a specific focus on academics. Then, drawing on state-of-the-art examples, we offer our integrated framework of the FoW of academics, where we outline how the jobs of academics could be impacted by using AI solutions. Finally, we offer a research roadmap, based on which future research projects and FoW scenarios can be developed.

2. Towards a conceptual framework

2.1. Future of Work and Artificial Intelligence

The FoW is a concept that has received increasing attention in different scientific disciplines and is mostly related to how employees will work in the future and how these employees are managed. The FoW is defined as "a result of many forces of change affecting three deeply connected dimensions of an organization: work (the what), the workforce (the who), and the workplace (the where)" (Schwartz et al., 2019). Schulte et al. (2020) concluded that technology is a shaping factor of the FoW, potentially changing labour markets, societal values, and types of work (cognitive vs. manual). Generally, studies on the FoW are embedded in broader discussions about technological change and employment, whereby they mostly focus on the influence of automation on unemployment and job polarization (Boyd & Huettinger, 2019).

One important technology that is discussed in relation to the FoW is AI (Bohr & Memarzadeh, 2020). The field of AI is rooted in various scientific disciplines, such as philosophy, mathematics, psychology, and statistics (Russell & Norvig, 2022). AI is an umbrella term that refers to systems that emulate natural intelligence characteristics such as sensing and learning to augment and automate human tasks (Strohmeier, 2022). IBM (2023) proposed that the types of AI can be understood by examining its capabilities and functionalities. In terms of AI capabilities, only Narrow (or Weak) AI exists for today (among General and Super AI, which are still mostly theoretical). Thus, it is the focus of this paper. Narrow AI comprises Reactive Machine AI (RMAI) with no memory developed to perform specific tasks (e.g., IBM Deep Blue or the Netflix Recommendation Engine), and Limited Memory AI (LMAI) that can retain data in its library for long-term period (e.g., Generative AI and Virtual Assistants and chatbots). In this paper, we draw on this IBM's AI classifications, as they allow us to bring together both generic studies on AI in academia (e.g., Anwar et al., 2019), as well as more specific publications on academia and Generative AI (Barros et al., 2023; Grimes et al., 2023). In our paper, we specify, whenever possible, when the focus is on LMAI or RMAI.

In future work(places), human workers would co-exist with AI applications (Einola & Khoreva, 2022) comprising different AI capabilities and functionalities (IBM, 2023); whereby some activities would be fully automated and other tasks supported by AI (Von Krogh, 2018; Raisch & Krakowski, 2021). Based on the aforementioned, in this research, we refer to Future of AI-enabled Knowledge Work: "the study of anticipated forthcoming changes in work(places) due to interconnected AI applications and societal developments."

Overall, labour economists discuss the FoW in relation to AI mostly in terms of *quantity* of jobs, however, we follow the calls to study FoW in terms of their *quality* (Willcocks, 2020): what do jobs entail, which activities are part of jobs, what is the quality of jobs, how is the workplace organized? To explore the FoW in a more qualitative way – we focus on three important FoW dimensions (Minbaeva, 2020) relevant to the future of academic work(ers):

- The "**What" dimension** is about the type of work employees perform, and the autonomy they have in deciding how to work – or in other words their decision-making freedom to determine what tasks to conduct and how to conduct them.
- The "**Where" dimension** is related to the location (or space) where people work. This is often related to telework (e.g., Minbaeva, 2020) and more recently to remote work – partly induced by the Covid-19 pandemic.
- The "**When" dimension** refers to temporal (or time-related) aspects of knowledge work, for example (flexible) working times, shift work, and the velocity of work. As Spieler et al. (2017) have shown in their review, working structures will no longer be based on 9-to-5 working days in a 5-day schedule.

2.2. Knowledge work(ers)

Since the term "knowledge worker" has been first coined in 1979 (Blackler, 1995), it has been defined in numerous ways. Knowledge workers were described as a new class of workers who can apply theoretical and analytical knowledge acquired through formal education (Janz et al., 1997), different from traditional worker's needs, values, and motivations, and those who could also produce more knowledge at work, the idea unusual for traditional hierarchical and decentralized organizations (Drucker, 1994). For knowledge workers, knowledge is an input, process, and output of their work (Newell et al., 2002). They perform *knowledge work*, described in terms of the actual job content or the balance between "thinking" (those who work with their heads) and "doing" (those who work with their hands) activities (Blackler, 1995). Knowledge workers were also categorized in a broader way: as a profession - circumscribed list of occupations typically comprising professional occupations (e.g., scientists, engineers, attorneys, physicians, and accountants) (Blackler, 1995; Kelloway & Barling, 2000). They rely on their individual characteristics such as creativity, which they can contribute to organizations more broadly, or to organizational products and services more specifically (Harris & Vining, 1987).

Research on the management of knowledge workers has extensively focused on occupations such as accountants, lawyers, consultants, and healthcare professionals (Susskind & Susskind, 2022). Interestingly, research focused on the jobs of academicians and/or scholars is limited – whereas AI technologies have the potential to disrupt academic work. Given the growing importance of the knowledge economy and the pervasive role of information technology (von Richthofen et al., 2022), it is crucial to understand the distinct work needs, attitudes, and behavior of academics, which differ from those of other types of knowledge workers. For academics, knowledge work is not only their profession, but also a combination of individual characteristics (i.e., being highly educated), individual activity (i.e., their daily tasks), and using their knowledge to create more knowledge.

Knowledge work can comprise of types and there are at least four forms of knowledge work activities in organizations: [a] acquiring knowledge; [b] creating new knowledge; [c] teaching of knowledge (see Bird, 1994; Nonaka, 1994); and [d] applying existing knowledge to current problems. Applying this perspective, we integrate such knowledge types with the three primary activities that constitute the work of academics: research (i.e., [a & b]), teaching (i.e., [c]), and academic service activities (i.e., [d]) (Rapert et al., 2002).

2.3. Framework on the FoW of academic knowledge workers

In this section, we propose and use a framework drawing on the FoW and knowledge work literature to outline and illustrate with concrete instances, how AI applications with different functionalities (IBM, 2023) can be used by academic employees working at universities who interact and co-exist with AI solutions and how AI can transform three main components of academics' job: (1) research, (2) teaching, and (3) academic services (Macfarlane, 2007; Rapert et al., 2002); in terms of work activities (what), when to work (timing), and where to work (space/location) (Macfarlane, 2007; Rapert et al., 2002); and in terms of knowledge acquisition, creation, dissemination, and application. After describing concrete examples of current developments, we outline directions for future research on the (potential) consequences of AI-usage in the three main components.

2.4. Research-related activities (knowledge acquisition and creation)

Our framework suggests that AI influences what and how scholars perform research (e.g., Kulkarni et al., 2024; Wagner et al., 2022). AI is an important study object for scholars, whereas AI can also influence the ways in which research is conducted, which we focus on here (see also Appendix 1) because the former is a distinct topic that has already received significant scholarly attention (Parker & Grote, 2020; Tursunbayeva & Renkema, 2022).

2.4.1. Research – what

Traditionally, research projects aimed at acquiring and creating new knowledge involve conception or design, data acquisition, analysis, interpretation, and drafting revisiting for intellectual content (BMJ, 2024). Below we briefly describe whether and how AI can change the characteristics of such activities, though this may vary between disciplines (Xu et al., 2021). Indeed, the idea of AI-enabled automated or partially automated research has sparked debates in different scholarly disciplines (Wagner et al., 2022). Recently, three main categories of RMAI have been identified that can aid scientific understanding: (1) serving as a computational microscope that can uncover novel patterns in data, (2) generating creative solutions to scientific problems, and (3) acquiring and explaining novel insights to humans (Krenn et al., 2022).

AI-based tools, such as programming libraries (e.g., supporting thematic analyses) and matching platforms, have the potential to assist researchers in identifying relevant research questions and cases. They can also lead to the development of new research methods (e.g., image recognition or data mining), blurring the lines between quantitative (e.g., statistical analysis) and qualitative (e.g.,

algorithmic text mining) approaches. In natural and life sciences, AI can assist in discovering new materials, powering nuclear physics, medical drug discovery, making modern agriculture smart, and making such research methods safer for humans (e.g., with the help of automation or robotics) (Xu et al., 2021). In management research, AI can be used as a methodology for data analysis or pattern discovery (e.g., Choudhury et al., 2021; Harrison et al., 2022; Sajjadiani et al., 2019).

AI tools can provide semi-automated support in tasks such as paper screening, synthesis (e.g., www.scholarcy.com or www.researchrabbit.ai), data extraction, generating or reviewing code for statistical analysis, coding qualitative data (e.g., Atlas.ti), descriptive syntheses, or even theory development and testing (Korinek, 2023; Wagner et al., 2022). With the exponentially growing number of publications in online literature databases such as Scopus (Thelwall & Sud, 2022), using AI tools for such activities could be indispensable for finding appropriate references and evaluating scientific articles (e.g., www.scite.ai). AI assistants also help academics in academic writing such as improving grammar (www.grammarly.com) and paraphrasing text (www.quillbot.com). OpenAI's GPT models even co-authored several papers (Stokel-Walker, 2023), which triggered debates and urgent development of guidelines for using LMAI across research life-cycles (Harvard Library, 2023) including research ideation, research planning, research execution, and research results dissemination by universities, funding bodies (EU-Horizon program), academic journals (e.g., Elsevier), or conferences (Petermann et al., 2022). This leads to discussions of whether AI *should* be used whenever it *can* be used. Finally, AI could influence academic articles' rankings on search engines (Steinhauer, 2022) and academic databases.

2.4.2. Research – *where*

The arrival of AI-related virtual/augmented reality and metaverse technologies (Pereira et al., 2023) promises to expand possibilities of and experiences about virtual research, social and professional online activities and events for scholars, allowing them to participate in these without the need for travel, and disregarding factors such as time-zones, language barriers, and lack of travel budgets (Chodor, 2022). The growing awareness of environmental and particularly climate-related impacts of travel is significantly influencing the FoW. Consequently, the prospect of working through virtual reality is not only about convenience and cost savings but also holds the potential to contribute to the achievement of sustainable development goals. Moreover, employing virtual or augmented reality for data collection can revolutionize the current qualitative data collection process (e.g., anonymization of research participants). For instance, both interviewers and interviewees will be able to choose whether to participate with their true identities or avatars.

2.4.3. Research – *when*

Considering the potential of AI to automate various research tasks such as systematic review processes, we can hypothesize that also academics may expect time savings (Clark et al., 2020; Deng et al., 2019; Matwin et al., 2010), which can potentially result in substantial changes in the way academics work or are evaluated. For example, researchers today are evaluated for positions based on their publications. Thus, any time saved with AI could be invested in producing more papers. Finally, AI can also produce scholarly papers faster than scholars usually working years on a single submission (Steinhauer, 2022).

Academics need to stay abreast of the latest research topics and (AI) methodologies, which requires a (significant) time investment. A potential game-changer lies in the possibility of generating AI summaries from scientific articles. Also recent breakthroughs like "dilated attention," as published by Microsoft researchers (Ding et al., 2023), hold the promise of transforming this process. For example, future academics could instantly acquire and apply knowledge, just like Neo in the Matrix movie learning martial arts in seconds.

The integration of AI has the potential to redefine the flexibility of academic work. For instance, university management could leverage AI technology to identify researchers who are working on weekends or during late hours, with the intention of promoting a healthier work-life balance for them. However, it is essential to acknowledge that such monitoring has raised concerns and has been a subject of discussion in the People Analytics literature, as it touches upon the concept of the digital surveillance (Tursunbayeva & Pagliari, Di Lauro et al., 2022).

2.4.4. Future research directions on research-related activities

Given the increasing use of AI for research purposes, we suggest exploring ***what*** the impact of AI is on *research methodologies* (e.g., inductive, deductive, and/or abductive research) (Choudhury et al., 2021), specifically regarding its ability to identify patterns within data and the dynamics of human-AI interaction in the research process (e.g., whether LMAI can be considered a valid reviewer or author). This exploration should include the examination of the boundaries for its application, the attribution of responsibility or credit/merit for research, potential decrease in human expertise, and ethical and responsible aspects related to the use of LMAI for research.

For example, it is crucial to consider the potential for *AI-introduced biases and errors*, as these may lead to flawed research outcomes and erroneous conclusions. So far, algorithmic biases in academia have been discussed primarily concerning education (Baker & Hawn, 2022; Baker et al., 2023). However, there are some emerging reports on their importance also in research with AI (Tursunbayeva & Moschera, forthcoming), as it becomes driven by large data sets and performed with AI (e.g., Avrahami et al., 2022). It is important to explore how the emergence of ethical guidelines on AI can add to the job demands of academics who now need to develop, or make sense and operationalize in their work what was recently accused of being difficult to apply, isolated, contested, or incoherent principles (Munn, 2023). As noted, through which channels and ***where*** research is conducted could lead to the (partial) elimination of the human component in research with humans. This is associated with ethical and practical issues, such as the inability to read nonverbal cues due to inconsistent and delayed connectivity (Deakin & Wakefield, 2014), opacity, explainability, and ethnicity of AI. Though to the best of our knowledge, none of these, have been investigated specifically or empirically for academics. We suggest to

further investigate these (un)desirable consequences.

Academics may find it challenging to keep up with rapidly changing technologies adding to their *job demands*, meaning that the potential utility of these platforms as research tools may be underrecognized and underutilized. However, this could also trigger more interdisciplinary research between technically savvy scholars and those who are ethically aware. Scholars could investigate how AI adoption in different contexts can contribute to the research productivity of academics.

Lastly, many studies discussing the ***temporal aspects (when)*** associated with the use of AI for research activities focus on (quantifying) the time that scientists can save. Meanwhile, none of these discuss in which scholarly activities such timesavings should be invested. Thus, it is unclear whether scholars should use this (extra) time to conduct more research, more teaching, more administrative or service activities, or for knowledge acquisition, development, application, or dissemination, or whether fewer scholars are needed. For example, the use of LMAI as writing assistants might have implications for how academics are evaluated – for example in their tenure track – if they can increase their productivity. Hence, it is warranted to study the potential impact of AI on academic performance management.

2.5. Teaching-related activities (knowledge dissemination)

Advanced technologies shape the ways in which academics conduct their teaching activities (Sife et al., 2007). They play a role in what is being taught and how, where, and at what times teaching takes place, and thereby how knowledge is disseminated. Here, we specifically focus on how AI technologies shape teaching activities, defined as the work of a teacher related to the content that is being taught (see Appendix 2).

AI-based applications are increasingly used in (higher) education and studied in education science – also referred to as AIEd (e.g., Hwang et al., 2020; Nemorin et al., 2023; Zawacki-Richter et al., 2019). There are several categories of RMAI usage in education: personal tutors; intelligent support for collaborative learning, intelligent virtual reality, and student profiling (Luckin et al., 2016; Zawacki-Richter et al., 2019). Strikingly, the teacher-perspective is almost absent in these studies (Zawacki-Richter et al., 2019), underscoring the caveat that we address in this paper.

2.5.1. Teaching – what

AI-based technologies offer myriad opportunities to improve the work of academic teachers (e.g., Farrokhnia et al., 2024; Peres et al., 2023; Zawacki-Richter et al., 2019). Multiple studies describe the promises and possibilities of AIEd tools, which can bring about changes in the type of teaching activities academics perform and the autonomy they must have in their work. The use of AIEd does not mean that robots immediately replace teachers, but it does bring about transformative changes to the classroom (Holmes et al., 2019). The goal of AIEd is to "make computationally precise and explicit forms of educational, psychological and social knowledge which are often left implicit" (Self, 1999, p. 350). In doing so, RMAI-based applications can be used to help with administrative tasks and provide relevant learning insights. For example, teacher-facing AIEd can support teachers by automating tasks related to administration, content development (e.g., exams), assessment, plagiarism checks, and feedback – thereby gaining additional insights about students, reducing teachers' workload, and freeing up time (Baker et al., 2019). RMAI applications can also support the work of academic teachers and the decisions they make, through aiding the assessment of student essays and (open-ended) exam questions (Aldea et al., 2020; Balfour, 2013).

Furthermore, teachers can use RMAI to identify students that are at risk of stopping their education – by tracking class attendance and assignment submission (Luckin et al., 2016). RMAI can also help teachers understand the learning process of students by analyzing where common mistakes are made (Luckin et al., 2016), and increasing student engagement by identifying and improving where students are bored or enthusiastic (Steinhauer, 2022). These are examples of learning analytics, focused on measuring, analyzing, and reporting educational data (e.g., Gašević et al., 2015), which help to provide personalized insights about learners. Eventually, it would be possible for AI to completely curate educational activities, which can then be presented by a social robot, chatbot, or voice assistant. For example, LMAI such as ChatGPT could be used to define course goals, outlines, and reading materials based on millions of available scientific texts.

Another important application of AIEd is intelligent tutoring. For example, RMAI technologies help to make individualized learning plans for students (Luckin et al., 2016). LMAI can be used to develop chatbots that respond to student inquiries,[3] intelligent tutees that students can instruct to learn (Hwang et al., 2020), and personal digital tutors called Intelligent Tutoring Systems (Luckin et al., 2016). Teachers might also adopt LMAI-chatbots together with students to create new modes of learning (Mollick & Mollick, 2022).

On the other hand, LMAI tools such as ChatGPT pose many challenges to educators (Milano et al., 2023), because it can be misused by students, for example by writing student essays (Stokel-Walker, 2022), which might require changes in assignments or new intelligent plagiarism checks. Moreover, LMAI chatbots might have long-term pedagogical implications as a learning tool because of consequences for academic writing and critical thinking of students, which poses challenges to academics (Milano et al., 2023).

In sum, by adopting AI in teaching, AI cannot only *automate* certain (administrative) teaching activities, it can also be deployed to *augment* teachers by providing relevant insights, whereas pitfalls related to academic misconduct should be acknowledged.

[3] https://dteach.deakin.edu.au/2021/01/the-qa-bot-that-answers-student-queries-in-microsoft-teams/; https://www.ocelotbot.com/blog/ai-chatbots-radically-improve-how-students-get-answers; https://www.researchgate.net/publication/221607643_An_intelligent_discussion-bot_for_answering_student_queries_in_threaded_discussions

2.5.2. Teaching – where

AI technologies theoretically facilitate teaching from anywhere. The AI-related metaverse, and virtual reality/classroom enable teaching to take place from anywhere. Novel applications such as Third Space Learning also allow teaching to take place through the internet, thereby connecting teachers with students all around the world, even outside their own classrooms (Baker et al., 2019). Today teachers even substitute traditional team buildings and serious strategic games with online or virtual realities or simulations (e.g., People Analytics Escape Room). AI technologies create more of these virtual learning environments where teachers and students can interact with each other from separate locations. Also, AI enables the use of the flipped classroom, where students for example use chatbots to prepare materials, while the materials are discussed in class (Dwivedi et al., 2023). At the same time, with advancements in student use of LMAI-powered chatbots, teachers might reconsider going back to classroom paper and pencil writing and testing.

Providing feedback to learners traditionally took place in real-time in the classroom. However, recent technological developments, integrated into LMAI-based tutoring systems, enable teachers to support their students and give them personalized feedback at any place (Deeva et al., 2021). Finally, there are also examples of educational (social) robots used in the classrooms as a "lead" teacher or a substitute for a teacher instead of a support "tool" in teaching activities, which are for example LMAIs used for language teaching (e.g. Anwar et al., 2019).

2.5.3. Teaching – when

Next to enabling teaching from anywhere around the world, AI technologies also facilitate time-independent teaching, where lectures and student feedback can be accessed by students at any time. AI applications can be used to provide just-in-time feedback and assessment to facilitate ongoing student learning (Luckin et al., 2016). For example, AI technologies enable academics to record their interactive personalized (micro)lectures, through which asynchronous teaching can take place at any time.

By adopting LMAI-based tutoring systems and chatbots, academic teachers make sure that their students receive personalized feedback independent of time (Deeva et al., 2021). Instead of academics replying to student questions and requests throughout the week, these smart systems could respond to students after office hours, enabling academics to better structure their working times and students to learn at their own pace.

2.5.4. Future research directions on teaching-related activities

Considering that there is a lack of research on the work design of teachers (Ouyang & Jiao, 2021; Zawacki-Richter et al., 2019), future studies should investigate how AI technologies can shape these in terms of the core *job components and outcomes* such as well-being and performance. Previously, teachers had full responsibility for designing teaching materials and activities. Now teachers integrate into their teaching additional LMAI-based tools and services mostly designed by third parties. Such "outsourcing" phenomenon should be investigated to understand whether teachers should actually be involved in the design of such applications, and/or in feedback loops. Furthermore, given that academics do not necessarily adopt the available learning technologies (Liu et al., 2020), future research should address factors that shape their perceptions, adoption, and use. Moreover, studies should investigate the pedagogical consequences and implications for academic work and knowledge creation due to both teachers and students using AI.

Future research should also study the ethical perspective on using AI for teaching. For example, establishing who is responsible for the *ethical design* and application of AI tools, understanding how AI could impact the relational aspect of academic jobs, and power relationships between academic teachers and students. Who ensures that AI applications do not discriminate against certain (groups of) students based on their race/ethnicity, gender, and nationality (Baker & Hawn, 2022; Roscoe et al., 2022)? And who is responsible for the important decisions (e.g., grading) prescribed or performed by these AI, as well as whether and how these should be framed and formalized (e.g., in the form of university guidelines)?

The use of AI applications that can permit to *work from anywhere (where)* might require additional financial resources (e.g., subscriptions), technology use competencies, and resources to actually try them, to understand how they work, and to explain these to the students. Such additional job demands are still limitedly discussed in relation to the use of AI applications, especially for academics. Future research should also evaluate what influence student adoption of AI has on where teaching and assessment activities can take place.

Finally, with the advancement of AI and the corresponding potential for time-independent and personalized teaching, academics are enabled to be more flexible in terms of working hours (*when*). At the same time, AI applications afford student learning around the clock, which could also affect the times during which teachers are expected to work. This poses questions such as: in what ways will the timing of the *workday of academics* change when they use AI solutions? How do AI solutions affect the work/non-work balance of academics?

2.6. Services-related activities (knowledge application)

Scholars must continually invest in services-related activities and knowledge application. This concept is sometimes also called academic citizenship behaviors – meaning that academics are members who serve an academic and broader social community. They provide academic services and apply their knowledge to benefit students, colleagues, their institution, their profession, and the general public (Macfarlane, 2007). AI could automate and augment such academic activities (see Appendix 3).

2.6.1. Services – what

Service-related activities include interviewing candidates, mentoring, evaluating colleagues, serving on committees, organizing conferences, consulting businesses, and interacting with media, and public through lectures, presentations, and debates (Macfarlane,

2007). In addition, academics are responsible for peer-reviewing academic articles, serving on editorial boards, applying for grants, and participating in career committees.

To stay abreast of the rapidly changing business landscape, scholars establish close links with industry to gain insight into real-world problems, and to secure external funding for consulting or research activities/services (Rapert et al., 2002). Searching and applying for grants could be laborious, complicated, and fruitless due to the time-consuming application process, and difficulty in finding suitable funding sources (Speller et al., 2019). Today there are platforms with sophisticated search engines that permit to easily search for grants (e.g., www.researchprofessional.com, to find partners (e.g., msca.b2match.io), and even to apply for grants (e.g., www.brevio.org or www.grant-ai.com). AI solutions can also aid funders in assessing grant applications (Checco et al., 2021).

Mentorship is an important aspect of academic work but finding the right mentor-mentee match can be challenging. This gap has been aimed to be addressed by matching algorithms (e.g., www.mentorloop.com). Additionally, AI-assisted peer review instruments are being developed to ease the strain of reviewing the increasing number of paper submissions (Checco et al., 2021) – which could diffuse more due to the increase of artificially generated papers (Dwivedi et al., 2023). Relatedly, systems such as Toronto Paper Matching, OpenReview and PeerReview4All are used to automatically assign papers to reviewers (Hutson, 2021) and thereby help to overcome the challenging task to identify suitable reviewers.

AI potentially could assist scholars with acting expert witness by enabling quicker analysis of evidence. Matching capabilities of AI can also assist scholars in finding "right" conferences and journals to discuss or disseminate their work. Growing administrative activities of academics, such as expense reporting or appointment scheduling, can be streamlined with intelligent systems, and virtual assistants. Finally, job interviews with PhD candidates or new colleagues can be (partly) delegated to LMAI-chatbots or social robots (e.g., Furhat).

Lastly, as scientific knowledge becomes more widely available to the broader society (e.g., chatbots, citizen science movement), the role of academics might change from sharing knowledge to helping stakeholders to apply knowledge. This might be accelerated by the public's use of LMAI chatbots (e.g., ChatGPT) to answer basic knowledge questions.

2.6.2. *Services – where*

AI-relevant metaverse or virtual/augmented reality technologies have the potential to revolutionize where academics conduct their service work by enabling them to virtually participate in meetings, conferences, or other events (e.g., television interventions). With holographic technology, academics can project a lifelike representation of themselves (i.e., avatar) into a remote location any time, and interact with others as if they were physically present, and representing whatever identity. This can be particularly useful for academics who are unable to travel due to health, family, travel budget cuts, or other reasons. This can potentially add to the productivity of future academics (Herman, 2018).

Considering that AI can assist scholars with communicating (reading and writing) in any language, they can potentially act as experts (e.g., for evaluating grant applications) or witnesses in any country.

2.6.3. *Services – when*

AI can help academics to multitask or to perform different activities simultaneously. For example, to automate repetitive routine administrative or service tasks. Specifically, to manage email and scheduling by sorting messages, prioritizing tasks, and sending automated responses. This could help academics to stay organized and focused on their core work, as well as potentially reduce their reliance on the administrative university staff.

2.6.4. *Future research directions on services-related activities*

Many service-related activities such as *serving as experts* are a result of scholarly reputation building, maintaining, or enhancing, as well as established power structures. It is not clear whether the use of AI could impact scholarly reputation built over a long period of time or such established power structures by being productive and impactful (Herman, 2018). Research could examine how the use of publicly available knowledge through AI-chatbots changes the role of academics in society. We also suggest scholars identify which service-related tasks can be best performed by (using) AI or whether some activities must be *performed in person*. For example, scientists as experts serving the court (Rubinfeld & Cecil, 2018). Such studies should be interdisciplinary involving legal, social, and technical scholars (at least).

Lastly, future studies could try to envision the implication of AI for the *distribution of work* between academics and administrative/support staff (e.g., task shift) of universities for service-related or administrative/support activities, and investigate whether there are activities that cannot performed with the help of AI (e.g., both too complex tasks requiring tacit knowledge, as well as those activities that are subject to confidentiality or privacy issues).

3. Discussion

Through the proposed framework and the exemplary examples of the (potential) use of AI by academics, we have provided an outline how the FoW of academics might be studied – and based on which future scenarios should be developed. This framework should be used to study *if* and *how* AI may be used to automate and/or augment knowledge work(places) such as universities in the future. If current developments continue and AI is widely deployed, this has important implications for the underlying core of academics' jobs as knowledge workers, namely their responsibility for the acquisition, creation, dissemination, and application of knowledge – summarized in Fig. 1.

Following Parker and Grote (2020), our model highlights that the use of AI shapes the primary work of academic workers – existing

of research, teaching, and academic services – and thereby changes the processes of knowledge work. At the same time, how AI shapes the FoW of academics over time is facilitated and constrained by *higher-level factors* such as AI-laws and regulations, and by *individual factors* such as academics' attitudes and motivations towards AI and their AI-related knowledge, skills, and competencies (AI literacy).

Lastly, how AI influences the FoW of academics is also shaped by the developments in AI technology itself. Although we have shown many examples of how AI is or might be used by academics, it should also be acknowledged that the current excitement around AI in academia could also be the *"Peak of Inflated Expectations"*- phase of the Gartner (2023) hype cycle. Despite Gartner's model being criticized (e.g., Dedehayir & Steinert, 2016), it corresponds with the *AI Summer* (hype) and *Winter* (disillusionment) throughout the historical development of AI (Haenlein & Kaplan, 2019). This perspective helps us to understand the development of such emerging technology in terms of expectations and its eventual role in organizations, whereby initial developments lead to overenthusiasm and unrealistic high expectations, followed by a disillusionment phase whereby expectations cannot be met (Fenn & Raskino, 2008). With (Generative) AI currently being at the Peak of Inflated Expectations (Gartner, 2023), disillusionment could be around the corner. In fact, Nemorin et al. (2023) argue that AI in education is currently hyped: evidence that supports the predictions and outcomes of AI implementations is (still) limited. Hence, also the developments, expectations, and realizations in terms of AI technologies play an important role in shaping the FoW of academics.

In combination, these three components influence if and how AI can shape the FoW of academics. Scenarios could help to identify how these developments might look like, and LMAI may also be used to develop such scenarios. For example, based on our conceptual framework, we have developed two future scenarios using OpenAI's GPT-4 model. Table 1 includes these two scenarios based on the developed framework (Fig. 1), adopting guidelines for high-quality and effective prompts (see bottom of the Table). Notice that the scenarios include the dimensions of our framework, contrasting the ends of a positive-negative continuum.

In sum, this work design perspective helps to understand how AI shapes the work of academics and what are the drivers of these changes – which eventually is likely to influence outcomes such as academic performance, well-being, and the body of knowledge.[4]

3.1. Implications for the future of academic knowledge work

The use of AI in academic knowledge work is likely to change the way in which knowledge workers acquire, develop disseminate, and apply knowledge, and may also change the level and value of their knowledge. Based on our framework and the concrete examples of AI-usage, there are opposing viewpoints on the FoW of academics in terms of implications for knowledge work.

On the positive side, AI technologies may make the work of academics more efficient and effective, as routine and administrative tasks can be automated, and LMAI writing tools may improve the quality of output. This allows academics to focus on higher levels (or quality) of production work, such as the acquisition and development (i.e., research), and dissemination and application of knowledge (i.e., teaching), which eventually leads to more knowledge being generated by academics as by other stakeholders (e.g., students), or can enhance creativity. It can spark novel ideas that were otherwise not thought of, by assisting knowledge workers in generating innovative ideas and making use of smart suggestions (Krenn et al., 2022). For example, academic journals use AI-based recommender systems for suggesting articles for further reading.

On the negative side, such enhanced productivity might also increase the evaluation requirements and work demands of academics. Moreover, the reliance on AI in knowledge work may hamper knowledge development and learning opportunities because of fewer opportunities for informal and incidental learning (e.g. Evers & Van der Heijden, 2016; Kulkarni et al., 2024). When (fully) relying on AI to make decisions, knowledge workers are less able to learn and control the technologies' performance (Faraj et al., 2018). Besides, the integration of LMAI in knowledge work enables (student) fraud and academic misconduct that may prove difficult to detect, at least in the immediate term. Indeed, generative AI such as ChatGPT has scholars scrambling to understand its implications for research and teaching (e.g., Dwivedi et al., 2023) and has colleges in emergency mode to shield academic integrity (Cotton et al., 2023). AI-enabled teaching, research, and services activities could also give rise to the "alignment problem" (Christian, 2020), where AI could backfire or make the decision considered unethical or misaligned with the academics and learners' goals and expectations. For example, the anticipated AI-enabled personalized learning, proposed as a solution for addressing issues like lack of motivation and achievement gaps, was noted to potentially undermine students' self-actualization, ultimately resulting in homogenized learning outcomes (Holmes, 2023).

The power dynamics and structures in academia might also be affected by those who know how to develop or use AI. Furthermore, the opacity of AI may impede traceability and transparency of recommendations, as well as understanding of their accuracy hindering learning and knowledge creation. De Regt et al. (2009) concluded that "in the eyes of most scientists, and of educated laypeople, *understanding* is the central goal of science" (p.1). But can we really understand a phenomenon explored by/with AI? For example, if AI applications recommend conducting a certain study or if AI peer-reviewers reject a paper, there is limited opportunity to learn the reasons behind these suggestions and to subsequently increase understanding. Research indicates that AI-usage influences expertise development and claims are made that AI can lead to deskilling and declining expertise (Ardichvili, 2022; Faraj et al., 2018), especially because knowledge workers have fewer opportunities to engage in deliberate practice and experimentation and cannot see the bigger picture of their work processes. This is the case when knowledge workers' decision-making procedure is changing, from being decision-makers to being (blind) followers of the technology. These developments are particularly threatening for junior professionals, who still need to develop their expertise, or more peripheral employees, who may find it difficult to collaborate or progress to the

[4] Similarly to Parker and Grote (2020), we also did not focus on the outcomes of AI usage by academics, as we were interested in the changes in academics' work.

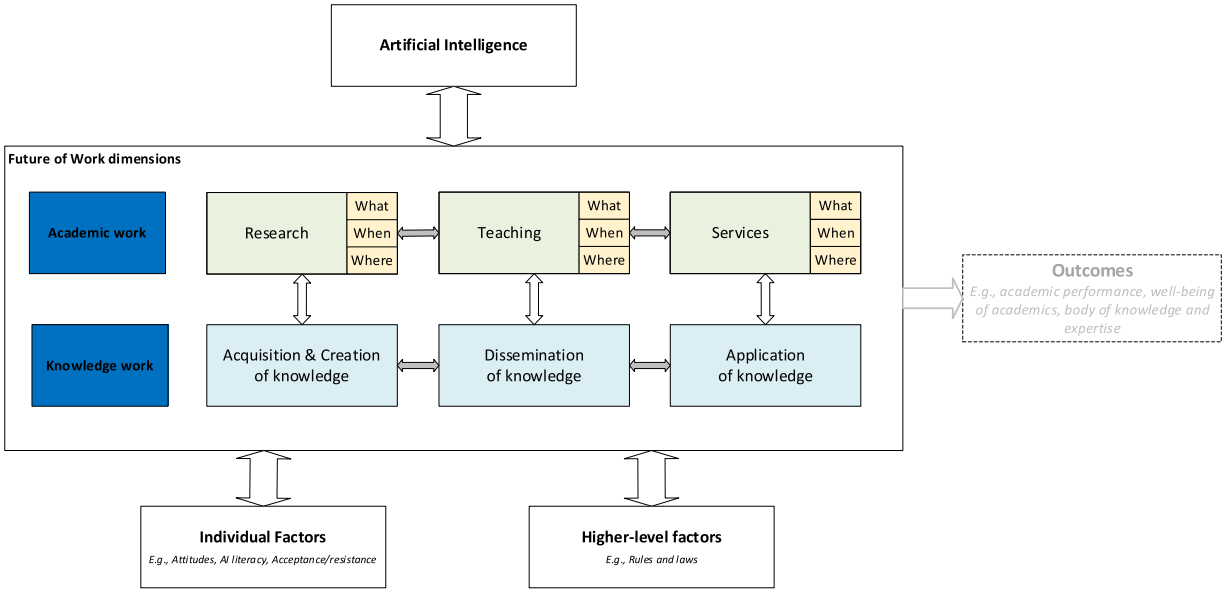

Fig. 1. Conceptual framework of future of academic knowledge work.

Table 1
AI-generated scenarios of the future of academic work.

Scenario 1 – optimistic future.

In this scenario, AI technology advances significantly, becoming a powerful tool that enhances academic work and knowledge creation. AI-powered research tools allow academics to analyze vast datasets with unprecedented speed and accuracy, leading to groundbreaking discoveries. AI-driven teaching assistants support personalized learning experiences, adapting to individual student needs and enabling more effective pedagogy. Academics embrace AI literacy, integrating AI tools seamlessly into their workflows. The acceptance of AI is widespread, with academics viewing it as a collaborator rather than a competitor. Regulatory frameworks evolve to support ethical AI use in academia, ensuring data privacy and promoting transparency. These laws encourage innovation while safeguarding against misuse, fostering a positive environment where AI enhances the quality and impact of academic endeavors.

Scenario 2 – pessimistic future.

In this scenario, AI technology evolves rapidly but outpaces the development of appropriate regulations and ethical guidelines. AI-driven research tools become prevalent, but a lack of understanding and acceptance among academics leads to misuse and over-reliance on these technologies. The quality of research suffers as AI-generated data and results are not critically evaluated. Teaching is negatively impacted as AI teaching assistants replace human educators, leading to a depersonalized learning experience. Laws and regulations struggle to keep up with AI advancements, resulting in inadequate protections for data privacy and academic integrity. The academic community becomes divided, with a significant portion resisting AI integration due to ethical concerns and fear of job displacement, ultimately hindering progress and collaboration in knowledge creation and dissemination.

Prompt: "*As a specialist in developing future scenarios, your task is to develop two scenarios for the future role of academics, where they are influenced by Artificial Intelligence (AI). Develop one positive and one negative scenario, based on our framework that includes the following dimensions:*
Academic work: existing of research, teaching, and academic services.
Knowledge work: existing of knowledge creation, acquisition, dissemination, and application.
The scenarios should be based on the following framework, including:

1. the developments in AI technology (technology factor)
2. developments in AI literacy and acceptance by academics (individual factors)
3. developments in laws and regulations (higher-level factors).

Develop the two scenarios of about 150 words each in one paragraph."
Note: these scenarios are meant as an illustration of the possibilities of Generative AI for building future scenarios – adopting the guidelines for prompting on the website https://www.promptingguide.ai/ and OpenAI's prompting resources https://platform.openai.com/docs/guides/prompt-engineering: writing specific prompts (task to develop two scenarios), adopting a persona (specialist scenarios), provide context (our FoW framework), and a desired outcome (number of words).

center of their practice communities (Sapir et al., 2016). Hence, such what we call "Algoacademia" could negatively influence knowledge work in the near future. However, this may change in the more distant future if the promises of the next generation of technologies, like dilated attention, verify true.

A nuanced view offered by Sutton et al. (2018) suggests that human expertise can be developed *in collaboration* with AI (e.g., with ChatGPT). Although they acknowledge that deskilling is a serious possibility, they highlight that the types of knowledge and their relative importance are likely to change. For example, instead of remembering declarative knowledge, which can be automated, knowledge workers become better at finding information – which is called transactive memory (Sutton et al., 2018). In a similar vein, knowledge workers can become better at using and interacting with LMAI effectively. Drawing on the examples outlined in our Framework in Section 2, such AI applications provide academics with opportunities to team up with AI aplications in research, teaching, and academic services and create so-called hybrid intelligence through Human-AI teams (Peeters et al., 2020).

Lastly, to understand the impact of AI on academics it is important to distinguish between (1) the work of the knowledge workers; and (2) the body of (specialist) knowledge available. Susskind and Susskind (2022) have argued that the work of professionals is likely to decline due to novel technologies because society is no longer (fully) dependent on knowledge workers to get access to (specialist) knowledge, but the relevance of knowledge is ever more important. For those reasons, AI technologies may be perceived as a threat to the legitimacy of professional expertise by knowledge workers, which could lead to resistance to their use (Faraj et al., 2018; Liu et al., 2020), especially by high-status academics whose position and expertise is threatened (Bailey & Barley, 2011) – underscoring the importance of understanding.

3.2. Limitations

Our paper has several limitations. Mainly, we described many examples of how AI technologies influence the work of academics. Thus, we would like to emphasize that we make interferences on how the *actual use* of AI applications can have important implications for the (at least nearest) future of academics, as we consider that the humans who use AI determine the consequences, rather than AI having (technological) deterministic effects. This approach is aligned with the Sardar (2010) fourth law on future studies stating that "since we can have no true knowledge of the future, the impact of all future explorations can only be meaningfully assessed in the present" (p.184). It is worthwhile to recognize that what may appear as current AI applications for some could represent the near or even longer-term future for many of the examples and implications we outline in this paper, while for others these developments might be reminiscent of earlier technological developments.

Another limitation is our focus on academic work activities, without focusing on how academics might be managed by AI (e.g., tracking academic performance), and without differentiating between various academic positions and integrating other stakeholders, such as students and administrative staff. Future research should address more socio-technical factors contributing to the consequences of AI implementation (e.g., environmental and organizational factors), the role of humans in shaping these consequences, potential moderating factors and interventions, and the potential differential effects on distinct groups of academic stakeholders.

We also acknowledge we did not map specific functionalities and types of AI in relation to all examples of academic FoW in our paper as many authors do not classify specific types of AI they refer to, as well as due to the technical complexity related to making such connections on our own. Additionally, we focused specifically on the individual-job-level consequences for academics and did not explore the various hybrid intelligence systems and Human-AI teams and their implications (Peeters et al., 2021).

Finally, our conceptual framework (Fig. 1) is a simplified and potentially incomplete representation of a complex interplay between academics' work, its knowledge components, as well as their implications for the FoW. Nevertheless, we believe that our analysis and our framework have a number of important implications for theory and practice.

3.3. Theoretical implications

FoW research that aims to estimate the impact of advanced technologies such as AI is rapidly growing (Boyd & Huettinger, 2019). Many of them focus on quantitative changes. We have challenged this perspective by focusing on the qualitative changes from AI and exploring the future of academic work as it is likely to fundamentally change with the growing diffusion of AI.

First, our paper offers a novel integrated framework (Klein & Potosky, 2019) and draws attention to whether and how AI can be used from the perspective of academics, in contrast to previous research that focused primarily on the perspectives of students (Zawacki-Richter et al., 2019), as well as FoW of jobs with low horizontal (i.e., number of tasks performed) and vertical (i.e., level of responsibility) specializations such as manufacturing (Zawacki-Richter et al., 2019). Our study enriches the current research by developing a framework that integrates previously fragmented literatures on research, teaching, and academic services. This perspective is needed to develop a more comprehensive understanding of how AI is shaping the work of academics, and also to recognize the fundamental changes in knowledge work. Our framework sets the stage for a more systems-level thinking approach, which could be further developed by considering the role of other stakeholders such as students, administrative staff, parents, policymakers, human resource managers, or societies in general.

Second, with our research, we propose main categories and drivers of change and illustrate how much is known about the application or consequences of AI on the WHAT aspect or the activities that academics perform, and to a much lesser extent how much is known about the WHERE or place where these activities are performed, as well as WHEN or temporal aspects of knowledge work. By developing the framework integrating different job activities of academics (i.e., research, teaching, and services-related) with general job dimensions (WHAT, WHERE, and WHEN) and knowledge work activities (knowledge acquisition, creation, dissemination, and application), we offer a more holistic approach to analyze how AI can shape the future work of academics, and other knowledge workers across space, time, and task dimensions. This can enrich the growing corpus of so far fragmented literature that focuses on the futures of diverse aspects of academics' work (e.g., Leahy et al., 2019), which in turn helps to explain how AI influences outcomes of academic work. Relatedly, whereas teaching and research are well-understood concepts, academic services are less clearly defined, although we highlight several potential uses.

Third, our analysis shows that, despite promising benefits for academic knowledge workers, AI applications can also be detrimental to knowledge development and may add to job demands and socio-relational aspects between scholars and students. Therefore, we suggest studying these different components drawing on established job design or identity theories (e.g., Parker & Grote, 2020), or professional identity and legitimacy of knowledge workers whose position and expertise are threatened (Faraj et al., 2018). This implies more attention should be focused on the agency of academics in adopting and using AI, because academics may respond and use AI differently depending on their status or group membership.

Finally, this study has implications for researchers. We recommend that scholars, especially those doing research at the intersection of technology, FoW, and ethics, be the target population to study the responsible application of AI for academics - comprising such aspects as intellectual property, privacy, trust, and governance of AI in academia - and suggest an autoethnography approach that treats researchers as important actors (Ellis et al., 2011). The findings from such studies could also be credible and generalizable for other knowledge workers. The research into how AI shapes the job of academics is perfectly suited to adopt said approach because we as academics are both the researcher and the research subject.

3.4. Practical implications

We describe and provide illustrative examples of cutting-edge AI applications that can be used in the daily activities of academics. Here we note that most of the AI solutions available for the use of academics are fragmented solutions addressing specific tasks or problems, instead of integrated tools aimed at teaching, research, and services activities. This reflects the difference between narrow AI and strong AI (Russell & Norvig, 2022).

Looking to the future, our research shows that AI *may* transform academia. Thus, scholars could study the future of academics by drawing insights from other sectors and considering how these could be applied in the academic world. For example, academic leaders could learn from organization and management studies how AI might change the ways in which managerial tasks, academic processes, and teamwork change. At the same time, academics need to familiarize themselves with the (im)possibilities of AI in their daily work and thereby develop AI literacy.

The (technological) developments in AI and their applications are progressing rapidly (such as ChatGPT), and some of the examples we have mentioned may soon be outdated. Hence, we call for more research into the future of academics and urge universities and policymakers to use our insights to develop and successfully implement rules and guidelines on ethical AI use in academia across teaching, research, and academic services.

4. Conclusion

We have explored how the use of AI applications is changing and may further change the future of academics. We demonstrate that AI has the potential to revolutionize when, where, and what aspects of research, teaching, and service-related activities of academics. Our analysis highlights current state-of-the-art applications and changes in academic knowledge work that AI-usage is bringing about, rendering a future workplace of Academics, where academics and AI might co-exist. Our framework helps to identify *if* and *how* AI could impact the acquisition, creation, dissemination, and application/use of knowledge and highlights the potential drivers of these changes. The integrated framework that we propose connects these complex points and offers a holistic perspective for studying FoW in academia such as developing potential scenarios and the future of knowledge work in general. We offer directions for further FoW research on AI in academia and policymaking to better understand these changes and their implications.

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CRediT authorship contribution statement

Maarten Renkema: Writing – review & editing, Writing – original draft, Visualization, Project administration, Formal analysis, Conceptualization. **Aizhan Tursunbayeva:** Writing – review & editing, Writing – original draft, Visualization, Formal analysis, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

No data was used for the research described in the article.

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Statement

During the preparation of this work the authors used ChatGPT (www.chatgpt.com) in order to improve the quality of some of the text (GPT-4 model) and to develop scenarios. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Appendix 1. AI-shaped Research

FoW dimension	Example(s)	Future research directions
WHAT		
Identify promising areas and questions or verify research gaps	Programming libraries supporting thematic analyses	• Whether and how AI can alternate the traditional research methods/phases
Identify suitable cases to study	Matching platforms	• Potential biases in AI use for research
Automated research phases (e.g., paper screening or data extraction)	www.scholarcy.com	• Ethical boundaries of AI use for research • AI impact on human expertise and critical thinking
Evaluate or draft scientific articles	www.scite.ai www.researchrabbit.ai www.grammarly.com www.quillbot.com www.openai.com	
Development of new research methods and blurred boundaries between qualitative and quantitative research	Algorithmic text mining	
WHERE		
Conduct research via metaverse or with the help virtual/ augmented realities	Clinical trials via Metaverse	• Empirical data on the approaches to use AI for such purposes or their outcomes
Conduct research in any language or in any country	Translation apps	• Ethical boundaries of AI use for research from any location • Constant up/re-skilling to stay up-to-date with the emerging technologies • Increased job demands
WHEN		
Increased speed and more time	Systematic Review Automation Tools	• Where this time should be invested

Appendix 2. AI-shaped Teaching

FoW dimension	Example(s)	Future research directions
WHAT		
Automating administrative tasks	Assessment, plagiarism checks, students' grades, and feedback are automated	• Validity and reliability of automated grading • Teacher perspective on accepting and using AI for tracking student performance • Decreased or new forms of interactions of teachers with students • Students' willingness to engage with intelligent tutors
Grading student work	Automated essay scoring and exam question assessment (e.g., EasyGrader)	
Student analytics	Identify students with problems; identify learning process of students	
Intelligent tutoring	Automatic responses to student questions; personal digital tutors and new modes of learning	
WHERE		
Teaching takes place through virtual classrooms	Metaverse, virtual learning environments, and flipped classroom	• Technology-mediated teacher-student interactions • Effect of distant education on learner performance • Teachers' acceptance and use of (social) robots in the classroom
Providing feedback to learners from anywhere	Intelligent tutoring can bypass teachers	
The use of (social) robots and chatbots in the classroom	Student interaction with (chat)bots for learning	
WHEN		
Asynchronous teaching	Recorded micro-lectures; intelligent tutoring systems; chatbots for time-independent learning	• Effects on the working week of teachers and their well-being

Appendix 3. AI-shaped Services

FoW dimension	Example(s)	Future research directions
WHAT		
Search or apply for grants	www.researchprofessional.com www.grant-ai.com	• Whether or how such ad-hoc activities could be more structured to be potentially automated
Mentor students or junior staff	www.mentorloop.com	• Impact on scholarly reputation
Assistance with paper reviews	AI-assisted peer review instruments	
Assistance with acting as expert witness	Text mining applications	
Administrative activities	Siri or Alexa	
WHERE		
Virtual participation in meetings or conferences	Virtual/augmented reality or metaverse	• Interdisciplinary investigations on the types of activities that can be performed in person and virtually
Act as an expert in any country		
WHEN		
Multitasking or performing different activities simultaneously	Automating administrative tasks	• Distribution of work between academics and administrative/support staff • The effect of AI adoption by academics on administrative jobs (e.g., task shift)

References

Aldea, A., Haller, S., & Luttikhuis, M. (2020). Towards grading automation of open questions using machine learning. *48th SEFI Annual Conference on Engineering Education, SEFI*, 2020.

Anwar, S., Bascou, N. A., Menekse, M., & Kardgar, A. (2019). A systematic review of studies on educational robotics. *Journal of Pre-College Engineering Education Research (J-PEER), 9*(2), 2.

Ardichvili, A. (2022). The Impact of Artificial Intelligence on Expertise Development: Implications for HRD [Article]. *Advances in Developing Human Resources, 24*(2), 78–98. https://doi.org/10.1177/15234223221077304

Autor, D. H. (2015). Why are there still so many jobs? the history and future of workplace automation. *Journal of Economic Perspectives, 29*(3), 3–30. https://doi.org/10.1257/jep.29.3.3

Avrahami, A., Pessach, D., Singer, G., & Chalutz Ben-Gal, H. (2022). A human resources analytics and machine-learning examination of turnover: implications for theory and practice. *International Journal of Manpower, 43*(6), 1405–1424.

Bailey, D. E., & Barley, S. R. (2011). Teaching-learning ecologies: Mapping the environment to structure through action. *Organization Science, 22*(1), 262–285.

Baker, R., Hawn, A., & Lee, S. (2023). Algorithmic bias: the state of the situation and policy recommendations. *OECD Digital Education Outlook 2023: Towards an Effective Digital Education Ecosystem.* OECD Publishing. https://doi.org/10.1787/09e55ac4-en

Baker, R. S., & Hawn, A. (2022). Algorithmic bias in education. *International Journal of Artificial Intelligence in Education*, 1–41.

Baker, T., Smith, L., & Anissa, N. (2019). Educ-AI-tion rebooted. *Exploring the Future of Artificial Intelligence in schools and colleges*, 1–56.

Balfour, S. P. (2013). Assessing writing in MOOCs: Automated essay scoring and calibrated peer review™. *Research & Practice in Assessment, 8*, 40–48.

Barros, A., Prasad, A., & Śliwa, M. (2023). Generative artificial intelligence and academia: Implication for research, teaching and service. *Management Learning, 54*(5), 597–604. https://doi.org/10.1177/13505076231201445

Bearman, M., Ryan, J., & Ajjawi, R. (2022). Discourses of artificial intelligence in higher education: A critical literature review. *Higher Education.* https://doi.org/10.1007/s10734-022-00937-2

Bird, A. (1994). Careers as repositories of knowledge: A new perspective on boundaryless careers. *Journal of Organizational Behavior, 15*(4), 325–344. https://doi.org/10.1002/job.4030150404

Blackler, F. (1995). Knowledge, knowledge work and organizations: An overview and interpretation. *Organization Studies, 16*(6), 1021–1046. https://doi.org/10.1177/017084069501600605

BMJ (2024). Authorship & contributorship. Retrieved from: https://www.bmj.com/about-bmj/resources-authors/article-submission/authorship-contributorship.

Bohr, A., & Memarzadeh, K. (2020). The rise of artificial intelligence in healthcare applications. In A. Bohr, & K. Memarzadeh (Eds.), *Artificial Intelligence in Healthcare* (pp. 25–60). Academic Press. https://www.sciencedirect.com/science/article/pii/B9780128184387000022.

Boyd, J. A., & Huettinger, M. (2019). Smithian insights on automation and the future of work. *Futures, 111*, 104–115.

Brynjolfsson, E., & McAfee, A. (2014). The second machine age: Work, progress, and prosperity in a time of brilliant technologies. WW Norton & Company.

Checco, A., Bracciale, L., Loreti, P., Pinfield, S., & Bianchi, G. (2021). AI-assisted peer review. *Humanities and Social Sciences Communications, 8*(1), 1–11. https://doi.org/10.1057/s41599-020-00703-8

Chodor, B. (2022). Council Post: Meetings In The Metaverse: Is This The Future Of Events And Conferences? *Forbes*. https://www.forbes.com/sites/forbescommunicationscouncil/2022/01/13/meetings-in-the-metaverse-is-this-the-future-of-events-and-conferences/.

Choudhury, P., Allen, R. T., & Endres, M. G. (2021). Machine learning for pattern discovery in management research. *Strategic Management Journal, 42*(1), 30–57. https://doi.org/10.1002/smj.3215

Christian, B. (2020). *The Alignment Problem: Machine Learning and Human Values* (1st edition.,). W. W. Norton & Company,.

Clark, J., Glasziou, P., Mar, C. D., Bannach-Brown, A., Stehlik, P., & Scott, A. M. (2020). A full systematic review was completed in 2 weeks using automation tools: a case study. *Journal of Clinical Epidemiology, 121*, 81–90. https://doi.org/10.1016/j.jclinepi.2020.01.008

Cotton, D. R. E., Cotton, P. A., & Shipway, J. R. (2023). Chatting and cheating: Ensuring academic integrity in the era of ChatGPT. *Innovations in Education and Teaching International*, 1–12. https://doi.org/10.1080/14703297.2023.2190148

De Regt, H. W., Leonelli, S., & Eigner, K. (2009). Focusing on scientific understanding. *Scientific Understanding. Philosophical Perspectives*, 1–17.

Deakin, H., & Wakefield, K. (2014). Skype interviewing: Reflections of two PhD researchers. *Qualitative Research, 14*(5), 603–616. ISO 690.

Dedehayir, O., & Steinert, M. (2016). The hype cycle model: A review and future directions. *Technological Forecasting and Social Change, 108*, 28–41.

Deeva, G., Bogdanova, D., Serral, E., Snoeck, M., & De Weerdt, J. (2021). A review of automated feedback systems for learners: Classification framework, challenges and opportunities. *Computers & Education, 162*, Article 104094. https://doi.org/10.1016/j.compedu.2020.104094

Dekas, K. H., Bauer, T. N., Welle, B., Kurkoski, J., & Sullivan, S. (2013). Organizational Citizenship Behavior, Version 2.0: A review and Qualitative Investigation of OCBs for Knowledge Workers at Google and beyond. *Academy of Management Perspectives, 27*(3), 219–237. https://doi.org/10.5465/amp.2011.0097

Deng, Z., Yin, K., Bao, Y., Armengol, V. D., Wang, C., Tiwari, A., Barzilay, R., Parmigiani, G., Braun, D., & Hughes, K. S. (2019). Validation of a Semiautomated Natural Language Processing-Based Procedure for Meta-Analysis of Cancer Susceptibility Gene Penetrance. *JCO Clinical Cancer Informatics*, (*3*), 1–9. https://doi.org/10.1200/CCI.19.00043

Ding, J., Ma, S., Dong, L., Zhang, X., Huang, S., Wang, W., & Wei, F. (2023). LongNet: Scaling Transformers to 1,000,000,000 Tokens. *arXiv Preprint arXiv, 2307*, 02486.
Drucker, P. (1994). The Age of Social Transformation. The Atlantic Monthly.
Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., Baabdullah, A. M., Koohang, A., Raghavan, V., & Ahuja, M. (2023). "So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. *International Journal of Information Management, 71*, Article 102642.
Einola, K., & Khoreva, V. (2022). Best friend or broken tool? Exploring the co-existence of humans and artificial intelligence in the workplace ecosystem. *Human Resource Management, N/a(N/a)*. https://doi.org/10.1002/hrm.22147
Ellis, C., Adams, T. E., & Bochner, A. P. (2011). Autoethnography: An Overview. *Historical. Social Research / Historische Sozialforschung, 36(4*, (138), 273–290. http://www.jstor.org/stable/23032294.
Evers, A., & van der Heijden, B.I.J.M. (2016). Competence and Professional Expertise. In M. Mulder (Ed.), Competence-based Vocational and Professional Education: Bridging the Worlds of Work and Education (pp. 83- 101). Springer. Technical and Vocational Education and Training: Issues, Concerns and Prospects (TVET) Vol. 23 https://doi.org/10.1007/978-3-319-41713-4_4.
Faraj, S., Pachidi, S., & Sayegh, K. (2018). Working and organizing in the age of the learning algorithm. *Information and Organization, 28*(1), 62–70. https://doi.org/10.1016/j.infoandorg.2018.02.005
Farrokhnia, M., Banihashem, S. K., Noroozi, O., & Wals, A. (2024). A SWOT analysis of ChatGPT: Implications for educational practice and research. *Innovations in Education and Teaching International, 61*(3), 460–474.
Fenn, J., & Raskino, M. (2008). *Mastering the hype cycle: how to choose the right innovation at the right time.* Harvard Business Press,.
Frank, M.R., Autor, D., Bessen, J.E., Brynjolfsson, E., Cebrian, M., Deming, D.J., Feldman, M., Groh, M., Lobo, J., Moro, E., Wang, D., Youn, H., & Rahwan, I. (2019). Toward understanding the impact of artificial intelligence on labor. https://www.scopus.com/inward/record.uri?eid=2-s2.0–85064058602&doi=10.1073%2fpnas.1900949116&partnerID=40&md5=4496f0df831ea73513fe8d5e1d5122cf.
Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change, 114*, 254–280.
Gartner (2023). Gartner Hype Cycle. Available at: https://www.gartner.com/en/research/methodologies/gartner-hype-cycle.
Gartner (2023). Gartner Places Generative AI on the Peak of Inflated Expectations on the 2023 Hype Cycle for Emerging Technologies Available at https://www.gartner.com/en/newsroom/press-releases/2023-08-16-gartner-places-generative-ai-on-the-peak-of-inflated-expectations-on-the-2023-hype-cycle-for-emerging-technologies.
Gašević, D., Dawson, S., & Siemens, G. (2015). Let's not forget: Learning analytics are about learning. *TechTrends, 59*, 64–71.
Grimes, M., Von Krogh, G., Feuerriegel, S., Rink, F., & Gruber, M. (2023). From scarcity to abundance: Scholars and scholarship in an age of generative artificial intelligence. *Academy of Management Journal, 66*(6), 1617–1624.
Haenlein, M., & Kaplan, A. (2019). A brief history of artificial intelligence: On the past, present, and future of artificial intelligence. *California Management Review, 61*(4), 5–14.
Harris, M., & Vining, G. W. (1987). The IE's future role in improving knowledge. *Industrial Engineering, 19*(7), 28–32.
Harrison, J. S., Josefy, M. A., Kalm, M., & Krause, R. (2022). Using supervised machine learning to scale human-coded data: A method and dataset in the board leadership context. *Strategic Management Journal, smj, 3480*. https://doi.org/10.1002/smj.3480
Harvard Library. (2023). The Research Lifecycle. Harvard Library. https://library.harvard.edu/research-lifecycle.
Herman, E. (2018). Scholarly reputation. *FEMS Microbiology Letters, 365*(18). https://doi.org/10.1093/femsle/fny200
Holmes, W. (2023). The Unintended Consequences of Artificial Intelligence and Education. Education International. https://www.ei-ie.org/en/item/28115:the-unintended-consequences-of-artificial-intelligence-and-education.
Holmes, W., Bialik, M., & Fadel, C. (2019). Artificial Intelligence in Education. Center for Curriculum Redesign.
Hutson, M. (2021). AI conferences use AI to assign papers to reviewers. Retrieved from https://www.science.org/content/article/ai-conferences-use-ai-assign-papers-reviewers.
Hwang, G.-J., Xie, H., Wah, B. W., & Gašević, D. (2020). Vision, challenges, roles and research issues of Artificial Intelligence in Education. *Computers and Education: Artificial Intelligence, 1*, Article 100001. https://doi.org/10.1016/j.caeai.2020.100001
IBM. (2023). Understanding the different types of artificial intelligence. IBM Blogs. ⟨https://www.ibm.com/blog/understanding-the-different-types-of-artificial-intelligence/⟩.
Janz, B. D., Colquitt, J. A., & Noe, R. A. (1997). Knowledge worker team effectiveness: The role of autonomy, interdependence, team development, and contextual support variables. *Personnel Psychology, 50*(4), 877–904. https://doi.org/10.1111/j.1744-6570.1997.tb01486.x
Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business Horizons, 62*(1), 15–25.
Kelloway, E. K., & Barling, J. (2000). Knowledge work as organizational behavior. *International Journal of Management Reviews, 2*(3), 287–304. https://doi.org/10.1111/1468-2370.00042
Kezar, A., & Holcombe, E. (2015). The Professoriate Reconsidered. AAUP. ⟨https://www.aaup.org/article/professoriate-reconsidered⟩.
Klein, H. J., & Potosky, D. (2019). Making a conceptual contribution at human resource management review. *Human Resource Management Review, 29*(3), 299–304.
Korinek, A. (2023). Generative AI for economic research: Use cases and implications for economists. *Journal of Economic Literature, 61*(4), 1281–1317.
Krenn, M., Pollice, R., Guo, S. Y., Aldeghi, M., Cervera-Lierta, A., Friederich, P., dos Passos Gomes, G., Häse, F., Jinich, A., Nigam, A., Yao, Z., & Aspuru-Guzik, A. (2022). On scientific understanding with artificial intelligence. *Nature Reviews Physics, 4*(12), 761–769. https://doi.org/10.1038/s42254-022-00518-3
Kulkarni, M., Mantere, S., Vaara, E., van den Broek, E., Pachidi, S., Glaser, V.L., … & Greenwood, M. (2024). The future of research in an artificial intelligence-driven world. Journal of Management Inquiry, 33(3), 207–229.
Leahy, S. M., Holland, C., & Ward, F. (2019). The digital frontier: Envisioning future technologies impact on the classroom. *Futures, 113*, Article 102422.
Liu, Q., Geertshuis, S., & Grainger, R. (2020). Understanding academics' adoption of learning technologies: A systematic review. *Computers & Education, 151*, Article 103857. https://doi.org/10.1016/j.compedu.2020.103857
Luckin, R., Holmes, W., Griffiths, M., & Forcier, L.B. (2016). Intelligence unleashed: An argument for AI in education.
Macfarlane, B. (2007). Defining and Rewarding Academic Citizenship: The implications for university promotions policy. *Journal of Higher Education Policy and Management, 29*(3), 261–273. https://doi.org/10.1080/13600800701457863
Matwin, S., Kouznetsov, A., Inkpen, D., Frunza, O., & O'Blenis, P. (2010). A new algorithm for reducing the workload of experts in performing systematic reviews. *Journal of the American Medical Informatics Association: JAMIA, 17*(4), 446–453. https://doi.org/10.1136/jamia.2010.004325
Meltzer, T. (2014). Robot doctors, online lawyers and automated architects: The future of the professions. *The Guardian.* ⟨https://www.theguardian.com/technology/2014/jun/15/robot-doctors-online-lawyers-automated-architects-future-professions-jobs-technology⟩.
Milano, S., McGrane, J. A., & Leonelli, S. (2023). Large language models challenge the future of higher education. *Nature Machine Intelligence, 5*(4), 333–334.
Minbaeva, D. (2020). Disrupted HR? *Human Resource Management Review, 31*(4), Article 100820. https://doi.org/10.1016/j.hrmr.2020.100820
Mollick, E. R., & Mollick, L. (2022). New modes of learning enabled by ai chatbots: Three methods and assignments. *Available at SSRN*. https://doi.org/10.2139/ssrn.4300783
Munn, L. (2023). The uselessness of AI ethics. *AI and Ethics, 3*(3), 869–877.
Nemorin, S., Vlachidis, A., Ayerakwa, H. M., & Andriotis, P. (2023). AI hyped? A horizon scan of discourse on artificial intelligence in education (AIED) and development. *Learning. Media and Technology, 48*(1), 38–51.
Newell,S., Robertson, M., Scarbrough, H., & Swan, J. (2002). Managing knowledgework. Palgrave Macmillan.
Nonaka, I. (1994). A Dynamic Theory of Organizational Knowledge Creation. *Organization Science, 5*(1), 14–37. https://doi.org/10.1287/orsc.5.1.14

Ouyang, F., & Jiao, P. (2021). Artificial intelligence in education: The three paradigms. *Computers and Education: Artificial Intelligence, 2*, Article 100020. https://doi.org/10.1016/j.caeai.2021.100020
Parker, S., & Grote, G. (2020). Automation, algorithms, and beyond: Why work design matters more than ever in a digital world. *Applied Psychology*, 1–45.
Peeters, M. M., van Diggelen, J., Van Den Bosch, K., Bronkhorst, A., Neerincx, M. A., Schraagen, J. M., & Raaijmakers, S. (2021). Hybrid collective intelligence in a human–AI society. *AI & Society, 36*(1), 217–238.
Pereira, V., Hadjielias, E., Christofi, M., & Vrontis, D. (2023). A systematic literature review on the impact of artificial intelligence on workplace outcomes: A multi-process perspective. *Human Resource Management Review, 33*(1). https://doi.org/10.1016/j.hrmr.2021.100857
Peres, R., Schreier, M., Schweidel, D., & Sorescu, A. (2023). On ChatGPT and beyond: How generative artificial intelligence may affect research, teaching, and practice. *International Journal of Research in Marketing, 40*(2), 269–275.
Petermann, M., Tempini, N., Kherroubi Garcia, I., Whitaker, K., & Strait, A. (2022). Looking before we leap: Expanding ethical review processes for AI and data science research (1739795067).
Pettersen, L. (2018). Why Artificial Intelligence Will Not Outsmart Complex Knowledge Work. *Work, Employment and Society, 33*(6), 1058–1067. https://doi.org/10.1177/0950017018817489
Pyöriä, P. (2005). The concept of knowledge work revisited. *Journal of Knowledge Management*.
Raisch, S., & Krakowski, S. (2021). Artificial Intelligence and Management: The Automation-Augmentation Paradox. *Academy of Management Review, 46*(1), 192–210.
Rapert, M. I., Kurtz, D. L., & Smith, S. (2002). Beyond the Core Triad: Just What Do Marketing Academics Do Outside of Teaching, Research, and Service? *Journal of Marketing Education, 24*(2), 161–167. https://doi.org/10.1177/0273475302242009
Roscoe, R. D., Salehi, S., Nixon, N., Worsley, M., Piech, C., & Luckin, R. (2022). Inclusion and equity as a paradigm shift for artificial intelligence in education. *Artificial Intelligence in STEM Education* (pp. 359–374). CRC Press.
Roth, G. (2019). 2019: When We Exceeded 1 Billion Knowledge Workers. Gartner. https://blogs.gartner.com/craig-roth/2019/12/11/2019-exceeded-1-billion-knowledge-workers/.
Rubinfeld, D. L., & Cecil, J. S. (2018). Scientists as Experts Serving the Court. *Daedalus, 147*(4), 152–163. https://doi.org/10.1162/daed_a_00526
Russell, S., & Norvig, P. (2022). Artificial Intelligence: A Modern Approach, 4th, Global ed. Pearson Education Limited.
Sajjadiani, S., Sojourner, A. J., Kammeyer-Mueller, J. D., & Mykerezi, E. (2019). Using machine learning to translate applicant work history into predictors of performance and turnover. *The Journal of Applied Psychology, 104*(10), 1207–1225. https://doi.org/10.1037/apl0000405
Sapir, A., Drori, I., & Ellis, S. (2016). The Practices of Knowledge Creation: Collaboration Between Peripheral and Core Occupational Communities. *European Management Review, 13*(1), 19–36. https://doi.org/10.1111/emre.12064
Sardar, Z. (2010). The Namesake: Futures; futures studies; futurology; futuristic; foresight—What's in a name? *Futures, 42*(3), 177–184.
Schulte, P. A., Streit, J. M. K., Sheriff, F., Delclos, G., Felknor, S. A., Tamers, S. L., Fendinger, S., Grosch, J., & Sala, R. (2020). Potential Scenarios and Hazards in the Work of the Future: A Systematic Review of the Peer-Reviewed and Gray Literatures. *Annals of Work Exposures and Health, 64*(8), 786–816. https://doi.org/10.1093/annweh/wxaa051
Schwartz, J., Hatfield, S., Jones, R., & Anderson, S. (2019). What is the future of work? Redefining work, workforces, and workplaces. *Deloitte Insights*, 1–12.
Self, J. (1999). The defining characteristics of intelligent tutoring systems research: ITSs care, precisely. *International Journal of Artificial Intelligence in Education, 10*(3-4), 350–364.
Sife, A., Lwoga, E., & Sanga, C. (2007). New technologies for teaching and learning: Challenges for higher learning institutions in developing countries. *International Journal of Education and Development Using ICT, 3*(2), 57–67.
Speller, M., Hodgson, P., Brandon-Jones, A., Dimov, D., & Padget, J. (2019). *UK Third Sector grant making: A summary of research by the University of Bath*.
Spieler, I., Scheibe, S., Stamov-Roßnagel, C., & Kappas, A. (2017). Help or hindrance? Day-level relationships between flextime use, work–nonwork boundaries, and affective well-being. *Journal of Applied Psychology, 102*(1), 67.
Steinhauer, J. (2022). Does History Have a Future? In J. Steinhauer (Ed.). *History, Disrupted: How Social Media and the World Wide Web Have Changed the Past (pp* (pp. 107–117). Springer International Publishing,. https://doi.org/10.1007/978-3-030-85117-0_10
Stokel-Walker, C. (2022). AI bot ChatGPT writes smart essays-should academics worry? *Nature*.
Stokel-Walker, C. (2023). ChatGPT listed as author on research papers: many scientists disapprove. *Nature*.
Strohmeier, S. (2022). Artificial intelligence in human resources-an introduction. *In Handbook of Research on Artificial Intelligence in Human Resource Management* (pp. 1–22). Edward Elgar Publishing,.
Susskind, R. E., & Susskind, D. (2022). *The future of the professions: How technology will transform the work of human experts, updated edition*. Oxford University Press,.
Sutton, S. G., Arnold, V., & Holt, M. (2018). How much automation is too much? Keeping the human relevant in knowledge work. *Journal of Emerging Technologies in Accounting, 15*(2), 15–25.
Thelwall, M. A., & Sud, P. (2022). Scopus 1900–2020: Growth in articles, abstracts, countries, fields, and journals. *Quantitative Science Studies, 3*, 37–50. https://doi.org/10.1162/qss_a_00177
Tursunbayeva, A., & Moschera, L. (forthcoming). Ethics in People Analytics Research: A Multi-Disciplinary Perspective. In Vicenc Fernandez, Eva Gallardo Gallardo (Eds.), A Research Agenda for HR Analytics. Eldar Research Agendas series.
Tursunbayeva, A., Pagliari, C., Di Lauro, S., & Antonelli, G. (2022). The ethics of people analytics: risks, opportunities and recommendations. *Personnel Review, 51*(3), 900–921. https://doi.org/10.1108/PR-12-2019-0680
Tursunbayeva, A., & Renkema, M. (2022). Artificial intelligence in health-care: implications for the job design of healthcare professionals. *Asia Pacific Journal of Human Resources*. https://doi.org/10.1111/1744-7941.12325
Von Krogh, G. (2018). Artificial intelligence in organizations: New opportunities for phenomenon-based theorizing. *Academy of Management Discoveries, 66*(6), 1617–1624.
von Richthofen, G., Ogolla, S., & Send, H. (2022). Adopting AI in the context of knowledge work: empirical insights from German Organizations. *Information, 13*(4), 199. https://doi.org/10.3390/info13040199
Wagner, G., Lukyanenko, R., & Paré, G. (2022). Artificial intelligence and the conduct of literature reviews. *Journal of Information Technology, 37*(2), 209–226. https://doi.org/10.1177/02683962211048201
Willcocks, L. (2020). Robo-Apocalypse cancelled? Reframing the automation and future of work debate. https://www.scopus.com/inward/record.uri?eid=2-s2.0–85086321093&doi=10.1177%2f0268396220925830&partnerID=40&md5=5899a3103d29ab67bf234c6a7e88ceae.
Xu, Y., Liu, X., Cao, X., Huang, C., Liu, E., Qian, S., Liu, X., Wu, Y., Dong, F., Qiu, C.-W., Qiu, J., Hua, K., Su, W., Wu, J., Xu, H., Han, Y., Fu, C., Yin, Z., Liu, M., Roepman, R., Dietmann, S., Virta, M., Kengara, F., Zhang, Z., Zhang, L., Zhao, T., Dai, J., Yang, J., Lan, L., Luo, M., Liu, Z., An, T., Zhang, B., He, X., Cong, S., Liu, X., Zhang, W., Lewis, J. P., Tiedje, J. M., Wang, Q., An, Z., Wang, F., Zhang, L., Huang, T., Lu, C., Cai, Z., Wang, F., & Zhang, J. (2021). Artificial intelligence: A powerful paradigm for scientific research. *The Innovation, 2*(4). https://doi.org/10.1016/j.xinn.2021.100179
Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education–where are the educators? *International Journal of Educational Technology in Higher Education, 16*(1), 1–27.