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THE IMPACT OF ARTIFICIAL INTELLIGENCE ON WORKERS' SKILLS: UPSKILLING AND RESKILLING IN ORGANISATIONS

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ABSTRACT

Aim/Purpose	This paper examines the transformative impact of Artificial Intelligence (AI) on professional skills in organizations and explores strategies to address the resulting challenges.
Background	The rapid integration of AI across various sectors is automating tasks and reducing cognitive workload, leading to increased productivity but also raising concerns about job displacement. Successfully adapting to this transformation requires organizations to implement new working models and develop strategies for upskilling and reskilling their workforce.

Correction Notice. This paper was revised for readability in 2024 and uploaded on October 21, 2024. The earlier version can be found here.

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Methodology This review analyzes recent research and practice on AI's impact on human skills in organizations. We identify key trends in how AI is reshaping professional competencies and highlight the crucial role of transversal skills in this evolving landscape. The paper also discusses effective strategies to support organizations and guide workers through upskilling and reskilling processes.

Contribution The paper contributes to the existing body of knowledge by examining recent trends in AI's impact on professional skills and workplaces. It emphasizes the importance of transversal skills and identifies strategies to support organizations and workers in meeting upskilling and reskilling challenges. Our findings suggest that investing in workforce development is crucial for ensuring that the benefits of AI are equitably distributed among all stakeholders.

Findings Our findings indicate that organizations must employ a proactive approach to navigate the AI-driven transformation of the workplace. This approach involves mapping the transversal skills needed to address current skill gaps, helping workers identify and develop skills required for effective AI adoption, and implementing processes to support workers through targeted training and development opportunities. These strategies are essential for ensuring that workers' attitudes and mental models towards AI are adaptable and prepared for the changing labor market.

Recommendations for Practitioners For practitioners, we recommend identifying the specific skills required for AI adoption and implementing comprehensive training and development programs. This approach will ensure workers are well-prepared for the evolving demands of an AI-integrated labor market.

Recommendations for Researchers We emphasize the need for researchers to adopt a transdisciplinary approach when studying AI's impact on the workplace. Given AI's complexity and its far-reaching implications across various fields including computer science, mathematics, engineering, and behavioral and social sciences, integrating diverse perspectives is crucial for a holistic understanding of AI's applications and consequences.

Impact on Society The societal impact of AI's continued revolution across sectors underscores the importance of considering diverse stakeholder perspectives, including those of employees, employers, and policymakers. Our research suggests that investments in upskilling and reskilling initiatives can promote a more equitable distribution of AI's benefits among all stakeholders.

Future Research Looking ahead, further research is needed to deepen our understanding of AI's impact on human skills, particularly the role of soft skills in AI adoption within organizations. Future studies should also address the challenges posed by Industry 5.0, which is expected to bring about even more extensive integration of new technologies and automation.

Keywords artificial intelligence, organisational learning, transversal skills, upskilling, reskilling

INTRODUCTION

The use of Artificial Intelligence (AI) is significantly impacting business and society. AI, defined as "a system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation" (Kaplan & Haenlein, 2019), has the potential to augment or even replace human tasks and activities through recognition, understanding, learning, and action (Dwivedi et al., 2021). Modern AI systems are currently bound to Machine Learning (ML). The development of machine learning methods and models enables computers to learn from data without explicit programming (Mohri et al., 2018). Machine learning involves providing large amounts of data to a computer system, which then uses statistical techniques to find patterns and relationships in the data. Based on the data it has learned, the system can use this information to make predictions or take action. Experts predict that ML and AI will significantly alter the nature of work in the coming decade (Rahman & Abedin, 2021; Tommasi et al., 2021).

The implementation of AI systems in industries such as finance, healthcare, manufacturing, retail, supply chain, logistics, and public services has led to a rapid pace of change. As examples of AI systems in some of the fields, some tools are helping doctors to diagnose cancer accurately, or various customer service chatbot leverage natural language processing (NLP) to simulate human-like conversations and provide information to customers. To successfully adapt to these changes, organisations need to adjust to new working and organisational models (Jaiswal et al., 2022). Among the main adaptation expected is the need for a re-evaluation of the required workforce skills, as the automation of certain tasks may lead to retraining or developing new skills (Hancock et al., 2020).

In this sense, the adoption of AI has implications for both knowledge workers and blue-collar workers, as AI has the potential to automate a variety of tasks currently performed by humans (Leinen et al., 2020). From this point of view, while there are arguments that this change may lead to increased productivity and efficiency for knowledge workers, it may also result in job erosion. Before 2030, it is estimated that 14% of the global workforce may need to change jobs due to AI-related technological advancements. This transition is similar to the shift of workers from fields to factories during the industrial revolution but will occur within a considerably shorter period. For blue-collar workers, the impact of AI may be more severe, as many tasks may be automated, potentially leading to job losses in sectors that rely on manual labour. The demand for so-called midrange skills, such as manual, operational, and visual-spatial skills, is declining. On the contrary, there are arguments suggesting that the AI introduction in the workplace may also lead to the creation of new jobs, especially in sectors focused on developing and implementing AI technology (Puzzo et al., 2020).

The impact of AI on human skills will probably depend on the specific tasks and skills being automated (Chuang, 2022). Some tasks may be more susceptible to automation than others, and the impact on human skills will depend on the specific skills required for those tasks. It is also suggested that certain skills, such as critical thinking and problem-solving, may become more valuable as AI continues to advance. The OECD International Conference on AI in Work, Innovation, Productivity, and Skills (Acemoglu, 2022) discussed the skills needed for the effective adoption of AI in organisations, success factors and challenges in training managers and workers, and opportunities for policy makers to help workers acquire the necessary skills. According to the experts, the window of opportunity for reskilling and upskilling workers in the new labour market has narrowed. The skills required will change in all occupations over the next five years, resulting in a large skills gap. This is true not only for those entering the labour market but also for those who will keep their jobs. It is estimated that the share of key skills will change by 40% in the next five years, and 50% of all workers will need retraining and further education (World Economic Forum, 2020). Key skills that are expected to increase in importance by 2025 include technical skills critical for the effective use of AI systems and soft skills (also called transversal skills) such as critical thinking and analysis, problem-solving, and self-management (World Economic Forum, 2020).

To address these changes, the European Commission recently launched a round of calls on upskilling in the industry, which led to co-funded international projects on the topic. An illustrative project is the Up-Skill project (www.upskill-horizon.eu) coordinated by Mälardalens Universitet. The European Project aims to improve the balance between humans and technology in manufacturing by focusing on the collaborative relationship between skilled workers and automation. The project identified skills that existing workers need to survive in the emerging digitalised workplace and create training courses, an Up-Skill Platform, and manuals for hardware and software up-skilling. These projects demonstrate the need to have a better understanding of how businesses, particularly in industrial environments, can lever value from human and machine integration.

This paper aims to investigate the recent developments in research and practice on the transformation of professional skills by artificial intelligence and to discuss some of these challenges. Prior studies (see, e.g., Jain et al., 2021; Rothwell, 2021) have suggested that creating market-responsive training routes for skills, responsibilities, and roles requires anticipating the nature of shifts in organisations caused by the introduction of AI systems. Therefore, we have analysed the main theories and approaches that explain the impact of AI on human skills in organisations. We then examined how the introduction of AI impacts the skills required by workers. Additionally, we explored the need for organisations to implement processes for upskilling and reskilling current and future workers, starting with the identification of skills shortages and the effective measures that can address these challenges. Finally, we addressed the issues and challenges related to the diversity of opportunities and resources for accessing upskilling and reskilling, considering differences in age, gender, and culture.

RECENT DEVELOPMENTS IN AI AND HUMAN SKILLS

There have been recent developments in the field of artificial intelligence (AI) in industry and the workplace. Historically, AI-based systems automated a variety of back-office processes, such as data entry, document management, customer service, and accounting, through the use of NLP. AI was used to understand and mimic human interaction with computer systems (Butler, 2016; Jaiswal et al., 2022).

A major game-changer has been "generative AI". Generative AI refers to systems that generate new content or data, rather than just processing or analysing existing data. These systems can learn from a set of data and then generate new content similar in style or meaning to the input data (Jovanovic & Campbell, 2022). One example of generative AI is a machine learning model trained on a large dataset of images. The model can then generate new, original images that are similar in style to the training data. Generative AI can be used in a variety of applications, including creating realistic images and generating text, but also designing new drugs or materials.

Generative AI systems are also used to replace or mimic human transversal skills, such as communication, problem-solving, and conflict resolution. For example, an AI system with NLP capabilities can understand customer conversations, interpret their emotions, and provide helpful and friendly responses (Jaiswal et al., 2022). It can also learn from customer interactions to improve its responses over time and provide personalised customer service tailored to each customer's individual needs.

Other generative AI systems can mimic human skills such as problem-solving and creativity. One example of this is ChatGPT, which uses natural language generation to create human-like conversations. These systems use techniques such as sentiment analysis, NLP, and machine learning to understand the context of the conversation and provide appropriate responses (Jaiswal et al., 2022). AI systems that generate images from text descriptions (e.g., DALL-E, Midjourney), using a combination of NLP and computer vision, can mimic or replace human thinking and creativity skills. These systems can learn from their mistakes and generate increasingly accurate images. They can also go beyond the scope of the text query to generate creative images.

Another recent development relevant in the industrial setting has been represented by "Edge AI". Edge AI, also known as edge computing, refers to the use of AI technologies that have their computational power at the edge of a network rather than in the cloud or a centralised data centre. In industry, edge AI is often used for applications that require real-time processing or decision-making, such as autonomous vehicles, industrial automation, and monitoring systems. Edge AI has the potential to impact human skills as it can lead to the automation of specific tasks, potentially leading to job displacement for workers who perform those tasks. On the other hand, it can also create job opportunities in sectors focused on developing and implementing edge AI technologies. Additionally, edge AI can augment human skills by enabling workers to make more informed and accurate decisions in real-time, potentially leading to increased productivity and efficiency.

Human-AI teaming is an important component of "Industry 5.0". Industry 5.0, as envisioned by the European Commission, is a human-centric, sustainable, and resilient approach to manufacturing that goes beyond Industry 4.0. It prioritizes collaboration between humans and machines, sustainability, and aims to create resilient industrial ecosystems that can adapt to changing demands and disruptions. According to this vision, the creation of new technologies, products, and services should prioritize the well-being of workers and society.

In a literature review, Al Mubarak (2022) discusses the potential benefits and challenges of human-machine interactions in the Industry 5.0 era, focusing on work-based learning. The author argues that technology can complement human efforts, leading to improvements in efficiency and production, as well as opportunities for upskilling and job security. However, at the managerial level it will be necessary to address legal, psychological, and ethical issues and increase standards of living and sustainable development, through the optimal balance of both human and technological capital in the context of Industry 5.0. Some ways to achieve this are to invest in training and development programs that help workers acquire the skills needed to effectively use new technologies and implement flexible work arrangements that allow workers to take advantage of AI-based efficiencies while also maintaining a healthy work-life balance. These solutions may allow workers to effectively use new technologies to improve efficiency and productivity while ensuring they are treated fairly and have opportunities to grow and advance in their careers.

THEORIES AND APPROACHES

There are various theories and approaches that may be adopted to explain the impact of artificial intelligence on human skills in organisations.

Technology-Mediated Learning (TML) Theory focuses on the integration of technology in learning processes, examining how technology can enhance or alter the learning experience (Bower, 2019; Gupta & Bostrom, 2009). This theory suggests that technology-mediated learning, such as online video tutorials or virtual simulations, can be an effective way for people to learn new skills and knowledge. Technological "affordances" and social contexts significantly influence learning outcomes. In that sense, AI technology can provide people with a wider range of information and tools, helping them to learn and perform more effectively. Thus, AI has the potential to automate certain tasks and processes, freeing up time and resources for human workers to focus on more complex and higher-level tasks. The theory does not seem to address the issue of the individual employee's access to technology, which the organisation must provide as a resource. An organisation might not always be so resourceful to provide all the technology needed to learn new skills and knowledge; even when it is, employees should be aware of its availability. Also, it might be expected that it is not technology *per se* that makes employees learn but rather a technology that employees feel comfortable with and find useful, relevant, satisfying, and easy to use. Thus, employees' perceptions of the technology and its characteristics become further factors to consider in the technology-mediated learning process.

Finally, the theory misses covering which factors lead workers to focus on more complex tasks rather than on any other type of activity when relieved from tasks taken over by AI.

The AI Job Replacement Theory developed by Ming-Hui Huang and Roland Rust (2018) addresses the significant impact of artificial intelligence (AI) on job markets, specifically focusing on how AI can replace human tasks in service industries. The theory identifies four types of intelligence required for tasks, particularly service tasks, and suggests that the introduction of AI follows a predictable order. The theory asserts that the replacement of human labour by AI occurs primarily at the task level and primarily for simple mechanical tasks. It also suggests that the progression of AI task substitution from lower to higher and complex tasks will result in predictable variations over time. For instance, the importance of analytical skills will decrease as AI takes on more analytical tasks, tasks that require logical and rule-based thinking. Eventually, AI will also be able to perform intuitive and empathic tasks, which has the potential to create innovative ways of integrating humans and machines in service delivery but also poses a threat to human employment. Chui and colleagues back in 2015 found that a significant percentage of tasks performed by humans in high-paying jobs such as portfolio managers, doctors, and executives could be automated by AI systems. Indeed, most jobs in business involve mechanical tasks (such as managing daily schedules and taking attendance), thinking tasks (such as analysing customer preferences and planning logistics) and feeling tasks (such as empathising with customers and advising patients).

This theory suggests that AI has the potential to automate tasks that are currently performed by humans, leading to job losses in sectors that rely heavily on manual labour or repetitive tasks (Georgieff & Hyee, 2022). However, an aspect that this theory seems not to consider is that jobs are not fixed pre-defined sets of tasks that do not vary across contexts of application. Rather, doing the same job in different settings (e.g., geographical, cultural, organisational) might imply a very different set of tasks implied by how the job is perceived or represented. Thus, the negative impact of AI could be rethought as much more variable than expected by this theory.

Despite this theory's great resonance, some authors have raised some criticisms. For example, Dengler and Matthes (2018) argue that the likelihood of automation and the resulting extent to which AI systems will replace workers is overestimated. The authors used about 8,000 tasks in German companies to investigate whether they could be replaced by computers or by machines controlled by computers according to programmable rules. The results confirmed that while some tasks in an occupation could be replaced, entire occupations could not. Another example can be found in a paper by Meskó et al. (2018), which discusses the potential of AI to alleviate labour shortages in healthcare by facilitating diagnostics, decision-making, Big Data analytics, and administration. The authors argue that AI does not cover the entire care process: empathy, proper communication and human contact will still be essential. No application, software, or device can replace personal relationships and trust. In other words, the role of the human doctor is inevitable, but AI could be a very useful cognitive assistant. The authors argue that AI is not meant to replace healthcare providers, but that those who use AI are likely to have a competitive advantage over those who do not know how to use it and who risk being left behind.

AI Job Replacement Theory and its criticisms underscore the complex interplay between AI and human skills across various occupations. Public discourse often focuses on jobs perceived as less vulnerable to AI impact, including masseurs, hairdressers, plumbers, electricians, psychologists, pet groomers, cooks, athletes, craftsmen, beekeepers, art restorers, babysitters, nurses, doctors, and club entertainers. These occupations can be categorized based on their required skills. Many demand direct human interaction, emphasizing empathy, interpersonal communication, and adaptability to individual needs. Others rely on manual and tactile skills, requiring physical dexterity and sensitivity that are difficult to replicate mechanically. Some necessitate specialized technical knowledge and problem-solving abilities in diverse contexts. Creative and performance-based roles center on artistic expression, entertainment, or physical prowess. Lastly, certain occupations focus on the care and management of living organisms. This classification suggests that jobs seen as less susceptible to AI automation typically require a blend of complex cognitive skills, refined manual abilities, situational adaptability, and emotional intelligence—elements that current AI technologies struggle to replicate effectively. While some tasks may be automated, distinctly human characteristics like forming personal relationships, building trust, and expressing genuine empathy remain challenging to replace with AI in the short term. However, as Gmyrek et al. (2023) noted, AI's impact on these occupations may be more nuanced than initially thought. The perception of AI-resistant jobs could evolve as AI capabilities advance, highlighting the need for ongoing assessment of AI's potential influence across various professions.

How human skills develop in this evolving scenario? The Dynamic Skills Theory, developed by Kurt Fischer and colleagues (Fischer et al., 2003), provides a framework for understanding the development of human skills in a dynamic and context-dependent manner. The theory posits that the value of a person's skills can change over time as technology and the economy evolve. Skills are highly context-dependent, meaning that a person's ability to perform a skill can vary significantly based on the specific environment and circumstances. The theory integrates ideas from constructivism, emphasizing that skills are constructed through interactions with the environment and are not static entities. In this context, workers need to identify the specific skills and knowledge that are necessary to effectively incorporate AI into their work, and then deconstruct existing skills and acquire new ones to remain employable and competitive. This may imply the need to constantly educate, retrain, relearn, or learn new skills to adapt to changing market conditions and take advantage of new opportunities (Kunnen & Bosma, 2003).

Skill decay, defined as the deterioration of knowledge and skills due to lack of use or practice (Klostermann et al., 2022), is an emerging phenomenon following the introduction of new technologies into organizations. According to Arthur and Day (2020), the prolonged use of AI systems by workers has the potential to cause their skill deterioration, and this can occur in two primary modalities. First, specific skills may decline: if AI systems are designed to perform tasks previously executed by humans, the frequency of applying these skills decreases, leading to a decline in competence over time. For example, AI systems are used in manufacturing for quality control or assembly, in finance departments to analyse financial data or produce reports, and in retail for inventory management, customer service, and sales. With the introduction of AI, employees who previously performed these tasks may lose their skills because they no longer need to perform them (Coombs et al., 2020). Second, there is a limitation of opportunities for skill growth: as AI systems take over tasks previously performed by humans, workers may have fewer chances to learn and develop new skills, resulting in stagnation in their skill sets and knowledge. For instance, in customer service, AI chatbots can handle a wide range of inquiries, reducing the need for human agents to engage in problem-solving or complex customer interactions. This reduction in diverse customer interactions can limit the development of critical thinking and advanced communication skills among customer service representatives (Prentice & Nguyen, 2020)

In healthcare, AI algorithms are already outperforming radiologists at spotting malignant tumours. A recent study by Aquino and colleagues (2023) sheds light on concerns about the risk of "competency loss" among healthcare professionals due to advances in AI. By analysing qualitative and semi-structured interviews with 72 healthcare professionals with experience in AI, the authors found two opposing views on the potential impact of AI on clinical skills, such as reasoning in diagnostic and screening procedures. The "utopian view" posits that AI can improve existing clinical skills and systems, increasing the accuracy and efficiency of medical procedures and enabling healthcare professionals to focus on more complex, patient-centred aspects. In contrast, the "dystopian view" argues that AI would lead to the replacement of tasks or roles by automation, thus eroding essential clinical skills over time. In this sense, AI takes over diagnostic and procedural tasks, healthcare workers could become overly dependent on technology, resulting in a decline in their ability to perform these tasks independently (Aquino et al., 2023). These contrasting perspectives highlight the dual potential of AI: while it has the capacity to increase human competence and improve services delivery, it also presents risks to the maintenance and development of essential skills. The challenge is to integrate AI in a way that supports and enhances human competencies, rather than reducing them.

The Organisational Learning Theory (Chiva et al., 2014) can represent a comprehensive theoretical framework to identify the key organisational factors that are crucial for achieving a competitive advantage in a changing market environment based on AI integration. According to this theory, organisations can acquire and maintain knowledge and skills through a process of experimentation, reflection, and adaptation. This may involve trying out different approaches and strategies, reflecting on their experiences, and adjusting their behaviour accordingly. This process of learning through trial and error allows organisations to continually improve and evolve in response to changing circumstances and demands (Basten & Haamann, 2018).

Organisational learning theory is based on four key components (Fenwick, 2008; Koukpaki & Adams, 2020). First, "collective learning" is the process by which organisations acquire and retain knowledge and skills through the interaction and collaboration of their members through teamwork, training, and knowledge sharing Second, "reflective practise" is the process of actively reflecting on one's experiences and behaviours to learn from them and increase adaptation to changing circumstances. Third, the "organisational culture" can facilitate or hinder the learning process. Finally, organisations need "structural supports" such as training programmes, knowledge management systems, and rewards to facilitate the learning process. Understanding and effectively managing these factors can help organisations to remain competitive and successful in a rapidly changing market disrupted by the introduction of a variety of AI products and functionalities.

Artificial Intelligence and Transversal Skills

The integration of AI systems into organisations has raised awareness about the importance to identify and cultivate transversal skills in their workforce. Transversal skills, also known as transferable skills or soft skills, are those that can be applied across various tasks and industries (Hart et al., 2021). These skills include critical thinking, problem-solving, communication, and collaboration, which are essential for working effectively with AI systems. They enable workers to adapt to new technologies and processes and to continuously learn and develop in the face of rapidly changing technology.

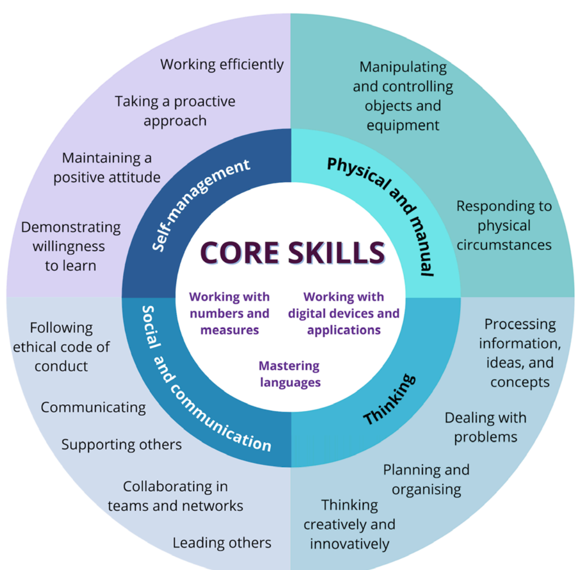

Figure 1. Graphical representation of the Transversal Skills and Competences model.
Adapted from Hart et al. (2021)

Hart and colleagues (2021) proposed a taxonomy model for Transversal Skills and Competences (TSCs) to be used at a European level. TSCs are defined as skills necessary or valuable for effective action in any kind of work, learning, or life activity. They are thus "transversal" because they are not exclusively tied to a particular context. This transversality – and the associated transferability – is seen as increasingly important (Hart et al., 2021). Transversality can be linked to what it calls "deeper learning", i.e., skills and competences that underpin and enable the more specific skills needed in, for example, a work environment. The TSC model (Figure 1) consists of five main categories: 1) core skills and competences, 2) thinking skills and competencies, 3) physical and manual skills and competencies, 4) self-management skills and competencies, 5) social and communication skills and competencies. The model facilitates the identification of relevant concepts and the relationships between them and is useful for different purposes and users from different sectors.

Core Skills

Core skills refer to the ability to understand, speak, read, and write one or more languages, work with numbers and measurements, and use digital devices and applications. They form the basis for interaction with others and development and learning as an individual.

Language skills can help employees better understand and use AI technologies. For example, many AI tools and platforms have user interfaces and documentation in English, so employees who are fluent in English are better able to navigate and use these tools (Irawan et al., 2022). In addition, employees who are comfortable with numbers and measurements can better understand and use machine learning algorithms to predict outcomes, classify data or optimise processes (Verma et al., 2022). Similarly, employees who are skilled in using digital devices and applications will be better able to manage and maintain AI systems, which often require technical knowledge and familiarity with programming languages (Allmann & Blank, 2021).

The literature provides evidence of how AI is changing the acquisition and continuous improvement of employees' "core skills and competencies". First, AI can help improve workers' language skills by providing automatic language learning tools (Chen et al., 2021). For example, some AI systems can provide personalised grammar and vocabulary courses tailored to individuals' needs by providing real-time feedback on language use and helping employees identify areas for improvement. In addition, AI-based translation tools can help bridge the communication gap between employees with different language backgrounds and help them communicate effectively (Piorkowski et al., 2021). Second, AI systems can promote the acquisition or improvement of measurement and digital skills among employees by providing access to real-time data and insights generated by AI itself (Sousa & Rocha, 2019). This data can help workers identify trends in their work, understand how their performance is affected, and develop strategies to improve their performance. In addition, AI-based platforms can provide personalised learning experiences that help workers acquire and refine digital skills (Kashive et al., 2020). This includes virtual coaching, on-demand exercises, personalised content, and automated feedback and assessment tools.

Thinking Skills

Thinking skills refer to the ability to apply the mental processes of collecting, conceptualising, analysing, summarising, and/or evaluating information obtained or generated through observation, experience, reflection, reasoning, or communication. This is reflected in the use of information of various kinds to plan activities, achieve goals, solve problems, address issues, and perform complex tasks in routine and novel ways.

Recent studies show that specific types of thinking skills may become more relevant when working with AI systems. Analytical, critical, and quick thinking enables employees to understand the data and insights generated by the AI system and use this information to make informed decisions (Delanoy & Kasztelnik, 2020; Süsse et al., 2018). AI can help organisations automate some processes, but employees still need to use their creativity to come up with new ideas, think outside the box, and solve problems that AI systems cannot. von Richthofen and colleagues (2022) found that introducing AI systems to automate repetitive tasks allows employees to focus on more complex and customer-facing tasks. This leads to employees developing problem-solving skills to effectively resolve such situations. AI systems can also be used in some phases of a complex problem-solving process (Seeber et al., 2020).

Moreover, AI's understanding of complex problems is time-dependent and dynamic, requires a lot of domain knowledge, and has no specific ground truth (Dellermann et al., 2019). This implies that employees are inherently inclined to integrate transversal skills typical of humans (i.e., intuitive and learning skills, and creative thinking) into the process to fill the gaps that AI systems bring (Xiaomei et al., 2021).

Recent discussions in the field of psychology and artificial intelligence have highlighted the distinction between explicit and tacit knowledge, which is particularly relevant when considering AI's capacity for learning and replicating human cognition. Explicit knowledge, being codifiable and transferable, is more readily accessible for AI systems to process and utilize. However, tacit knowledge, often acquired through personal experience and difficult to articulate, presents a significant challenge for AI implementation (Andrews & Smits, 2018; Oranga, 2023). While AI may excel in processing deeper, explicit knowledge, it faces considerable obstacles in replicating the higher-order cognitive functions associated with understanding, wisdom, and purpose. This underscores the importance of recognizing the current limitations of AI in fully emulating the nuanced, experiential learning processes inherent to human psychology. Consequently, the integration of human thinking skills, particularly those related to tacit knowledge and higher-order cognition, remains crucial in complementing and enhancing AI capabilities in complex problem-solving scenarios.

Self-Management Skills

Self-management skills refer to a person's ability to understand and control their strengths and limitations and to use this self-knowledge to direct activities in a variety of contexts. This is reflected in the ability to act in a reflective, responsible, and structured manner in accordance with values, to accept feedback, and to seek opportunities for personal and professional development (Hart et al., 2021).

For example, we will consider time and task management as key self-management skill for employee performance. AI systems in organisations can potentially reduce the time it takes to complete certain tasks by automating them or providing more efficient ways to complete them. AI systems can analyse and process data faster than a human. In this way, a task that would normally take several hours can be completed in a few minutes. According to Yu and colleagues (2021), effective time management includes harnessing the power of technology and using the remaining time to complete purely human tasks. This enables the employees to use their time as productively and efficiently as possible, as well as fostering the value creation process in organisations. Workers can focus on tasks requiring creativity, innovation, empathy, or other qualities that are unique to humans. By enhancing self-management skills and prompting employees to focus on tasks requiring a "human touch", organisations can potentially create more value through the development of new ideas, the provision of personalised customer service, or the creation of meaningful work experiences for employees. In this way, AI-enhanced self-management skills can be an important part of an organisation's strategy for creating value.

Artificial intelligence systems can also provide personalised suggestions and advice to employees on how to better manage their time, set goals, and prioritise tasks, helping them to manage workflows (N. Malik et al., 2021). Some AI systems can also provide performance feedback and help employees recognise their successes so they can develop their self-management skills (Tong et al., 2021). Recent evidence shows that AI systems can help employees monitor their daily activities and analyse their performance (A. Malik et al., 2022). This leads to them developing the ability to identify areas where they need to improve and take appropriate action. From an organisational perspective, this data can also be leveraged to greatly increase the quality of planning and scheduling in organisations. AI can be used to automate the scheduling of tasks, events, and resources based on various factors such as deadlines, dependencies, and resource availability or to assist with decision-making by providing recommendations or alternatives based on data analysis and predictive modelling.

A recent EU-project named TUPLES (Tuples, n.d.) is bringing together experts from different disciplines to develop AI-based hybrid planning and scheduling (P&S) tools that combine the efficiency and adaptability of data-driven approaches with the robustness and reliability of model-based methods. These tools can have a significant impact on a variety of industries and wide a range of applications such as aeroplane manufacturing, pilots' assistance, or even power-grid management and waste collection. By providing efficient, reliable, and adaptable AI tools, the TUPLES project helps individuals and organisations manage their time more effectively and efficiently. For example, in the case of aeroplane pilot assistance, P&S tools could potentially help pilots optimise their flight plans and make more informed decisions, improving the efficiency and safety of their operations. One of the main challenging aspects in AI design and implementation (Wesche et al., 2022) of this tool is "explainability", or the ability to understand and interpret the decisions and actions of an AI system. In fact, if an AI system provides clear explanations for its recommendations or actions, users may be more likely to rely on it and may be less inclined to question its decisions.

Social and Communication Skills

Social and communication skills refer to the ability to interact positively and productively with others. This is demonstrated by communicating ideas effectively and empathetically, aligning one's goals and actions with those of others, seeking solutions to disagreements, building trust, and resolving conflicts, as well as caring for the welfare and progress of others, managing activities, and offering leadership.

Effective and empathetic communication can enable employees to share information and ideas effectively with colleagues and other stakeholders. AI systems are often complex and can be difficult to understand. Effective communication can help ensure that all stakeholders are on the same page and working towards the same goals (Kalogiannidis, 2020). First, innovative AI systems can help managers and employees improve their social and communication skills by providing feedback on their online interactions, helping them identify potential communication gaps or problems, and giving them tools to improve communication (Ryan et al., 2019). Some AI systems are designed to provide employees with communication-oriented games and activities to help them practise their communication skills and change their communication strategies (Butow & Hoque, 2020).

In addition, an AI system can facilitate communication between employees and customers by providing automatic responses and intelligent support. AI can also be used to automate customer service processes using chatbots that can answer customers' questions or provide them with information. This often leads to employees being inspired by the performance of AI in effectively handling communicative interactions with customers, thereby also improving their own communication performance (Prentice & Nguyen, 2020).

Working with AI also means the need to build trust. Employees need to be able to trust that the technology is reliable and that their colleagues are working towards the same goals. This helps to create a sense of unity and collaboration within the organisation, which is essential for effective performance and competitive advantage (Ramchurn et al., 2021).

Effective leadership can help teams manage and make the best use of technology to ensure that everyone is using it as productively and efficiently as possible. This can help improve overall team performance and ensure effective organisational performance. Strong leadership skills can be critical in overcoming challenges or obstacles that may arise when working with AI and ensuring that the team remains focused and motivated despite setbacks (Frick et al., 2021). This can help ensure that the team is able to overcome new challenges and continue to make progress towards the organisation's goals.

AI systems could provide managers with real-time feedback on their performance and help them identify areas for improvement. They can also provide managers with personalised guidance and advice to help them improve their leadership skills and gain insights into team dynamics to understand better how their employees interact with each other and how to guide them in an effective communication process (Moldenhauer & Londt, 2018). Finally, AI systems can enable managers to better understand the needs and motivations of their team members, creating an environment that fosters collaboration and encourages growth.

Physical and Manual Skills

Physical and manual skills refer to the ability to perform tasks and activities that require manual dexterity, agility, and/or physical strength. They can be performed in difficult or dangerous environments that require endurance or strength. These tasks and activities may be performed by hand, with other direct physical interventions, or by using equipment, tools, or technologies that require guidance, movement, or strength, such as ICT devices, machines, hand tools, or musical instruments.

Recent studies have highlighted several reasons why employees should enhance their physical and manual skills in the era of AI integration. Firstly, improved physical and manual skills can significantly boost efficiency when working with AI tools. Haslgrübler and colleagues (2019) found that employees with advanced hardware and software proficiency or superior hand-eye coordination utilize AI tools more effectively. Additionally, Niehaus et al. (2022) highlighted that as AI often involves interaction with physical systems like robots or automated machinery, enhanced physical and manual skills are crucial for ensuring workplace safety and preventing accidents or injuries. Lastly, developing these skills increases adaptability to new technologies and evolving work environments. Wamba-Taguimdje et al. (2020) revealed that workers who are adept at handling various types of equipment are better positioned to adapt to new AI technologies as they are introduced in the workplace. Thus, the improvement of physical and manual skills remains vital in complementing and effectively leveraging AI technologies in the modern workplace.

There is some evidence in the literature about the impact of AI on workers' physical and manual skills. For example, according to Parker and Grote (2022), AI tools can automate some tasks that require physical and manual skills, allowing workers to focus on more complex and demanding tasks. This can help workers improve their skills in more valuable areas of the business and increase their overall productivity. In addition, AI tools can also improve the accuracy and precision of physical and manual tasks, helping employees to work more efficiently and effectively. AI-controlled robots and machines, for example, can be programmed to perform tasks with a high degree of accuracy and repeatability, reducing the risk of error and improving overall quality (Tong et al., 2021). Lastly, AI systems can be used to provide employees with targeted training and development programmes to help them improve their physical and manual skills. For example, employees can use simulations or virtual reality programmes to practice and improve their skills in a safe and controlled environment (X. Li et al., 2018).

Table 1 outlines the opportunities and limitations of using AI to acquire or improve Transversal Skills and Competencies (TSC). It categorizes TSC based on the model we described. For each specific skill within these categories, the table presents potential opportunities for skill development, such as personalized learning tools and AI-powered assistants. It also highlights limitations, including risks of over-reliance on AI, potential loss of fundamental skills, and the inability of AI to fully replicate human aspects like empathy or creativity.

Table 1. Opportunities and limitation of the use of AI in Transversal Skills and Competences

Transversal Skills and Competencies (TSC)		*Opportunities and limitations of the use of AI in the acquisition or improvement of the TSC*
Core skills	Working with numbers and measures	Opportunities: AI-powered calculators and data analysis tools; adaptive learning systems for STEM education; visualization tools for complex numerical concepts. Limitations: may reduce mental math abilities if overused; over-reliance on AI for basic calculations.
	Working with digital devices and applications	Opportunities: personalized tutorials and guides; predictive text and autocomplete features Limitations: constant upskilling due to rapid changes in AI technologies; privacy concerns tracking user behavior.
	Mastering languages	Opportunities: AI-powered language learning apps with personalized lessons; real-time translation and interpretation tool. Limitations: not capturing cultural nuances and context; risk of over-reliance on translation tools instead of true language mastery.
Thinking skills	Processing information, ideas, and concepts	Opportunities: mind mapping and concept visualization tools; intelligent summarization of complex texts. Limitations: potential for AI bias in information processing; risk of reducing critical thinking if AI is relied upon too heavily.
	Dealing with problems	Opportunities: simulation tools for problem-solving practice; AI-powered decision support systems. Limitations: not accounting for unique or unprecedented problems; risk of becoming dependent.
	Planning and organizing	Opportunities: AI-powered project management tools; smart scheduling assistants; predictive analytics for resource allocation. Limitations: not accounting for human factors and unexpected changes; loss of organization skills if over-relied upon.
	Thinking creatively and innovatively	Opportunities: genAI for exploring new design possibilities; collaborative AI systems for brainstorming. Limitations: risk of homogenizing creative output; stifle unique human creativity if overused.
Self-management skills	Working efficiently	Opportunities: productivity trackers and analytic; task prioritization systems; automated routine task handling. Limitations: pressure to constantly optimize and quantify work; loss of personal time management skills.
	Taking a proactive approach	Opportunities: trend analysis and forecasting tools; intelligent reminders and nudges. Limitations: reduction of intrinsic motivation if external prompts are overused.
	Maintaining a positive attitude	Opportunities: positive affirmation and mindfulness tools. Limitations: risk of replacing genuine human support and connection.
	Demonstrating willingness to learn	Opportunities: Adaptive learning systems that adjust to individual progress; gamification elements to increase engagement. Limitations: risk of reducing intrinsic motivation for learning.
Social and communication skills	Following ethical code of conduct	Opportunities: Automated checks for bias and ethical considerations in decision-making. Limitations: not grasping complex ethical nuances; risk of oversimplifying ethical decision-making.
	Communicating	Opportunities: writing assistants for clear and effective communication; real-time speech analysis. Limitations: not capturing subtle human communication cues and context; risk of over-reliance.
	Supporting others	Opportunities: coaching and mentoring systems. Limitations: lack ok genuine human empathy and connection; risk of depersonalizing social support.
	Collaborating in teams and networks	Opportunities: collaboration platforms with smart features; automated coordination and task distribution. Limitations: risk of reducing face-to-face collaboration skills.
	Leading others	Opportunities: systems for team performance analysis; automated feedback collection and analysis. Limitations: impossibility to replicate human inspiration and charisma; risk of data-driven decisions in leadership.
Physical and manual skills	Manipulating and controlling objects and equipment	Opportunities: simulation and training systems (e.g., augmented reality). Limitations: may not replace hands-on physical practice; not accounting for individual physical differences and limitations.
	Responding to physical circumstances	Opportunities: situational awareness training (e.g., virtual reality simulations). Limitations: lack of preparation for unpredictable real-world scenarios; risk of over-reliance on technology in critical situations.

The Dual Nature of AI's Impact on Workers' Skills

The incorporation of AI into the workplace can provide opportunities for workers to acquire and develop a wide range of skills (i.e., transversal skills). However, it is important to recognise that there might be a "dark side" of AI when applied uncritically, so there are pitfalls and shortcomings to pay attention to. For instance, individual workers may approach learning and development processes with different attitudes and motivations, and may have varying mental models towards the changes expected using AI at work. Moreover, there might be differences in experiencing AI based on personal disadvantages or socioeconomic challenges. For example, Smith and Smith (2021) provide first-hand empirical evidence on how AI technology can assist and frustrate the lives of disabled people, both at the same time. In general, artificial intelligence is not always exempt from bias - such as ethnicity-based or gender-based (e.g., Ntoutsi et al., 2020). Suppose that organisations do not take these elements and differences into consideration, thus applying AI-based skill development strategies without regard for the vulnerabilities and needs of their workforce. In that case, these strategies may exacerbate existing inequalities within the organisation and society at large. Therefore, organisations must carefully consider the impact of AI on learning and development, ensuring that any implemented strategy considers the diverse needs and perspectives of their workforce (Zajko, 2022). AI should be thoughtfully implemented and consciously managed to provide every worker with equal opportunities for learning and development of their set of skills. Awareness of such a dual nature of the impact of AI on workers' skills might help managers and organisations execute sustainable AI deployment programs in their workplaces.

Although AI systems can bring many benefits to the workplace, it is important to recognise that their use does not automatically lead to a systematic improvement in employees' skills. The use of AI in the workplace may enhance workers' skills but, if not properly managed, it may also limit work pacing and reduce employees' autonomy (Alsheibani et al., 2019; Bérubé et al., 2021; Nylin et al., 2022). In other words, poorly implemented AI in the workplace can create performance constraints (e.g., need to troubleshoot the AI). This, in turn, might create a non-favourable environment to acquire employees' job-relevant skills, causing delays in this process. Indeed, AI in the workplace introduces increased complexity and more need for interaction and adaptability.

Moreover, the impact of AI varies according to the skill level of the job. For example, Holm and Lorenz (2022) found that using AI to support decision-making in high-skill jobs can lead to less autonomy but also a faster pace of work, less monotony, more learning, and greater use of a range of high-performance work practices. In middle-skilled jobs, the impact of decision-making AI systems on work is similar (albeit to a lesser extent), while using AI to give instructions leads to a faster work pacing, greater autonomy, and less learning. For low-skilled jobs, using AI to make decisions has no impact on work, while using AI to give instructions increases work pacing. These findings highlight the complexity of the relationship between AI introduction and workers' skills, as well as the need to consider the specific context and skill level of the job when implementing AI systems. Therefore, it is important to assess not only whether AI can promote the development of workers' skills, but also the organizational configurations that optimize its use and the reasons why it is effective. This includes identifying the moderating and mediating factors that can facilitate the effective introduction of AI in the workplace.

UPSKILLING AND RESKILLING IN ORGANISATIONS

"Upskilling" and "reskilling" are the processes that develop and retrain employees' skills. Even though they are similar concepts, in that they both involve learning new skills, there is a key difference between the two. The term "upskilling" typically refers to the process of improving existing skills that are directly relevant to an employee's current job or industry. The aim of upskilling is either to advance one's career or to become more effective in the current position (Moore et al., 2020). "Reskilling", on the other hand, involves learning completely new skills outside one's current field. The aim of reskilling is usually to move an employee to another occupation or industry (Sawant et al., 2022).

Upskilling employees can help organisations to foster a culture of continuous learning and development. While improving work engagement and employees' motivation, it also supports organisations in attracting and retaining top talent. In addition, a culture of continuous learning and development can help organisations to adapt to changing business needs and to remain competitive in a rapidly evolving business environment (Cukier, 2020). Not surprisingly, academics point to rising turnover rates and unemployment as AI takes over mundane tasks previously done by humans. Although a technological revolution may be imminent, its scale and timeframe are currently unknown. In an increasingly competitive labour market, strong transversal skills can help aspiring workers stand out from other applicants and become more attractive to potential employers (Avanzo et al., 2015). Therefore, in the coming era, people will need to upskill appropriate capabilities for newly defined jobs and work closely with AI technologies to thrive in their employment (Jaiswal et al., 2022).

Reskilling is an important process for organisations that introduce AI systems, as it can support employees adapting to technology-related changes. According to Makarius et al. (2020), reskilling helps employees develop the knowledge and skills they need to work effectively with the technology - but in a new role. This includes training in areas such as data analytics, machine learning, and programming. Reskilling can help organisations to improve their overall competitiveness, as employees with the right skills are better equipped to drive innovation and create value for the company (L. Li, 2022). Therefore, reskilling can cushion the negative impact of AI on the workforce. For example, some employees may be concerned that the introduction of AI threatens their job security (Bhargava et al., 2021). Reskilling can help alleviate these concerns, adjust their mental models towards the use of AI at work, and ultimately provide employees with the skills they need to take on new roles or responsibilities within the organisation. Reskilling can also help organisations retain their top talent, as employees who feel they are not offered opportunities for career growth are more likely to switch companies (Tenakwah, 2021).

As the introduction of AI into the workplace keeps transforming the nature of work and the skills required to perform it, it is increasingly important for both workers and organisations to address the gap between their current skillset and the necessary skills to navigate these changes successfully. Identifying and understanding this skill gap is a crucial first step in developing effective strategies for upskilling and reskilling the workforce. Organisations can then develop strategies to bridge the identified skill gap, ensuring that employees have the necessary skillset to use AI effectively. This ensures that all workers can benefit from the advantages of AI (Kar et al., 2020).

SKILL GAP ANALYSIS

There are several ways in which organisations can assess the skill gap within their workforce. It is crucial to consider both external factors (such as industry trends and market demands) and the specific capabilities of adopted AI systems to identify the skills needed to effectively leverage AI in organisations. Skill gap analysis is a technique that helps organisations achieve such objective. A skill gap analysis is a process used to identify the skills that are needed in a specific job or industry, comparing them to the skills that are currently possessed by workers in that field (Hay, 2003; Reich et al., 2002). This analysis can identify discrepancies between the skills required for a job and the skills that workers currently have, helping organisations make informed decisions on employees' training and development. By identifying skill gaps, organisations can easily tailor training programs to address specific needs, while individuals can target their own learning and development efforts to improve their job performance, ultimately advancing their careers.

Several methods can be used to conduct a skill gap analysis. Some common methods include (1) surveying workers and managers to gather information about the skills that are needed in a specific job or industry, as well as the skills that workers currently have, (2) analysing job postings and job descriptions to identify the skills and qualifications that are most frequently mentioned, (3) conducting focus groups or interviews with workers and managers to gather more detailed information about the skills that are needed in a specific job or industry, and (4) comparing the results of the analysis to industry standards or benchmarks to determine the extent of any skill gap.

A study conducted by McGuinness and Ortiz (2016) aimed to identify the key factors that determined the correct identification of skill gaps in an Irish company. The skill gaps were identified by disseminating a survey to managers and workers of the company. By cross-referencing the data, the level of agreement in the perception of skill gaps within the organisation was assessed, measuring their impact on firm-level performance. Based on average responses, the areas with the most severe skill gaps were identified (i.e., information technology and communications, technology, and management). The analyses and results support the added value of the skill gaps identification methodology, as well as the importance of upgrading and retraining in areas that can be improved for business performance.

In a 2019 study, Aiswarya and colleagues used interviews and focus groups to conduct a skill gap analysis among trainers and managers from three training institutions in the Indian state of Kerala. Eight core competencies were identified for intervention to improve trainers' performance: communication skills, subject knowledge, professionalism, programme planning and implementation, leadership skills, resource mobilisation, ICT, and management skills. These results enabled the planning and implementation of tailored training programs, allowing trainers and managers to bridge gaps in corresponding transversal skills, and to improve their work performance.

A skill gap analysis conducted in the EU project FIT4FoF (www.fit4fof.eu) identified over 100 new job profiles across six technological areas, including data analytics, cybersecurity, collaborative robotics, and human-machine integration. This analysis addressed new job market scenarios in advanced manufacturing. Examples of these new roles include Robotics Technicians, who install, maintain, and program industrial robots and automated systems, and Human-Machine Interaction Designers, who develop intuitive user interfaces and interactions for AI systems.

MEASURES FOR UPSKILLING AND RESKILLING

Establishing innovative methodologies is crucial to implement new skills and minimise skill gaps. In other words, once the need for skills has been defined, a long-term plan and methodology should be implemented to develop new skills and minimise the gaps between organisations and its current workforce. This should include tools that provide solutions for attracting new talent, organised training programs for current workers, and redesign of work processes. Several training and development solutions are available to support and guide upskilling and reskilling of workforce skillsets (Ceschi et al., 2022).

ADDIE MODEL OF TRAINING.

Skill, knowledge, and performance gaps can be bridged by designing meaningful training programs with tools like ADDIE (J. Li, 2016). One of the most used methods to develop new training programmes is called Instructional Systems Design (ISD). There are several ISD models, but most are represented by the acronym ADDIE (Analysis, Design, Development, Implementation and Evaluation). Each letter represents a phase, ordered in a logical sequence to ensure a practical approach to training programme design. A study conducted by Guevarra and colleagues (2021) showed the development of a training programme based on the ADDIE model that aimed to improve health workers' decision-making skills in evaluating data generated by technological tools. The programme involved 128 Filipino public health workers who were asked to rate the clarity and relevance of the objectives, the discussion of the topics, the methods of delivery and the time spent on addressing the topics. By comparing participants' ratings with follow-up data showing improvement in their decision-making capacity, the results demonstrated the value and reliability of the ADDIE model in developing a training programme to improve staff capacity.

TRAINING FOR SKILFUL HUMAN-AI TEAMING

In some sectors, for example healthcare, the adoption and scale-up of artificial intelligence can help alleviate the shortage of human resources. AI has transformed some areas, such as patient care, administrative tasks, and clinical decisions. Rizvi and Zaheer (2022) analysed how healthcare professionals can be trained to provide services supported by AI. In healthcare, AI can reduce human errors due to human fatigue, support and replace labour-intensive tasks, minimise invasive surgeries, and reduce mortality rates. There is an urgent need to train healthcare professionals, leading to skilful interactions between medicine and machines.

In the IT sector, hackathons are adopted to facilitate education by offering participants the opportunity to learn new skills and technologies. Hackathons can facilitate both upskilling and reskilling by providing participants with the opportunity to learn new skills and knowledge, applying them in a real-world setting (Medina Angarita & Nolte, 2020). A hackathon is an event where people work together on a project over a relatively short period of time. Participants often work in teams at hackathons, allowing them to learn from each other and share their expertise. This kind of collaborative learning environment can help to understand how to work in teams with AI tools and systems.

LIFELONG LEARNING AND "HANDS-ON" LEARNING MODULES

Industry 4.0 systems and related technologies are widely adopted due to the efficient implementation of lifelong learning and training initiatives addressing upskilling and reskilling challenges. Oliveira and colleagues (2022) propose hands-on learning modules for upskilling in industry 4.0 technologies. The authors describe the implementation of a series of short learning modules relying on solid hands-on practical experimentation on upskilling in emergent ICT technologies. Feedback from participants shows that these short hands-on learning modules strongly contribute to qualifying the workforce and undergraduate students in emergent ICT.

Quality Circles

Since employee training and development is of great interest to organisations, the design of a Future of Work programme should focus on the company's offer to its employees (Ellingrud et al., 2020). Organisations need to develop clear and compelling value propositions so that employees see the benefits of acquiring new skills to use AI systems. As Japanese companies have traditionally emphasised lifelong employment, they have created a valuable culture of training programmes for their employees. One of the most well-known programs is the Quality Circle, which can be successfully used for employees' AI-related upskilling and reskilling. This programme aims to involve employees in decision-making, leading the company towards a more participatory culture, and trains employees to think critically, fostering problem-solving skills when performing AI-based tasks at work. The circles usually meet four hours a month during working hours. A team leader, who is usually a trained member of the management team, helps train the circle members and ensures that everything runs smoothly. Members receive recognition when their suggestions for improving production are accepted (Lawler et al., 1984).

Costs and Benefits of Upskilling and Reskilling

The ability of AI systems to perform certain tasks more efficiently or accurately than humans can lead to skill mismatches among workers. Skill mismatch means that some workers' skills are not fully utilised or are utilised in a way that does not match their strengths (Brunello & Wruuck, 2019). To mitigate this problem, upskilling and reskilling processes seem to be crucial for training and supporting employees (Giabelli et al., 2021). However, like any major change, implementing these processes comes with costs and benefits for both organisations and employees. According to a report by the European Centre for the Development of Vocational Training (Cedefop, 2020), there are 128 million adults in the EU-28 Member States, Iceland and Norway (hereafter referred to as EU-28+) with the potential for upskilling and reskilling (46.1% of the adult population). The return on investment in upskilling and reskilling can be significant, with estimates ranging from 10% to 30% depending on the sector and the specific interventions implemented (Cedefop, 2020). This suggests that, despite the costs involved, investing in the upskilling and reskilling of workers can bring about significant benefits for both workers and organisations in the EU.

Recent studies have highlighted the main benefits of upskilling and reskilling for individuals and organisations that face skill mismatch. First, they increase productivity: by providing their employees with needed skills to do their jobs effectively, companies can increase the efficiency of their workforce (Zapata-Cantú, 2022). Second, they foster competitiveness: upskilling and reskilling can help organisations remain competitive by ensuring that they have a skilled and adaptable workforce that can meet the changing needs of the business (Ponce Del Castillo, 2018). Thirdly, they improve employee satisfaction: by allowing their employees to learn and develop, organisations increase their job satisfaction and engagement, which can lead to better retention and lower turnover (Lee et al., 2022).

However, implementing upskilling and reskilling programmes can require a significant investment in terms of time and resources. According to Abe and colleagues (2021), these processes are primarily associated with financial costs: upskilling and reskilling can be costly for the organisation, especially if it has to hire external trainers, pay for training materials, or pay employees to attend courses and workshops. In addition, upskilling and reskilling involve time costs: employees may have to be absent from work to attend training, causing interruptions to business, reduced productivity, and possible delays in completing tasks (Hiremath et al., 2021). Finally, organisations need to know how to invest resources to overcome resistance to change. Some employees may resist upskilling and reskilling measures because they are sceptical about the value of training or because they are reluctant to learn new skills. This may lead to resistance to change and, possibly, lower participation (Aguiar et al., 2022).

Overall, the benefits of training can outweigh the costs, especially if programmes are well-designed and effectively implemented. When companies invest in workforce development, they can create a more adaptable and skilled workforce that is better equipped to meet the challenges and opportunities of the future. Table 2 outlines the main costs and benefits for organizations planning to implement up-skilling and reskilling interventions, along with some examples related to these efforts.

Table 2. Costs and benefits of upskilling and reskilling for organisations

	Examples of programs	Benefits	Costs
Upskilling	Food producers in small businesses learning to use AI for quality control; Customer service reps training to use AI chatbots alongside their work.	-Improved efficiency and productivity through augmented work processes -Increased employee value in an AI-integrated workplace	-Investment in AI-specific training programs and courses (e.g. A literacy courses) -Time spent by employees learning new tools
Reskilling	Administrative assistants transitioning to AI systems manager; Manufacturing workers retraining to maintain and oversee an AI robotic systems.	-Creation of high-value roles within the organization -Improved organizational adaptability -rPotential for innovative applications	-Time and financial investment -Potential loss of traditional skill sets as employees fully transition -Risk of skill mismatch if AI adoption does not progress as anticipated

CHALLENGES FOR UPSKILLING AND RESKILLING

Are skills a panacea? Not always. Upskilling and reskilling can be difficult or counterproductive for a variety of reasons. It can be challenging for workers to find the time and resources to learn new skills, particularly if they are working full-time and have other responsibilities. Some workers may be resistant to change or may not see the value in learning new skills, which can make upskilling and reskilling efforts difficult. If there are limited opportunities for workers to advance their careers or use their new skills, they may be less motivated to invest in upskilling and reskilling. If the skills that workers are learning do not align with the needs of the organisation, upskilling and reskilling efforts may be counterproductive (Hammer & Karmakar, 2021). Without adequate support from the organisation, including training, resources, and support for learning, upskilling and reskilling efforts may be difficult or unsuccessful. Therefore, to be effective, upskilling and reskilling efforts must be well-planned and well-supported by both the organisation and the individuals involved.

At a broader level, countries with poor education and structures may be reluctant to invest in up-skilling and reskilling. To address the challenges and opportunities of AI, skills have been identified as key in their national strategies. Yet, little attention is paid to the underlying social relations of production in which the practises of skills development occur, which is crucial for understanding the outcome of skills policies and practices (Hammer & Karmakar, 2021; Petersen et al., 2022). Up-skilling and reskilling might be difficult in some countries with poor education, with firms' reluctance to invest in training, and with people relying on informal skilling (Hammer & Karmakar, 2021; Ramaswamy, 2018). In developing countries, access to education and skilling is difficult and does not translate into employment opportunities. In this context, except for a few highly skilled workers in the automotive and IT sectors, the inability of most workers to access skills development initiatives, as well as the lack of recognition of informally gained skills, are likely to be persistent challenges for upskilling and reskilling. Organisations need to find strategies to reverse these trends.

Hammer and Karmakar (2021) point out that the adoption of new technologies can be uneven and inconsistent. It may improve employment conditions for some workers but could not change employment conditions for the majority. Public policies are needed to ensure that emerging technologies are used responsibly to complement rather than replace labour, which would have negative distributional effects. Public sector investment in skills initiatives is much lower in developing countries like

India than in developed countries like Germany. India has tried to change this through public-private partnerships in Industrial Training Institutes and industry-led vocational training programmes. In Europe, governments are working with technology companies to solve employment problems and fill skill gaps, as the skill demand will change in the near future for different occupations. European policies aim to foster a national skills ecosystem for emerging digital technologies.

In addition, the impact of technology on the labour market has the potential to disproportionately affect different groups of workers, including men and women belonging to different age groups. A gender-sensitive approach to upskilling and reskilling workers is necessary to ensure that both men and women can benefit from technological advances and to prevent further gender inequalities in the labour market. In this context, it is important to consider the different needs and challenges of men and women, as well as the potential impact of these programmes on gender equality in the workplace when designing training and retraining programmes.

The digital divide in access to technology and the internet can negatively affect reskilling. There is a significant gender-related digital divide in access to technology and the internet, which has a negative impact on skills development initiatives. Women's access to digital technologies is likely to increase as the affordability of internet services and devices decreases. In those countries where gender inequality is particularly pronounced, low levels of literacy, education, and skills are likely to prevent women and other socially disadvantaged groups from leveraging new technologies. The number of jobs requiring extensive knowledge in science, technology, engineering, and mathematics has increased over the last decade, and advances in AI will require even more expertise in STEM. According to Billionniere and Rahman (2022), it is important to build capacity and widen participation in computing through training women with the emerging technology gateway. A gender-sensitive approach to upskilling and reskilling requires a comprehensive understanding of how existing gender inequalities in the labour market are exacerbated or mitigated by technological change. That means ensuring that both men and women can benefit from technological progress and contribute to the future of work.

The age-related digital divide can also have significant implications for the way individuals are able to perform their jobs and for both upskilling and reskilling. Older individuals who lack proficiency in using new technologies may be at a disadvantage when it comes to finding and maintaining employment, as many jobs now require mastering digital skills. This can lead to age discrimination in the workplace and contribute to age-related inequalities in employment and income (Truxillo et al., 2015). In addition, the age-related digital divide can impact organisational performance and productivity. Organisations that do not invest in supporting older workers to use new technologies may miss out on the valuable knowledge, experience, and perspective that these employees bring to the workplace. This can result in a missed opportunity for organisations to benefit from the diversity of their workforce and may lead to a less inclusive and innovative work environment. Therefore, organisations need to consider the age-related digital divide and take steps to support the adoption of new technologies by all employees, regardless of age. This can include providing training and resources, offering flexible work arrangements, and promoting a culture of inclusivity and continuous learning. In a systematic review, Longoria and colleagues (2022) highlight the importance of considering inclusive and accessible ICTs design in engineering and design programs. Addressing ICTs design with a diverse approach might foster students' innovation capabilities and sensibility towards vulnerable populations throughout the design process. There are plenty of possibilities to bridge this gap using technology as a responsive, empathetic, and learning tool to address the age-related digital divide, ultimately enhancing workers' skills to maximise organisational performance and productivity.

CONCLUSIONS

AI is a complex and multifaceted field that encompasses a wide range of disciplines, including computer science, mathematics, engineering, behavioural, and social sciences. A transdisciplinary approach allows for the integration of knowledge and perspectives from different fields, which is essential for understanding the full range of implications and applications of AI. With its interdisciplinary approach, this paper joins the ongoing discourse on the extent to which the implementation of AI systems in organisations has - and will continue to have - an impact on the nature of work in the coming decade. A thorough and critical examination of the literature has revealed that AI has the capacity to augment and to disrupt existing work practices and processes. From this perspective, the findings highlight the importance of considering both individual and organisational factors when introducing AI into organisations. In particular, the focus should be on upskilling and reskilling employees because AI is increasingly able to take over tasks previously performed by human workers, as predicted by AI Job Replacement Theory and demonstrated by recent developments in AI.

The importance of investing in human capital is a crucial aspect to successfully integrate AI into companies and maximise its potential benefits for organisations and employees. The adaptation process involves and combines several organisational strategies. Firstly, capturing the soft skills needed by workers is critical to address the current skill gap in the workplace. Organisations can then help workers identify the skills needed for AI adoption and develop new skills. Then, organisations need to provide training and development opportunities, ensuring that workers' attitudes and mental models towards AI are open and prepared for the challenges of the evolving labour market.

As with all major changes, the transition to new organisational models comes with both costs and benefits and requires careful consideration of individual factors such as the gender gap, age differences, and cultural diversity. The benefits outweigh the costs if programmes are designed with these factors in mind and implemented effectively. Therefore, one of the most pressing challenges for organisations is to guide employees through the transition to Industry 5.0 by considering the cost of training and ensuring equality and inclusion for all, regardless of age, gender, and cultural diversity.

Given the evidence from the literature, we believe that a transdisciplinary approach to enhancing AI skills and retraining workers can provide a more comprehensive and nuanced understanding of the potential impact of AI on the future of work and society, helping to ensure that the benefits of AI are shared equitably across all stakeholders. Hence, practitioners and stakeholders need to invest in upskilling and reskilling workers, as these processes will likely create a more adaptable and skilled workforce that can meet the challenges and opportunities of the future.

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