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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 aims to investigate the recent developments in research and practice on the transformation of professional skills by artificial intelligence (AI) and to identify solutions to the challenges that arise.
Background	The implementation of AI in various organisational sectors has the potential to automate tasks that are currently performed by humans or to reduce cognitive workload. While this can lead to increased productivity and efficiency, these rapid changes have significant implications for organisations and workers, as AI can also be perceived as leading to job losses. Successfully adapting to this transformation will lead companies and institutions to new working and organisational models, which requires implementing measures and strategies to upskill or reskill workers. Organisations, therefore, face considerable challenges such as

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guiding employees towards the change process, dealing with the cost of training, and ensuring fairness and inclusion posed by age, gender, and cultural diversity.

Methodology: A narrative review has been conducted to analyse research and practice on the impact of AI on human skills in organisations.

Contribution: This work contributes to the body of knowledge by examining recent trends in research and practice on how AI will transform professional skills and workplaces, highlighting the crucial role played by transversal skills and identifying strategies that can support organisations and guide workers toward the upskilling and reskilling challenges.

Findings: This work found that introducing AI in organisations combines many organisational strategies simultaneously. First, it is critical to map the transversal skills needed by workers to mitigate the current skills gap within the workplace. Secondly, organisations can help workers identify the skills required for AI adoption, improve current skills, and develop new skills. In addition, the findings show that companies need to implement processes to support workers by providing ad hoc training and development opportunities to ensure that workers' attitudes and mental models towards AI are open and ready for the changing labour market and its related challenges.

Recommendations for Practitioners: Practitioners should identify the skills needed for the adoption of AI and provide training and development opportunities to ensure their workers are prepared for the changing labour market.

Recommendations for Researchers: AI is a complex and multifaceted field that encompasses a wide range of disciplines, including computer science, mathematics, engineering, and behavioural and social sciences. Researchers should take a transdisciplinary approach to enable the integration of knowledge and perspectives from different fields that are essential to understanding the full range of implications and applications of AI.

Impact on Society: As AI continues to revolutionize various sectors and industries, it is important to consider the perspectives and needs of different stakeholders, such as employees, employers, and policy makers. Our findings suggest that investing in upskilling and reskilling workers may help to ensure that the benefits of AI are shared equally among all stakeholders.

Future Research: Further research is needed to understand the impact of AI on human skills and the role of soft skills in the adoption of AI in organisations. Future studies should also consider the challenges presented by Industry 5.0, which is likely to involve the integration of new technologies and automation on an even greater scale.

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

INTRODUCTION

The use of technology, particularly Artificial Intelligence (AI), significantly impacts the global economy, 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 new advances in algorithmic machine learning and autonomous decision-making will enable organisations to innovate further and optimise processes through automation.

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, referred to as Industry 4.0. As examples of AI systems in some of the aforementioned fields, we can mention PathAI, a tool that helps doctors diagnose cancer accurately, or the various customer service chatbots, tools that leverage natural language processing (NLP) to simulate human-like conversations and quickly 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 displacement. Before 2030, it is estimated that 375 million people (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 mid-range 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 (WEF), 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 (WEF, 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 will identify 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 (AI) and to identify solutions to the challenges that arise. 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 and how AI can help workers improve and develop key skills. 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.

The present study suggests several contributions. First, it examines recent trends in research and practice on how AI will transform professional skills and workplaces. Second, it identifies strategies that can support organisations and workers to face the challenges due to upskilling and reskilling proclivities. Third, it provides recommendations for practitioners to identify the skills needed for the adoption of AI, ultimately to tailor training and development opportunities to the changing labour market. Fourth, it stresses the importance of taking a transdisciplinary approach to generate valuable knowledge in the AI-field, as well as the role of psychology in understanding the complete applications of AI and its impact on society. Finally, it provides suggestions for future research opportunities according to the identified labour market trends.

RECENT DEVELOPMENTS IN AI AND HUMAN SKILLS

There have been numerous 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 and AI to understand and mimic human interaction with computer systems (Butler, 2016; Jaiswal et al., 2022).

A major game-changer is "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 reasoning, 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). By recognising certain keywords and providing answers based on them, these systems can be creative in their responses and challenge the user like a human could.

AI systems that generate images from text descriptions (e.g., DALL-E 2), 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 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.

AI is also crucial to lead the way to the so-called "Industry 5.0". Industry 5.0 refers to the current trend of automation and data exchange in manufacturing technologies, including the Internet of Things (IoT), AI, and cyber-physical systems. 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, to realise these benefits, it will be necessary to address legal, psychological, and ethical issues at the managerial level. It is also fundamental to highlight the importance of positive externalities, such as increased 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, as well as implementing 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 that they are treated fairly and have opportunities to grow and advance in their careers.

Finally, Artificial General Intelligence (AGI) is a form of AI that has the ability to perform any intellectual task that a human can, including tasks that require general knowledge and problem-solving abilities. It has been suggested that the development of AGI will bring about significant changes in organisational processes and outcomes and may surpass human intelligence. AGI could have a significant impact on human skills in organisations, either by automating tasks currently requiring human intelligence and problem-solving abilities and the need for workers to acquire new skills or retrain for different roles, or by augmenting human intelligence and problem-solving abilities, leading to increased productivity and efficiency, as well as the opportunity for workers to focus on more complex tasks requiring higher-level thinking. Organisations should consider the potential impact of AGI on human skills as they adopt and integrate these technologies into their operations.

THEORIES AND APPROACHES

There are various theories and approaches that seek to explain the impact of artificial intelligence (AI) on human skills in organisations. One of the most popular approaches foresees a positive change brought about by the introduction of AI, in which human capabilities are enhanced and lead to increased productivity and efficiency. According to the Technology-Mediated Learning Theory (Bower, 2019; Gupta & Bostrom, 2009), people learn best when they have access to a range of resources and tools that help them understand and process information. 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. In that sense, AI 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. This can lead to the development of new skills and the optimisation of existing skills, enabling workers to be more productive and innovative. Despite the justified enthusiasm shown by this theory regarding the positive impact of AI on human capabilities in organisations, it 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.

On the opposite side, another approach considers AI as a replacement for certain tasks that will lead to job displacement (Georgieff & Hyee, 2022). 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. However, there is also a growing consensus around the idea that adopting AI may create new jobs in different sectors, especially in those focused on the development and implementation of AI technology. Furthermore, 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.

A more recent theory that can be seen as a combination of the different approaches is the "AI Job Replacement Theory", developed by Huang and Rust in 2018. The authors argue that the impact of artificial intelligence (AI) on employment is reshaping jobs and can be both a source of innovation and a threat. 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).

Even if the scope of these tasks and the intelligence required can vary from job to job, as AI has pushed back mechanical labour, humans will need to focus on tasks that AI is unlikely to take on, namely those that require "thinking" and "feeling" skills (Huang & Rust, 2018; Huang et al., 2019). Therefore, companies' growth in the near future will hinge on the employees' ability to upskill and retool, leading employees not to lose jobs but rather to have different assigned tasks relying more on "feeling skills" (Strack et al., 2021). However, some authors have recently argued that even "thinking skills" do not protect service workers from replacement by artificial intelligence (Vorobeva et al., 2022).

Despite this theory's great resonance in the scientific community, 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.

Some theories can explain how organisations can effectively utilise AI by redefining or reconfiguring the skill set of their employees. The Dynamic Skills Theory (Fischer et al., 2003) posits that the value of a person's skills can change over time as technology and the economy evolve. While AI experts relentlessly develop and train machine learning algorithms to mimic human skills, workers should be able 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, re-learn, or learn new skills to adapt to changing market conditions and take advantage of new opportunities. Dynamic Skills Theory views skills development as a network of context-specific and outcome-oriented activities (Kunnen & Bosma, 2003). At a time when organisations are being disrupted by the introduction of new and changing AI systems, workers need to master different skills (social, emotional, technological, and physical) to perform well and remain competitive in the labour market and avoid losing their expertise. At the same time, organisations need to adapt and learn to acquire and retain the knowledge and skills necessary to remain competitive in a changing market.

Various theoretical frameworks have been proposed to explain the phenomenon of skill decay and skill retention following the introduction of novel technology (Arthur & Day, 2020). Skill decay is generally described as the deterioration of knowledge and abilities due to a lack of utilisation or practice. AI systems can cause skill decay in two modalities. First, decreased usage of specific skills: if AI systems are designed to fulfil tasks which were formerly conducted by humans, these individuals may no longer require to apply these skills as frequently, and this can result in a decrease in their proficiency in those skills over time. Second, limited chances for skill growth: if AI systems are tackling tasks which were previously done by humans, there may be fewer chances for those workers to learn and develop new skills, and this can lead to stagnation in their skills and knowledge.

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). Therefore, skill decay needs to be prevented by providing training and development opportunities, and this can include on-the-job training, as well as more formal education and training programs.

Another example is in healthcare, where AI can perform better than humans at key healthcare tasks – such as diagnosing diseases. 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" was that AI could improve existing clinical skills and systems, while the "dystopian view" was that AI would lead to the replacement of tasks or roles with automation.

From an organisational perspective, the Organisational Learning Theory (Chiva et al., 2014) can identify the key organisational factors that are crucial for achieving a competitive advantage in a changing market environment. 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. 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 (Fenwick, 2008). Second, "reflective practise" is the process of actively reflecting on one's experiences and behaviours in order to learn from them and increase adaptation to changing circumstances (Koukpaki & Adams, 2020). 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.

In addition to being important for working with AI systems, transversal skills can also be developed and improved with AI. By automating certain tasks and processes, AI can free up staff time and resources to focus on more complex and demanding tasks that require transversal skills. By leveraging AI to optimise and streamline certain processes, organisations can enable their employees to develop and improve their transversal skills, leading to higher productivity and innovation.

In the 3rd report, published in 2021 by the ESCO Member States Working Group, the authors (Hart et al., 2021) propose a new taxonomy model for transversal skills and competences (TSCs). TSCs are skills that are considered 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. In a world facing rapid technological and social change, this transversality – and the associated transferability – is seen as increasingly important (Hart et al., 2021). This expert group notes that 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 six main categories, namely, core competencies, thinking competencies, self-management competencies, social and communication competencies, physical and manual competencies, and life skills. These, in turn, comprise a number of individual clusters to assist in the mapping of each skill. The model facilitates the identification of relevant concepts and the relationships between them and is useful for different purposes and users from different sectors. In terms of organisational contexts characterised by the adoption of AI systems, three of the six categories of TSCs (i.e., thinking skills, self-management, and social and communication skills) predominantly comprise skills that are considered 'soft' or transferable and therefore relevant to Industry 4.0 workers.

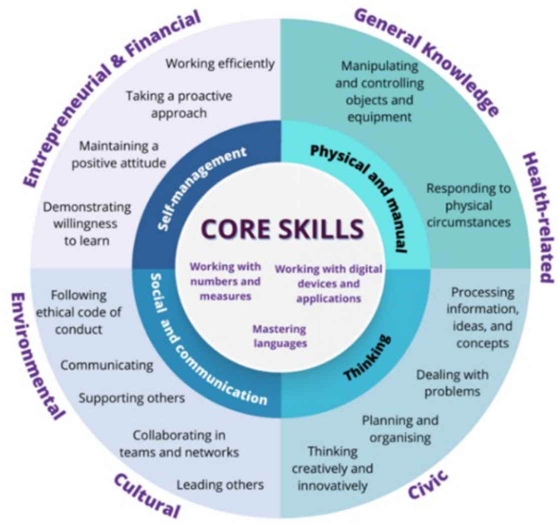

Figure 1. Graphical representation of the TSC model. Adapted from Hart et al., 2021

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. When working with AI, it is crucial to improve both employees' ability to understand, speak, read, and write multiple languages and their ability to work with numbers and units of measurement and to use devices and applications.

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 can promote the acquisition and continuous improvement of employees' core 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 thinking skills are crucial for working effectively 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., creativity, empathy, intuitive and learning skills, and creative thinking) into the process to fill the gaps that AI systems bring (Xiaomei et al., 2021).

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 through the use of 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.

According to recent studies, there are several reasons why it is important for employees working with AI to improve their physical and manual skills. First, improving physical and manual skills can help employees work more efficiently when using AI tools. For example, employees who are skilled in using hardware and software or have good hand-eye coordination can use AI tools more effectively and efficiently (Haslgrübler et al., 2019). Secondly, employees who work with AI tools may need to handle equipment or materials such as robots or machines. Improving physical and manual skills can help employees work safely and avoid accidents or injuries at work (Niehaus et al., 2022). Third, improving physical and manual skills can increase adaptability to new technologies and work environments. For example, workers who are skilled in using different types of machines or equipment can better adapt to new AI technologies that are introduced in the workplace (Wamba-Taguimdje et al., 2020).

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 summarises the key findings on how the demand for certain skills changes among workers in organisations that implement AI systems and how AI can help enhance the acquisition or continuous improvement of workers' skills.

**Table 1. Skills of the TSC Models:
Key skills needed in AI era and potential of AI potentials in enhancing skills**

Skills of the TSC model	Key skills needed in the AI era	How AI can enhance skills
Core skills	Better understanding and use of AI technologies Better use of machine learning algorithms to predict outcomes, classify data or optimise processes Improvement of skills in understanding programming languages to effectively manage and use AI	Enhancement of language skills through AI real-time feedback and identification of areas for improvement Improvement of measurement and evaluation skills through access to AI-provided data Acquiring and refining digital skills through AI-provided personalised learning experiences
Thinking skills	Increasing creativity skills to come up with new ideas and think outside the box Development of problem-solving skills to effectively solve complex situations Development of analytical, critical, and rapid thinking to understand AI-generated data and make informed decisions	Improvement of problem-solving of complex tasks through automation of repetitive tasks by AI Augmentation and integration of creativity, empathy, learning, and creative thinking skills to fill AI gaps
Self-management skills	Development of effective time management skills to take benefit of AI's power and use the remaining time to complete purely human tasks Improvement of self-management skills for the development of new ideas, while the management and monitoring of the workflow is up to the AI	Improvement in time management, workflows management and prioritisation through AI-provided personalised advice Improvement in the quality of planning skills by automating the scheduling of activities, events, and resources by AI Development of critical thinking skills through AI explainability
Social and communication skills	Development of effective communication skills to share information on the use of complex AI systems Development of effective communication skills to build trust in AI work Development of effective leadership skills to ensure that staff use AI systems productively and efficiently	Improvement of social and communication skills through AI-powered feedback on employees' online interactions Improvement of employees' communication skills in interactions with customers thanks to AI's automatic responses and intelligent support Development of managers' leadership skills through AI's identification of the needs and motivations of team members
Physical and manual skills	Improvement of physical and manual skills to work more efficiently with AI tools Development of physical and manual skills to work safely with AI tools and to prevent accidents or injuries at work Improvement of physical and manual skills to increase adaptability to new AI technologies and work environments.	Development of physical and manual skills to perform complex tasks by automating simple tasks through AI systems Improvement of accuracy and precision in physical activities and manual skills through the capabilities of AI Enhancement of physical and manual skills in a safe and controlled environment through AI-based training programs

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

As previously discussed, the incorporation of AI into the workplace can provide opportunities for workers to develop a wide range of skills, including transversal skills. However, it is important to recognise that there might be a "dark side" or downside of AI when considering how it can help with the acquisition and development of skills. When used uncritically, AI might even undermine the development of skills, so there are pitfalls and shortcomings to pay attention to. For instance, individual workers may approach learning and development processes differently, 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 terms of starting points based on personal disadvantages or socioeconomic challenges. For example, Smith and Smith (2021) provide first-hand empirical evidence on how AI technology can, at the same time, assist and frustrate the lives of disabled people. In general, artificial intelligence is not always exempt from bias, such as race-based or sex-based (e.g., Ntoutsi et al., 2020). Suppose organisations do not take these elements and differences into consideration and apply AI-based skill development strategies without regard for the vulnerabilities and needs of their workforce. In that case, these strategies may be counter-productive and exacerbate existing inequalities within the organisation and society at large. Therefore, organisations must carefully consider the impact of AI on learning and development and ensure that any strategies they implement take into account the diverse needs and perspectives of their workforce (Zajko, 2022). Thus, it can be argued and recommended that AI should be thoughtfully implemented and consciously managed to provide all workers with equal opportunities for learning and developing 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 always and automatically lead to a systematic improvement in employees' skills. According to the literature (Alsheibani et al., 2019; Bérubé et al., 2021; Nylin et al., 2022), if not properly managed, the use of AI in the workplace and the related organisational changes may improve or increase employees' skills while limiting the pace of work and reduce employees' autonomy. Indeed, increased complexity and more need for interaction and adaptability are introduced when AI is introduced. In other words, as we have argued so far, AI can be useful in increasing employees' job-relevant skills. However, if not properly managed, it can create performance constraints on the employees because they need to troubleshoot the AI. This, in turn, might create a non-favourable environment for the employees to acquire skills that are relevant to their jobs, causing delays in this process.

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 using AI to make decisions is similar, albeit to a lesser extent, while using AI to give instructions leads to a faster pace of work, greater autonomy, and less learning. For low-skilled jobs, using AI to make decisions has no impact, while using AI to give instructions increases the pace of work. These findings highlight the complexity of the relationship between AI introduction and workers' skills and the need to consider the specific context and skill level of the job when implementing AI systems in the workplace. It might therefore be important to recognise not only if AI is able to promote workers' skills development but also the reasons why and the organisational configurations under which AI works at its best to facilitate the development of skills among workers, that is, to understand moderating and mediating factors that can prompt its introduction effectively.

UPSKILLING AND RESKILLING IN ORGANISATIONS

Processes to develop and retrain employees' skills are called upskilling and reskilling. They are similar in that both involve learning new skills, but there is a key difference between the two. The term "upskilling" typically refers to the process of acquiring new or improving existing skills that are directly relevant to an employee's current job or industry. Upskilling is done with the aim of advancing one's career or becoming 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, e.g., in a different occupation or industry. Reskilling is usually done with the aim of moving to another occupation or industry (Sawant et al., 2022).

Upskilling employees can help organisations to foster a culture of continuous learning and development. This helps employees to stay engaged and motivated, and it can help organisations to attract and retain 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 do well in their employment (Jaiswal et al., 2022).

Reskilling is an important process for organisations that introduce AI systems, as it can help employees adapt to the changes the technology brings. According to Makarius et al. (2020), reskilling is crucial for companies looking to adopt AI as it helps employees develop the knowledge and skills they need to work effectively with the technology but in a new role. This can include 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 they will lose their jobs or that their job security will be threatened by the introduction of AI (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). In addition, reskilling can help close the skills gap that often exists between older and younger workers.

As the introduction of AI into the workplace will continue 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 skills that will be needed to navigate these changes successfully. Identifying and understanding this skills gap is a crucial first step in developing effective strategies for upskilling and reskilling the workforce. Once the skills gap has been identified, organisations can then develop strategies for upskilling and reskilling their workforce to bridge this gap and ensure that they have the necessary skills to utilize 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 current skills gap within their workforce and determine the skills that will be needed to utilize AI effectively. This may involve considering external factors such as industry trends and market demands, as well as the specific capabilities of AI tools and systems being adopted, to identify the skills that will be required to leverage AI in their work effectively. In addition, organisations may also need to conduct a skills audit or skill gap analysis. A skill gap analysis is a process used to identify the skills that are needed in a specific job or industry and to compare those needs to the skills that are currently possessed by workers in that field (Hay, 2003; Reich et al., 2002). This analysis can identify any gaps or discrepancies between the skills required for a job and the skills that workers currently have and can help organisations and individuals make decisions about training and development. By identifying skill gaps, organisations can tailor their training programs to address specific needs, and individuals can target their own learning and development efforts to improve their job performance and advance 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 and 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 gaps.

A study conducted by McGuinness and Ortiz (2016) aimed to identify the key factors that determine the correct identification of skills gaps in an Irish company. The skills gaps were identified in the company through a survey of managers and workers. By cross-referencing the data, the level of agreement in the perception of skills gaps within the organisation was assessed, and the impact of the gaps on firm-level performance was measured. Based on the average responses, the areas where the most skills gaps were reported were identified (i.e., information technology and communications, technology, and management). The analyses and results support the added value of the skills gap identification methodology and the importance of a process 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 on conducting 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 that allowed trainers and managers to fill gaps in identified transversal skills and improve their performance.

A skill gap analysis has been performed in the Eu project FIT4FoF (www.fit4fof.eu) for six technological areas, including data analytics, cybersecurity, collaborative robotics, and human-machine integration, allowing identification of more than 100 new job profiles to face this new job market scenario associated with advanced manufacturing, for instance, Robotics Technicians, whose role involves installing, maintaining, and programming industrial robots and other automated systems, including those used in manufacturing and other settings, or Human-Machine Interaction Designers, whose role involves designing user interfaces and other interactions between humans and machines, including the development of intuitive and user-friendly interfaces for AI systems.

MEASURES FOR UPSKILLING AND RESKILLING

Innovative methodologies should be established to implement new skills and minimise the skills gap. Once the need for skills has been defined, a long-term plan and methodology should be established to implement new skills and minimise the skills gap between organisations and the current workforce. This should include tools that not only provide solutions for attracting new talent but also well-organised training and education programs for current workers and redesign of work processes. Several training and development solutions are available that can support and guide the upskilling and reskilling of the workforce skillsets (Ceschi et al., 2022).

ADDIE MODEL OF TRAINING.

The skill, knowledge, and performance gaps can be bridged by designing meaningful training programs using tools like ADDIE (J. Li, 2016). One of the methods most commonly used by organisations 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). These phases are in a logical sequence and ensure a practical approach to designing a training programme. A study conducted by Guevarra et al. (2021) shows the development of a training programme that aims to improve health workers' decision-making skills in evaluating data generated by technological tools based on the ADDIE model. 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 interaction

In some sectors, for example, healthcare, the adoption and scaling 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 interaction between medicine and machines.

Hackathons

A hackathon is an event where people work together quickly on a project over a relatively short period of time. The goal of a hackathon is to develop working software or hardware by the end of the event. Hackathons can facilitate further education by offering participants the opportunity to learn new skills and technologies. Many hackathons focus on specific topics or technologies and provide participants with resources, workshops, and mentors to help them learn and develop their skills in these areas. In addition, participants often work together in teams at hackathons, allowing them to learn from each other and share their expertise. This kind of collaborative learning can help participants develop a broader range of skills and knowledge. Hackathons can facilitate both upskilling and reskilling by providing participants with the opportunity to learn new skills and knowledge and apply them in a real-world setting (Medina Angarita, & Nolte, 2020). For individuals looking to improve their performance in their current job, hackathons can be an opportunity to learn new technologies. For individuals seeking a new career, hackathons can learn about different industries or fields and develop the skills and knowledge needed to succeed in those fields.

Lifelong Learning and "Hands-On" Learning Modules

The wide adoption of the I4.0 systems and related technologies is dependent on the efficient implementation of lifelong learning and training initiatives that address these challenges. Oliveira et al. (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 that relies on solid hands-on practical experimentation regarding upskilling in emergent ICT technologies. The feedback from the 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 and learning to use AI systems. Because 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 employee upskilling and reskilling to those who work with AI. This programme aims to involve employees in decision-making and lead the company towards a more participatory culture. The Quality Circle trains employees to think critically and solve problems as they perform their 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).

Certification and Re-Certification

Many professional associations offer certification by examination. As continuing education and skills development must be ongoing, regular recertification is critical to ensure that staff keep up with new AI technologies and innovative organisational practices. For example, nurses care for patients in the midst of the information age. This means that the knowledge they need to do their jobs will increase exponentially over time. Therefore, certified nurses need periodically to recertify by taking the appropriate examination or meeting the clinical practice and continuing education requirements established for recertification.

AI for Training and Development

AI can also be used to enhance employee training and development through personalised learning experiences and real-time feedback. Some AI systems are being used to provide virtual coaching to employees, including real-time feedback on performance and personalised development plans. AI systems can also provide employees with access to on-demand exercises and challenges that can help them learn and develop new skills. AI-powered tools provide automated feedback and assessments to help employees understand their strengths and areas for improvement and guide their learning and development efforts. By using AI to provide personalised learning experiences and real-time feedback, organisations can help their employees learn and develop new skills more effectively and efficiently.

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 avoid or 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 both costs and benefits for the organisation and its 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 facing skill mismatch. First, increasing productivity: by providing their employees with the skills they need to do their jobs effectively, companies can increase the efficiency and productivity of their workforce (Zapata-Cantú, 2022). Second, increasing 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, improving 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 the authors (see, e.g., Abe et al., 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 or workshops. In addition, upskilling and reskilling involve time costs: employees may have to be absent from work to attend training, causing interruptions to business. To attend training, employees must be absent from their usual duties. This can lead to 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 their 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.

Figure 2 represents the main costs and benefits for organisations planning to implement upskilling and reskilling interventions.

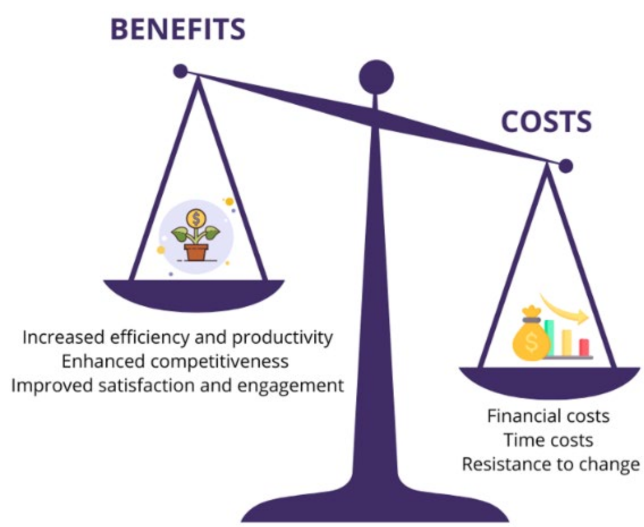

Figure 2. Costs and benefits of upskilling and reskilling for organisations

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. Without adequate support from the organisation, including training, resources, and support for learning, upskilling and reskilling efforts may be difficult or unsuccessful. Therefore, in order to be effective, upskilling and reskilling efforts must be well-planned and well-supported by the organisation and the individuals involved.

At a broader level, countries with poor education and structures are reluctant to invest in upskilling 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 practices of skills development occur, which is crucial for understanding the outcome of skills policies and practices (Hammer & Karmakar, 2021; Petersen et al., 2022). Skilling and reskilling, which are so central to harnessing and managing the impact of new technologies, might be difficult in some countries with poor education and skill structures, exclusion of vulnerable segments of the workforce in the informal economy, and firms' reluctance to invest in training and reliance of informal skilling (Hammer & Karmakar, 2021; Ramaswamy, 2018). In developing countries, there might be difficulty in investing in upskilling and reskilling. 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 and the lack of recognition of informally gained skills are likely to be persistent challenges to the up/reskilling that is so essential for the adoption of high technologies. Organisations need to find strategies to reverse the 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 individual workers but will 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 some developed 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 the skills gaps as the skills in demand in different occupations will change in the near future. 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 have the opportunity to benefit from technological advances and to prevent further gender inequalities in the labour market. In this context, it is important to take into account 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 gender-related 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 and penetration of internet services and devices increases. In some countries where gender inequality is particularly pronounced, low levels of literacy, education, and skills, reinforced by social norms, 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 and retraining 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 have the opportunity to 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 on both upskilling and reskilling. Older individuals who lack access to and proficiency in using new technologies may be at a disadvantage when it comes to finding and maintaining employment, as many jobs now require digital skills and the ability to use technology effectively. 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 training and supporting their older employees 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 and use 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 including design considerations for inclusive and accessible ICTs in design or engineering programs. Addressing the ICTs design in a diverse approach might foster students' innovation capabilities and sensibility towards vulnerable populations during the design process. There are plenty of possibilities to bridge the age-related digital 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, and 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 organizations 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, as 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 (e.g., chatGPT).

The importance of investing in human capital is proving to be a crucial aspect of successfully integrating AI into companies and maximising 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 addressing the current skills gap in the workplace. Organisations can then help workers identify the skills needed for AI adoption and improve and develop new skills. Then, organisations need to put processes in place to support workers by providing training and development opportunities to ensure that workers' attitudes and mental models towards AI are open and prepared for the evolving labour market and its challenges.

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 and help ensure that the benefits of AI are shared equitably across all stakeholders. Hence, practitioners and stakeholders need to invest in upskilling and reskilling workers to create a more adaptable and skilled workforce that can meet the challenges and opportunities of the future.

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