CHANGING LANDSCAPE OF SKILLS IN THE AGE OF AI

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EXECUTIVE SUMMARY

Today, current AI systems can execute many tasks that were once the sole domain of humans, including both routine and non-routine intellectual work. The increasing adoption of AI technologies within workplaces is altering the way individuals utilise cognitive, socio-emotional, and physical abilities to perform tasks across a broad range of occupations. This shift is reshaping the variety and depth of different skills that are expected from workers.

Rising demand for cognitive skills

Studies highlight a growing demand for cognitive skills as a result of AI adoption, particularly those associated with higher-order analytical abilities, critical thinking and problem solving. The depth of cognitive abilities expected from workers is increasing and becoming more diverse, often leading to a shift in the occupational structure towards roles that require advanced skills. This trend is likely to persist and expand to a wider range of jobs, especially if the newly created jobs are concentrated in the non-routine and the cognitive or metacognitive categories.

Human-AI collaboration and overseeing AI

The proliferation of AI-generated content is redefining the use of cognitive skills, moving away from pure creation towards tasks such as editorial review and appraisal. This shift elevates the importance of contextualising, overseeing, and making judgements, which are tasks that, so far, are better performed by humans. Effective human-AI collaboration requires individuals to provide framing, oversight, and context, which cannot be delivered without a strong area-specific expertise as well as scientific and computational literacy, even for those in non-technical roles.

Further boost in the value of digital skills and hybrid roles

AI technologies are driving further demand for digital skills, both in terms of variety and depth of skills. In particular, intermediate and advanced digital skills are required to integrate and use AI tools within several sectors and occupations. This shift is reshaping what it means to be a digitally competent worker, while also extending and deepening hybrid roles that combine traditional expertise with computational skills. Digital and data literacies are prerequisites for effectively interacting with AI systems.

Intensifying the value of socio-emotional skills

Despite advances in AI, the technology cannot still perform tasks requiring emotional intelligence and complex human interaction. This limitation further heightens the importance of socio-emotional skills, which remain uniquely human. Such skills are also essential for the fair and human-centric adoption of AI, functioning as the human enablers of technological advancement while safeguarding ethical principles.

Human strengths in an AI-driven workplace

Human cognition, emotion, judgement, and creativity are essential for a meaningful human-AI collaboration. In a world where machines can process information rapidly, recognise patterns on a large scale, and optimise routine decisions, the distinct strengths humans offer include the ability to adapt to the unexpected, judge ethical implications, communicate across disciplines, and learn continuously. This is part of a broader transition in how we value work, navigate uncertainty, relate to others, and integrate meaning and fairness into technology-driven processes.

Shifts in manual skills and complementarities

Execution of simple manual tasks in controlled environments by AI-enabled robots is diminishing the relative importance of manual skills for routine activities. However, more refined manual skills for performing non-routine tasks are less affected. For example, robots can efficiently move goods along predefined routes and handle uniform packages. However, human workers with refined manual skills are needed to resolve issues. Human involvement continues to be essential in real-world dynamic environments with unstructured tasks.

Emerging demand for technical AI skills/workforce

Perhaps the most immediate impact of AI has been the emergence of new demand for specialised technical skills that were previously non-existent, that are necessary to develop, maintain, and implement AI systems. As a result, the expanding 'AI workforce' now encompasses individuals with varying levels of technical competency, ranging from highly sophisticated frontier AI researchers and engineers to professional users who incorporate AI technologies into their daily work.

Small but growing size of the AI workforce

Research indicates that only a small share of the workforce is involved in the development and professional use of AI technologies. Depending on the analytical methods and definitions applied, the share of the AI workforce ranges from as little as 0.3% to as much as 5% of total employment, with variations across countries and over time. Nevertheless, the demand for AI-related skills has increased rapidly over the past decade, driven by the growing necessity to design, apply, and manage these systems.

Profile of AI workforce, occupations and sectors

The majority of AI workforce are highly educated white men with prime working age, particularly visible among AI developers. Specialised AI skills are found at the intersection of mathematics, science, and computer science, with AI concentrated thus far in a few high-skilled occupations, notably mathematician, actuary, statistician, software and application developer, ICT manager, and database and network professional. The majority of the AI workforce is, therefore, among professionals and associate professionals in ICT, finance and professional, scientific and technical fields, although AI skill demand is gradually expanding to other sectors.

Proficiency levels of AI workforce

Technical AI skills can be understood as existing along a hierarchical spectrum. This ranges from task-based familiarity with AI tools to sophisticated competencies in AI development and engineering. The 'AI developer' profile is the most clearly defined, focusing on designing and building AI systems. Meanwhile, the 'AI user' profile encompasses workers with varying degrees of technical skills, from those capable of redesigning or implementing AI tools to non-specialist users who interact with AI-enhanced systems. Consequently, AI skills are categorised from basic to intermediate and advanced levels, each building upon the previous.

Emergence of AI literacy as a foundational skill

As AI becomes increasingly integrated into our daily lives and workplaces, the need for individuals to comprehend and safely use AI tools in an ethical manner has emerged as a new fundamental skill. AI literacy is now regarded as a core requirement for the new digital era, enabling individuals to exercise agency and participate fully in AI-enhanced environments. It is vital not only for workers who interact directly with AI technologies, but also for all citizens affected by the expanding reach of these tools in government services, media, privacy, finance, healthcare, and education.

Three domains of AI literacy to learn

AI literacy encompasses three closely linked domains. The first is technical literacy, which involves a basic understanding of how AI systems function, including familiarity with machine learning, algorithms, and data-driven technologies. The second domain is analytical and data literacy, or the capacity to interpret and assess AI outputs in real-world situations. The third domain is ethical and societal literacy. As AI becomes woven into work and everyday life, individuals must be aware of issues related to data privacy, algorithmic bias, transparency, accountability, fairness, and sustainability.

Integrating AI literacy into education and training

Embedding an AI competence framework into initial and continuous education and training is considered essential to prepare current and future generations for an AI-driven world. There have been efforts to operationalise AI literacy as a structured, teachable, and measurable competence, integrated across the curriculum as a transversal skill from primary to higher education, as well as adult learning programmes and workplace training. Various frameworks are now available to support the teaching and learning of AI to students, teachers, and adults.

Policy responses to low levels of AI literacy and skills

As current levels of AI literacy among workers remain low, several countries have incorporated AI skilling into their national AI strategies and actions. Also, short and diverse learning pathways exist for workforce AI skilling, including employer-led training, collaborations between academia and industry or bootcamps. However, the existing supply of training may be insufficient to meet the growing and rapidly evolving demand, particularly for general AI literacy. Policies need to expand AI literacy programmes to reach more diverse groups, as most workers will require the skills necessary to use and interact with AI systems to stay employable and autonomous in the AI-driven world of work.

Revising occupational standards, qualifications and curricula and adapting quality assurance

Adjusting occupational standards and learning outcomes to reflect changing workplace realities has become a necessity. Learners and workers not only need general AI literacy, but also sector- and occupation-specific guidance on how AI changes workflows, decision-making processes, quality standards and human interaction within specific occupations and sectors. The growing use of AI technologies in education and workplace also requires significant adaptation of assessment, certification and quality assurance systems in education. However, successful integration of AI-related competences into education and training systems depends heavily on the preparedness of teachers, trainers and institutions.

Beyond AI: Future-readiness and empowerment

AI is not the sole force transforming labour markets. Given multiple disruptions, the concept of 'future-ready skills' has emerged, emphasising the need for individuals to adapt and thrive in a rapidly evolving world. As information becomes more accessible, the focus shifts from simply acquiring knowledge to developing 'wisdom' through robust foundational skills, socio-emotional learning, and future-readiness. These broader skillsets are essential not only for handling more complex workplace tasks but also for empowering citizens in an uncertain future.

Developing human capabilities in an AI-powered future

An AI-powered future calls for citizens who are resourceful, resilient, and adaptable to perform effectively in different work-related settings. This requires a shift in focus from teaching specific skillsets to the cultivation of broader human 'capabilities'. Such capabilities go beyond particular skill domains and underpin human agency and the ability to learn, apply, and adapt knowledge and skills for future needs. Capabilities are built within skills ecosystems – coordinated through life-course education and training investments, firm practices, labour market institutions, and social dialogue. Ethical AI governance and robust workplace safeguards are as critical as investment in skills to enhance human capabilities.

INTRODUCTION

Artificial intelligence (AI) refers to a machine-based system designed to operate with varying levels of autonomy, which may exhibit adaptability after deployment. It derives, from input data, the means to generate outputs—such as predictions, content, recommendations, or decisions—that can influence physical or virtual environments[1]. Although still in the early stages of evolution, AI has attracted substantial attention as one of the greatest labour market disruptions of recent times. Due to the broad and multifaceted nature of AI technologies, their potential to exert widespread and rapid influence across diverse sectors and occupations is increasingly evident. AI may eventually become a general-purpose technology, comparable to computing, electrification and the steam engine, with similar historical effects on economic systems.

A substantial body of research studying AI's impact on labour markets illustrates how technologies can simultaneously automate, augment and redefine tasks and change how work is performed and valued (for an overview, see ETF, 2026). Existing AI systems and tools already support the execution of several tasks that have long been unique to humans, including those routine and increasingly non-routine and intellectual in nature. At the same time, differing degrees of technical AI skills that are combined with digital skills are emerging which range from the basic level of simply using AI applications to a more sophisticated level involving the development of AI systems. Few studies discuss how the wider adoption of AI systems could alter the variety and depth of skills demand across the whole employment spectrum.

The aim of this report is to discuss the skills implications of AI technologies used in the workplace and reflect on learning needs in an AI-driven future to support experts, practitioners and policymakers in the field of skills development and employment policies. In essence, it is a brief review of existing knowledge and examples on the topic, drawing extensively on the existing work of the members in the IAG TVET working group which is synthesised into key findings.

The questions that this report attempts to answer are as follows:

- How does AI adoption change the variety and depth of skills' use in general? What are the implications for the demand of cognitive, socio-emotional and manual skills?
- What is the emerging demand for technical AI skills and an AI workforce?
- What are the first implications of these developments for skills policies?

The report is structured around four chapters. The first chapter sets the scene and provides the conceptual framework for later discussion on AI's impact on skills. It begins by presenting an overview of the AI's use in workplaces, including examples of task domains that are increasingly executed by or with AI technologies. The chapter then links the tasks that can be performed by AI tools to the use of three categories of skills, all of which require the performance of tasks across many occupations and sectors.

The second chapter examines how AI adoption is likely to change the variety and depth of skills' use, assuming extensive use of ready-made AI tools by the majority of workers in the future. The changes are discussed according to the cognitive, socio-emotional and manual skills categories. Given current AI capabilities at the time of writing, this chapter highlights the shift in human use of certain cognitive skills, psychomotor abilities, and socio-emotional skills. Automation of simpler tasks often leaves workers to perform more complex tasks, whose performance may require higher-order cognitive and socio-emotional skills as well as general digital and data science skills – reflecting a more gradual shift towards more 'human-centred' skills across many occupations.

The third chapter focuses on the specific demand for technical skills required in the labour market to develop and maintain AI systems. Jobs for developing AI systems are usually technical in nature and represent newly emerging occupations that involve specialised tasks which did not exist previously. In

[1] See Article 3 of the EU AI Act, https://artificialintelligenceact.eu/article/3/

addition, certain occupations already existed before AI but are being transformed as the tasks involved and the competencies required are changing due to its adoption. The chapter reviews the size of the technical AI workforce overall, its characteristics, degrees of technical proficiency, and trends in hiring AI talent. Although the demand for technical AI skills is currently small, it is set to grow exponentially as the uptake and application of AI technologies expand.

The fourth chapter discusses the implications of these developments for skills policies. It starts with a new 'basic' skill: the ability to understand and use AI tools safely and ethically. AI literacy is increasingly seen as a foundational skill for the new digitalisation phase – an essential enabler of human agency and inclusion in AI-augmented environments. Experts propose the integration of AI literacy as a new transversal skill across the curricula from primary to higher education, as well as adult learning programmes and workplace training. Considering several simultaneous disruptions and more fragile employment forms, citizens must be more resourceful with higher agility, resilience and adaptability to manage greater uncertainty[2]. These developments require greater emphasis on broader capabilities and human agency than in pre-AI contexts, rather than narrowly defined skill sets, an approach that is also central to advancing ethical and human-centred AI.

Finally, it is important to note that changes in skills demand associated with the adoption of AI are not automatic or driven by technology alone. They depend on how AI is introduced and used in workplaces, how tasks and jobs are organised, and on the education, training and labour market institutions that shape skills development. As a result, skills demand outcomes reflect not only technological change, but also employer practices and public policy choices.

[2] For a good discussion of skills policies for resilience, please see the second report of the IAG Working Group: OECD/Cedefop/European Commission/ETF/ILO/UNESCO, 2024.

CHAPTER 1: LINKING THE USE OF AI WITH TASKS AND SKILLS

This chapter sets the scene by providing a brief overview of the use of AI tools for work and identifies some task domains that are increasingly executed with the help of AI technologies in different sectors. A presentation of an analytical framework of tasks and skills according to the three categories of cognitive, socio-emotional and manual skills follows. This framework is then used in the subsequent chapter to identify changing skills demand in the workplace after AI adoption.

1.1. Increasing use of AI tools in workplaces

Simulating human intelligence, AI has distinct features that set it apart from past technologies. Its learning, reasoning, perception and decision-making capacity enable the performance of both routine and some non-routine cognitive tasks, leaving highly educated people in white-collar professions particularly exposed (OECD, 2021a). By analysing vast amounts of data to identify patterns, AI systems can perform complex tasks autonomously, including language and image recognition/generation and predictive analytics. Wherever large amounts of data are available, AI improves intelligence and decision-making in that area. Not only does AI improve over time through the input expertise of inventors or developers, but also through its capability to learn by itself from data and its previous predictions. These developments open the way to the execution of several new knowledge tasks that were not thought possible before.

Today, AI systems and tools are used by a significant number of workplaces. Cedefop's 2024 AI skills survey, for example, shows that about 28% of European adult workers are already using AI at their workplace (Cedefop, 2025)[3]. About 5% of those AI users do so for the purpose of developing, programming or maintaining AI systems, while 6[3]% of them use AI to do their job. AI use is more common in some western European countries (Belgium, Germany, France, Luxembourg) than in southern European countries (Greece, Spain, Portugal) and Poland. The use of AI tools to perform tasks is often learnt on-the-job by workers, but they are not always aware of their limits or data and ethical risks (Cedefop, 2025).

The more recent AIM-WORK survey (Analysis on Impacts of Artificial Intelligence and Algorithmic Management in the Workplace) conducted in 2024–2025 confirms that over 90% of European workers use digital devices, and a third of workers use AI for work-related purposes (JRC, 2025a)[4]. The 2024 European Working Conditions Survey (EWCS) by Eurofound found that 12% of EU workers use generative AI tools that simplify complex mental tasks or make recommendations on how work should be carried out (such as ChatGPT, Llama, Dall-E, Midjourney and Jasper) (Eurofound, 2026a)[5]. Similar trends of AI use are also found in the OECD AI surveys of employers and workers in the finance and manufacturing sectors in several member states (see OECD, 2023c)[6]. Another small and medium-sized enterprises (SME) survey shows its wider use even in smaller firms: 31% of SMEs are found to be using generative AI, ranging from 24% in Japan to 39% in Germany – despite concerns about copyright, legal and regulatory issues (OECD, 2025f)[7].

[3] Cedefop surveyed a total of 5342 adult employees in February-May 2024 in 11 EU member states: Belgium, Czechia, Germany, Ireland, Greece, Spain, France, Luxembourg, Poland, Portugal, and Slovakia.
[4] The AIM-WORK survey (Analysis on Impacts of Artificial Intelligence and Algorithmic Management in the Workplace) was conducted by JRC and European Commission and it collected responses from 70,316 individuals aged 16–65 across all 27 EU Member States.
[5] Eurofound's EWCS covers 36,644 respondents in 35 countries: the 27 Member States, Norway, Switzerland and the 6 Western Balkan countries (Albania, Bosnia and Herzegovina, Kosovo, Montenegro, North Macedonia and Serbia).
[6] This OECD survey includes nearly 100 case studies of AI technologies implemented in workplaces in the finance and manufacturing sectors in Austria, Canada, France, Germany, Ireland, Japan, the UK and the US.
[7] This is a representative 2024 OECD survey of over 5 000 SMEs in Austria, Canada, Germany, Ireland, Japan, Korea and the UK on how SMEs use generative AI.

Extended algorithmic management (AM) in traditional workplaces is another AI-related trend confirmed by studies (JRC, 2025a; OECD, 2025b; Cedefop 2025). In Cedefop's 2024 AI skills survey, 1 in 7 employees report working with digital tools or systems that algorithmically determine how to do some of their tasks, and 16-17% have algorithms monitoring or evaluating their performance or providing task instructions to them. The AIM-WORK survey found that algorithms determine the workflow or task prioritisation at work for 24% of EU workers (JRC, 2025a). According to OECD (2025b)[8], AM in workplaces is particularly prevalent in the US, where 90% of employers have adopted at least one tool to instruct, monitor or evaluate workers. Adoption is slightly lower in the European countries surveyed (France, Germany, Italy and Spain, with an average adoption of 79%) and moderate in Japan (40%). Integrating AM at work can enhance organisational efficiency, while raising some data protection and privacy issues in workplaces, for which a limited level of awareness and knowledge is available among workers.

Studies indicate higher AI use in knowledge-intensive sectors, especially in ICT, financial services, and professional-scientific and technical services (Cedefop, 2025; OECD 2023b, 2023c) and among workers in higher-skilled occupations (Eurofound, 2026a). For example, *AI in IT* is used for software development, data analysis, cybersecurity, and managing IT infrastructure, enabling the development of smart applications that can understand, learn and predict. *AI in finance* makes analyses and predictions and improves financial forecasting, while enabling real-time fraud detection and algorithmic trading. *In manufacturing,* AI-powered robotics assist production, digital twins (i.e., virtual replicas of physical production systems) simulate, monitor and optimise workflows, while predictive maintenance helps prevent equipment failures. *In retail, marketing and advertising,* AI enables personalised content creation, dynamic pricing, optimised advert targeting and provides 24/7 virtual assistance.

In other sectors, like healthcare, deep learning[9] is enhancing diagnostic tools that rival human accuracy and analyse medical data, supporting medical care from patient monitoring and safety and personalised treatment planning to planning and coordination, and administrative and reporting tasks. *In transport and logistics,* AI enables autonomous vehicles for ride-sharing services and delivery logistics, while AI-powered traffic management systems optimise traffic flow, reduce congestion and enhance safety. *In human resources,* AI data-driven tools and algorithms are available for recruitment and selection, worker evaluation, promotion, termination, learning and development. Personalised learning platforms, adaptive training systems, recruitment and well-being monitoring tools are used by large firms to find and keep talent, promote workforce resilience and professional development[10]. Despite these advances, AI use in human resources remains limited, partly due to ethical and regulatory concerns (Gulia and Rastogi, 2024). Developing ethical safeguards and governance is necessary before widespread AI use in human resources (ILO, 2025a).

Based on a wealth of labour market research to date *advances in automation, digitalisation and AI seem to change first and foremost the task content of jobs.* The findings of many studies often portray a combination of automation and augmentation resulting in job reorganisation (Cedefop, 2025; McGuinness et al., 2026), while much less drastic change is noted on aggregate employment (Fossen and Sorgner, 2022; Brynjolfsson et al, 2025; Hartley et al, 2026; Humlum and Vestergaard, 2025; Eurofound, 2025a). Automation often reduces the amount of labour in routine tasks, while digitisation facilitates the routinisation of previously non-routine tasks (JRC, 2025b)[11]. Similar to previous technologies, AI replaces humans in the execution of some tasks through automation, creates demand for new tasks/ skills that were uncommon or non-existent, and increases the weight of

[8] The study is based on an employer survey which covered over 6 000 mid-level managers in six countries (France, Germany, Italy, Japan, Spain, and the US) between June-August 2024. The survey asked managers to provide information about algorithmic management tools used to manage workers.

[9] Deep learning is a specialist branch of machine learning that uses large neural networks with many layers to process the data and can autonomously learn patterns from large datasets (ETF, 2026 forthcoming).

[10] Examples of AI-powered tools are Coursera with AI, Workday Learning, IBM SkillsBuild, Docebo, SC Training, 360learning, HireVue, Pymetrics, SeekOut, Textio, Resumeworded, Vervoe, MyInterview.

[11] Historically, automation has always been preceded by standardisation, and digitisation seems to facilitate this process. While computers can enable the automation of some routine cognitive tasks – thus reducing employment in these routine-intensive occupations – they also tend to facilitate standardisation and bureaucratisation of procedures through digitised processes in non-routine occupations (JRC, 2025b).

existing demand for certain skills. This can bring uneven benefits and harms within the workforce, with the risk of exacerbating inequality (IMF, 2026).

There is considerable evidence of the changing task content of jobs after AI adoption. Cedefop's AI skills survey in 2024 shows that about one-third of European workers who participated in the survey no longer do some tasks after the adoption of AI as part of their main job, while about 4 in 10 workers now do some new or different tasks. Moreover, 67% of workers do some tasks faster than before (Cedefop, 2025). Similarly, OECD's AI case studies in finance and manufacturing sectors in eight countries show a high degree of task reorganisation: 66% and 72% of employers in finance and manufacturing, respectively, report that AI had automated tasks previously done by workers, while around half of employers in each sector reported that AI had created tasks that were not previously done by workers (OECD, 2023c).

According to OECD (2023c), *the automation of routine tasks is expanding as AI's new capabilities enable new solutions, while automating non-routine tasks is also advancing with AI* (e.g. predictive maintenance in manufacturing that helps technicians by identifying equipment issues before they happen)[12]. AI systems are increasingly adept at replicating and augmenting human tasks; their impact is going beyond simple automation, leading to the redefinition of whole work processes. When (simpler) tasks are automated, workers often get allocated more complex tasks, and their tasks shift towards those in which human workers have a comparative advantage. Case studies analysed by OECD suggest that AI adoption generates multi-dimensional skills change. It increases demand for more complex and higher-order cognitive and interpersonal skills, as well as more diverse skill sets (e.g. specialised AI skills, new domain knowledge such as data science), besides the increasing demand for business and management skills (OECD, 2023b; 2023c).

Several groups of task domains can be identified that are increasingly executed with the support of AI technologies. As mentioned, today AI is increasingly used in the *execution of several knowledge tasks*, including both routine and non-routine cognitive tasks[13], especially in sectors with well-structured and repetitive workflows, such as finance, logistics, and customer service. AI-powered systems are now managing data entry or standardising customer interactions (ETF, 2026). *Data-driven business intelligence* is widely used by companies, illustrating the predictive function of AI systems. Firms are increasingly relying on AI-powered analytics to extract insights from large datasets, support strategic planning, and improve forecasting in areas such as finance, marketing, and operations[14].

Perhaps c*ontent creation and improvement by Generative AI (GenAI)* have been the most important examples of AI's groundbreaking ability to replicate some important human tasks so far[15]. Based on user prompts, authors, journalists and advertisers now can use AI support in creating text (articles, social media posts, emails, product descriptions, and conversations); artists can use tools like ChatGPT to create images and art illustrations, audio for music compositions, or videos and animations; while IT engineers can use tools like GitHub copilot for software coding and programming scripts; and educators to create educational materials for using in their classes.

Enhanced communication and collaboration supported by AI has become almost universal in the modern workplace. This surge has been catalysed by the global shift to remote and hybrid work models, particularly in the aftermath of the Covid-19 pandemic. AI-enhanced tools now embedded in common workplace platforms enable real-time translation, meeting summarisation, sentiment analysis, and intelligent scheduling (e.g., Microsoft Teams, Google Workspace, or Meet AI, Zoom IQ, Grammarly Business, etc.). *Execution of organisational and coordination tasks* is also made possible through algorithmic management of work (AM), automating organisational functions traditionally

[12] This OECD survey includes nearly 100 case studies of AI technologies implemented in workplaces in the finance and manufacturing sectors in Austria, Canada, France, Germany, Ireland, Japan, the UK and the US.
[13] Typical AI applications in this domain are UiPath, IBM Watson Assistant, Amelia, Microsoft Power Automate, ChapGPT, Claude, Grammarly, DeepL, Predictive Index, Quinyx, Deputy, Zapier, Asana.
[14] Typical AI applications in this domain are Tableau with Einstein AI, SAS Viya, Sisense, Microsoft Power BI, Amazon SageMaker AI, Google AutoML Tables, ThoughtSpot.
[15] Generative AI is a class of deep learning systems designed to recognise and utilise textual, visual or auditory patterns from extensive datasets to produce new content in response to prompts that cannot be distinguished from human content.

carried out by human managers with the use of software algorithms. AM tools are gradually being extending in traditional workplaces and used for work instructions, scheduling, coordination, monitoring and evaluation of tasks in operations.

Agentic AI is another recent step in supporting human tasks, referring to autonomous AI systems capable of independently performing complex, multi-step tasks by employing sophisticated reasoning and iterative planning (Acharya et al, 2025). Different from previous AI applications, agentic AI systems further develop the stage of task automation, as they can coordinate sequences of interdependent activities and generate context-sensitive recommendations. They serve as intelligent virtual assistants, providing real-time insights and data-driven recommendations to support complex decision-making processes, effectively reducing cognitive load and fostering a more efficient work environment[16]. The integration of agentic AI in the workplace is poised to further transform employee roles and responsibilities, as it augments, substitutes, and reorganises cognitive and coordination tasks.

These are just some examples of what tasks AI technologies can support or perform today at work. With new advancements every day, it is difficult to predict its full potential in the future. Nevertheless, it is reasonable to expect that the demand and value of skills that are replaced by AI technologies will probably decrease in the medium-to-long term, while the demand and value of skills that would be complementary to AI tools will increase. The OECD case studies mentioned above already point to demand for higher-order skills and extended skill sets in workplaces that have adopted AI; therefore, a broader range of skills may be needed by most workers as AI becomes pervasive within economies.

1.2. Analytical framework of tasks and skills

Tasks are the characteristics of a job, while skills belong to people. Similar tasks are grouped into domains that employers aggregate into jobs. Likewise, similar skills make up skill domains, while competence is the ability to master skills across domains (JRC, 2022a). As skills are generally defined as the ability to perform tasks, the two concepts are intricately linked. Changes in task composition often drive the need for skilling not solely through training but also job redesign or organisational adjustments. Although each task category is associated with relevant skills, linking skills to tasks in a conceptually sound way remains complex.

A useful taxonomy of tasks created by JRC (2022a) separates the material content of work (what people do at work) from the organisational form of work (how people do what they do at work). While the content of work originates from the type of production of goods or services (the activity that transforms inputs into outputs), the methods and tools originate from the type of work organisation and technology used across tasks. The taxonomy classifies tasks based on the type of object upon which they are performed: *physical tasks* that operate on things, *intellectual tasks* that operate on ideas, and *social tasks* that operate on people. It is further complemented by the methods and tools used at work, helping to explain why workers in the same occupation may require different levels of digital skills, or experience varying degrees of routine, autonomy or teamwork (JRC, 2022a). A recent survey in EU countries provides a good illustration of wide variation in tasks within the same occupations, reflecting the differences in methods and tools used by organisations (Eurofound, 2025b)[17].

Skill categories are inherently more complex, as they are closely linked to individuals, their personal traits and life experiences. Skills are often intertwined with personal qualities, and their application is strongly shaped by context. Personal beliefs, fears, and personality directly impact how skills are applied, making them inseparable from the individual. Moreover, not all skill types can be easily or objectively measured and the proliferation of multiple terms for same types of skills reflects this conceptual complexity and potential confusion[18]. Nonetheless, the most common classification distinguishes three broad categories aligned with the task typologies above: *cognitive or intellectual skills,* referring to the ability to perform intellectual tasks, *socio-emotional or non-cognitive skills linked*

[16] Some examples of agentic AI are Microsoft 365 Copilot, Google Duet AI, ChatGPT Enterprise, Salesforce Einstein GPT.
[17] The findings of the Eurofound study come from data of the 2022 EU labour force survey module on ‘job skills’.
[18] See for example discussions on different skill categories in JRC, 2021b; World Bank, 2016; OECD, 2024c.

to the ability for undertaking social tasks, and *physical or manual skills, relating to the capacity to perform manual* tasks (see Table 1).

Cognitive (or intellectual) skills are mental abilities to think, learn, process, and apply information. They encompass core functions such as memory, attention, logical reasoning, auditory and visual processes, perception, introspection and mental arithmetic, problem solving, language and communication. These are the core brain functions that enable people to process information, understand the world, and solve problems in daily life, at work, and in school. They are commonly reflected in abilities which denote cognitive skills such as literacy and numeracy, self-reflection, logical reasoning, abstract thinking, critical and analytical thinking, and problem-solving.

Some researchers extend this list to include additional foundational literacies: For example, the ILO defines these as not only literacy and numeracy but also financial, scientific, health, cultural, and civic literacy (ILO, 2021a). A further distinction is made between *cognitive* and *metacognitive skills*, with the latter referring to awareness of one's own thought processes (e.g. self-reflection, learning-to-learn). Finally, digital skills including computer use, software proficiency, and capabilities related to AI and machine learning are closely linked to cognitive skills; and can be considered sub-categories within this domain (Escudero et al, 2024).

Table 1: Three broad categories of skills domains/ taxonomy

Cognitive/ Intellectual	Non-cognitive/ Socio-emotional	Manual/ Physical
Mental abilities to think, learn, process and apply information: Memory, attention, logical reasoning, auditory and visual processes, perception, problem solving, introspection, mental arithmetic, language/ communication.	Ability to manage one's thoughts, emotions and behaviours to function well at work and in social life. An umbrella term to describe social skills, motivational and self-regulatory skills, and personality traits.	Ability to perform tasks which require manual dexterity, agility or bodily strength. It involves using the body, especially the hands, with efficiency and precision to complete tasks.
Literacy and numeracy, logical reasoning, abstract thinking, critical and analytical thinking, problem-solving, the ability to make logical/ reasoned decisions. *Metacognitive skills* are awareness of own-thought processes such as self-reflection, learning-to-learn. *Digital literacy and other foundational literacies are often included here.*	Perseverance, collaboration, teamwork, emotional maturity, empathy, self-control, persistence, interpersonal/ social skills, resilience, grit that are essential for people to deal with various contexts. *Many other terms are also used interchangeably for this skills domain, such as soft skills, life skills, character skills, personality traits, etc.*	Manual dexterity and fine motor skills; bodily strength and gross motor skills; agility and coordination; endurance and stamina; and flexibility and range of motion without restriction.
Influenced by genetics, education, and environment. Measured by IQ and standardized tests to identify the level of mental processing (higher/ lower order).	Influenced by genetics, environment, pre-school experience and lifelong training. Pre-school parental education is crucial. Measured by self-reporting, experiment or behavioural observation.	Influenced by genetics, training, environment. Often used in lower-skilled occupations. Measured by manual tests.

Source: Based on the sources cited in the text.

Cognitive skills are typically developed in school and often measured by IQ and standardised tests to identify the level of mental processing (higher/ lower order) in reasoning, memory, understanding, and problem solving. However, IQ only explains a small percentage of the variance in academic test scores and later life outcomes (such as earnings), pointing to the importance of other, non-academic skills. The latter are commonly referred to as *'non-cognitive' skills*[19]*,* while terms such as 'socio-

[19] This is an umbrella term originally coined by the sociologists Samuel Bowles and Herbert Gintis to denote skills that are not cognitive and cannot be captured by standardised tests (e.g. IQ or literacy). Although widely used, the term 'non-cognitive skills' is somewhat controversial, because these skills may also involve intellect, but more indirectly and less consciously than cognitive skills (OECD, 2024c).

emotional skills', 'soft skills', 'character skills', 'life skills' or 'personality traits' are also commonly used (see OECD 2024c, 2025c; JRC, 2021b; World Bank, 2016)[20]. Despite limited consensus in defining and measuring these similar sets of 'soft traits', a substantial body of research finds that they are often stronger indicators of long-term outcomes, including test scores for academic success, employment, financial stability, health and wellbeing, and criminal behaviour (Bjorklund-Young, 2016; OECD, 2024c; 2025c).

Non-cognitive skills or socio-emotional skills are closely related to personality, behaviour, temperament and attitudes, enabling individuals to manage their thoughts, emotions and behaviour, and to work and live well with other people[21]. They encompass a range of abilities such as motivation, integrity, perseverance, collaboration, teamwork, emotional maturity, empathy, self-control, interpersonal/ social skills, and resilience. The capacity to regulate impulses and emotions, sustaining long-term motivation, and cooperate with others is considered as important as purely cognitive skills such as literacy and numeracy. Evidence from the World Bank's STEP survey highlights the labour market returns for skills such as 'grit' (a combination of passion and perseverance), conscientiousness and decision-making that are particularly significant for women and low-income groups (World Bank, 2016)[22].

Thus, *'socio-emotional skills'* serve as an umbrella term encompassing *social*, *motivational and self-regulatory skills, as well as personality traits*. These abilities to understand and manage emotions, set and achieve positive goals, and show empathy are crucial to developing resilience and adapting to today's rapidly evolving labour markets. Yet measuring these skills remains challenging, as existing methods, including self-reporting, experimental methods or behavioural observation, have limitations. While some evidence suggests that *socio-emotional skills* can be shaped, fostered or boosted over the life course through supportive environments, monitoring and guidance, pre-school education has been found to be most effective in their development (Bjorklund-Young 2016; Orrell 2025)[23]. Promoting or discouraging particular non-cognitive traits remains challenging but embedding *'socio-emotional learning (SEL)'* into formal education systems, non-formal learning and workplaces is increasingly proposed as a way forward (UNESCO 2024b; OECD, 2025c).

There is no trade-off between cognitive and non-cognitive skills as they are mutually reinforcing. Both have both independent and complementary effects on life outcomes with non-cognitive skills often providing significant incremental and predictive power for success beyond cognitive skills (OECD, 2024c). They interact and mutually reinforce with non-cognitive skills often reinforcing cognitive skills, as they continuously cross-fertilise each other. In practice, it is difficult to distinguish them: IQ test scores reflect not only innate intelligence but also factors such as focus and self-motivation (Bjorklund-Young, 2016). It is therefore debatable whether skills like critical thinking and problem solving can be considered purely cognitive skills as they are strongly shaped by emotional skills as well (JRC, 2021b).

Lastly, *'manual or physical skills' are the ability to perform tasks and activities which require manual dexterity, agility or bodily strength.* They involve using the body efficiently and precisely to complete a task and can be categorised into fine motor skills (like typing or sewing) and gross motor skills (like lifting or walking). Key components of physical and manual skills are dexterity, strength, agility, coordination, endurance, stamina, flexibility. Although these skills are more prevalent in lower-skilled

[20] Stable definitions of these skills have not been settled. For some experts, these concepts largely overlap with each other as well as terms like 'transversal skills' or 'core skills', but they are not always identical. Non-cognitive skills may be 'facets' of personality and influence socio-emotional skills as 'reactions'. Please see JRC 2021b for a review of different terminology, frameworks and models used to cover these skills.

[21] The theoretical background of these abilities comes from *'Big Five' personality traits model* used in psychology: Openness to experience, Conscientiousness, Extraversion, Agreeableness and Neuroticism.

[22] The role of non-cognitive skills is also crucial for academic success via academic behaviours (e.g. regular attendance, completing homework), academic perseverance (e.g. grit and self-discipline), learning strategies (e.g. goal setting), and social skills (e.g. interpersonal skills and cooperation) (Bjorklund-Young, 2016).

[23] The unified framework of tasks, skills and competences developed by JRC suggests that knowledge and attitudes are mostly acquired in childhood and early youth, while skills grow quickly through practice at work. Expertise is only acquired after starting the work period. The gains from expertise throughout the lifetime compensate for the loss of knowledge and skills to keep competence high until retirement. These elements of competence development can form the building blocks of a lifelong learning framework (JRC, 2021a).

occupations – such as services (waiters, cooks, cleaners), manufacturing and logistics (production line workers, warehouse staff, drivers, machine operators), and construction and trades (bricklayers, plumbers, electricians), they are also essential in some high-skilled occupations (e.g. surgeons and nurses) and practitioners in the creative arts, such as painters, sculptors, and musicians.

In many jobs, a singe task may require the use of multiple skills from all three categories, applied in different ways by workers. For example, providing patient care requires medical/ technical knowledge, cognitive skills to assess symptoms and make decisions and socio-emotional skills to communicate effectively. The same task may be accomplished through different skill combinations, depending on how work is organised. However, employers do not necessarily describe skill requirements using these analytical categories. Instead, they reflect how tasks are bundled into jobs by employers and how skills are utilised. In most job vacancies, for example, skills are often described in a binary term: hard (technical) skills versus soft skills. Moreover, among the 'soft skills' listed, intellectual tasks (critical thinking, problem solving), social tasks (interacting with people), and methods of work (autonomy and teamwork) are frequently mixed. Furthermore, job postings tend to emphasise positively valued attributes, such as teamwork, but under-emphasise undesirable features of work, such as monotonous or routine work.

Finally, work organisation is the ultimate determinant of the skills used in performing tasks. It shapes how tasks are structured, and consequently which combination of skills required. Labelling work methods (e.g. teamwork or autonomy) or attitudes (adaptability or resilience) as 'soft skills' ignores the dynamic interaction between individual personal traits and work organisation. Collaboration and teamwork are not only personal attributes but also work methods shaped by the work organisation and governance process. As Nurski explains, "good communication skills can facilitate teamwork, but they cannot fix role ambiguity or unclear decision-making process. More importantly, good people should not have to make up for bad systems" (JRC, 2025b, p.78).

CHAPTER 2: CHANGING SKILLS DEMAND IN WORKPLACES ADOPTING AI

This chapter uses the conceptual framework of tasks and skills presented in the previous chapter to examine changing patterns in the demand for cognitive, socio-emotional and manual skills in the context of AI adoption. As AI technologies are likely to become more widespread in the workplace, the level and composition of skill requirements are expected to evolve across the whole employment spectrum. The chapter begins by exploring shifts in demand for cognitive skills in AI-adopted workplaces, with particular emphasis on the increasing need for digital skills. This is followed by a review of the changes in demand for socio-emotional skills and a further review of evolving requirements for manual skills.

2.1. Changes in demand for cognitive skills

The advent of AI has had its most immediate impact on knowledge work, where cognitive skills are central to processing and applying new information. AI technologies excel at routine knowledge tasks and increasingly some non-routine cognitive tasks. Machine learning (ML) algorithms can quickly analyse data and identify patterns. Generative AI (GenAI), which is a more recent class of AI systems that can generate human-like text, translation, videos, audios and programming code based on cognitive skills, is already prevalent in many work settings. They show how AI technologies are already capable of carrying out several knowledge tasks, potentially reducing the demand for human cognitive input in areas that can be automated. At the same time, as workers off-load a significant share of such tasks to AI technologies more time can be spent on non-routine tasks that are currently are beyond the limits of AI tools. The demand for individuals with higher-order cognitive skills is therefore expected to rise.

Several OECD studies confirm *increasing demand for cognitive and digital skills as a result of AI adoption* (OECD, 2023a; 2023c; 2024a). Typically, jobs involving AI tools require high-level cognitive skills such as creative problem-solving, originality and analytical reasoning, socio-emotional skills and diversified skill sets (OECD, 2023c). Skills complementary to AI that are becoming increasingly important include critical thinking, for example, to identify errors or spot 'hallucinations' in AI outputs and those needed for the overall effective use of these technologies. Another OECD study (2024a) finds that, in occupations with high AI exposure, demand is concentrated in management and business processing skills including project management, budgeting and accounting, as well as administration, clerical and customer support tasks[24]. Finally, an SME survey on the use of GenAI confirms the increased need for highly skilled workers in the GenAI context with data analysis and interpretation, and creativity and innovation skills are the most in-demand skills areas (OECD, 2025f).

Changing skills demand can be illustrated through several sector-specific examples. For example, in the ***financial services sector,*** Robotic Process Automation (RPA) is being used to automate repetitive tasks such as customer onboarding processes, managing insurance claims, and streamlining regulatory compliance protocols. AI is also used for risk management, fraud detection, loan decisions and developing credit-scoring metrics (ILO, 2024). As routine data entry tasks become automated, the content of many roles is shifting allowing workers to free up time for data-led decision making and other higher value-added tasks, such as product innovation, enhanced customer service and expanding the customer base. There is also a steady emergence of roles requiring humans to conduct 'supervision', 'oversight' and 'rationalisation' of the outputs generated by AI technologies, to

[24] This study used OJVs from Lightcast covering 10 OECD countries (Austria, Belgium, Canada, Czechia, France, Germany, the Netherlands, Sweden, the UK and the US) and focusing specifically on the vacancies that are exposed to AI but do not require specialised AI technical skills. These high-exposure occupations comprised a third of all vacancies in OECD countries in the sample. The period of OJVs collected for English-speaking countries (Canada, UK, US) is 2012-2022, while for the rest it is 2018-2022 (see OECD, 2024a).

mitigate biased outputs and actions, such as racial and gender bias in credit-scoring algorithms (ILO, 2024).

Similarly, in the ***media and culture sector,*** AI technologies are being applied across activities ranging from journalism to music and film production. In journalism, AI technologies can process large datasets, identify trends and verify claims much faster than humans. Journalists therefore leverage AI technologies for data analysis, fact checking and content creation, which can be refined and contextualised, thus reducing the time required to produce content. In addition, media outlets can deliver more personalised and relevant content for audiences (ILO, 2025b). In music production, producers and sound engineers are increasingly using GenAI to mix and refine music, and even to create new songs. In film production, GenAI is increasingly used for generating scripts, images and visual effects. With GenAI automating some tasks, job roles are evolving and putting more emphasis on oversight of AI-generated content rather than direct content creation (ILO, 2025b).

The growing use of AI-generated content reshapes the composition of cognitive skills required in many occupations, increasing the importance of contextualising, overseeing and exercising judgement (OECD, 2023b). The limitations of AI-generated content including the potential decline in content quality, in terms of nuance, cultural context and linguistic subtleties, and the reproduction of biases embedded in large datasets requires careful human scrutiny and correction (ILO, 2025b). In the financial sector, for instance, compliance analysts must detect anomalies flagged by AI systems but also judge their relevance in real-world legal and regulatory contexts. In journalism, editors using AI-assisted summarisation tools still have responsibility for verifying facts, detecting bias, and maintaining editorial standards. This shifting use of cognitive skills from ‘raw creation’ towards editorial and appraisal tasks enhances the value of higher-order skills, while more routine cognitive skills such as basic data analysis, drafting and summarisation may decline in value and prevalence (see Box 1).

Box 1: What does critical thinking mean in AI-adopted workplaces?

According to Autor (2024), AI technologies shift what *‘thinking critically’* means in three main ways:

- ***From gathering information to verifying information.*** AI tools can gather and curate large amounts of information in response to a prompt. They are far more efficient than we are at it—but it falls to us to check the AI’s accuracy. In order to do that, humans will need to have not only a certain level of subject-matter expertise but also higher level analytical and critical skills.
- ***From solving problems to integrating AI output.*** As AI becomes more proficient at providing solutions to prompts with clear answers, humans will be able to spend more time deciding whether models’ responses fit the context of the request. Exercising good judgment—knowing what makes something not just correct but also meaningful—will take on increased importance.
- ***From executing tasks to overseeing them.*** With the launch of AI agents, humans will focus more on allocating resources and managing different AI models. The new paradigm of service as a software—a product model in which software provides an end-to-end service (instead of being just a tool) by taking on the tasks that would otherwise require significant human effort—is an extreme version of this shift.

These emerging oversight tasks, however, may increase cognitive load and accountability for workers, raising new risks of work intensification and stress if not accompanied by appropriate job design, training support and organisational safeguards.

As AI generates ever more complex outputs in all areas, the ability to question, interpret, and challenge algorithmic results becomes fundamental. Thus, many jobs today demand people with highly critical thinking skills and the ability to solve non-routine problems alongside technology. An illustrative example of missing critical thinking skills in an AI-enhanced workplace is ‘*workslop’*, a new term that has recently emerged for the AI-generated low-value content that is incomplete or missing crucial context, while it appears professionally productive on the surface. When AI tools are used to create content without the judgment of humans’ expertise and critical analysis, the AI-generated content that seems professionally formatted shifts the cognitive burden of the work to others, requiring the receiver to interpret, correct, or redo the work (Niederhoffer et al, 2025). In other words, an AI tool does not replace skills that are lacking but simply transfers the necessity of human cognitive effort from the creator to the receiver[25].

Using AI in management through algorithmic management (AM) is another example of changing skills demand in the execution of managerial, organisational and coordination tasks. AM tools illustrate the importance of digital fluency and AI literacy for human managerial roles. In an OECD survey of employers, they report an increasing need for general managerial skills and analytical skills (e.g. ability to use or interpret data) when using AM tools (OECD, 2025b). Social skills (e.g. active listening skills) are also in high demand particularly in the workplace in the United States. However, this pattern is not consistent across diverse contexts: European managers report a sizeable decline in the demand for social skills. These results point to different expectations of the managerial role depending on context. Nevertheless, it remains clear that mid-level managers are expected to have sufficient analytical skills to work effectively with new technological tools but to also retain uniquely human qualities that set them apart from technology (OECD, 2025b).

According to WEF (2025a), analytical thinking remains the most sought-after core skill among employers, with seven out of 10 companies included in the WEF sample considering it as essential in 2025. This is followed by creative thinking, innovation and technology-related skills. Humans must judge whether AI-generated results are accurate, properly interpreted and consistent with societal values and cultural context (WEF, 2025a). Therefore, higher-order analytical skills, critical thinking, creativity and problem solving are becoming the most demanded cognitive skills. While increasing *the value of higher-order cognitive skills, the use of AI performing several knowledge tasks may reduce the value of lower-order cognitive skills* – or as it is sometimes called the *'deskilling of knowledge work'* (Orrell, 2025).

The demand for higher-order cognitive skills will gradually expand to more jobs, until AI becomes a general-purpose technology with increased capacity to perform all routine and non-routine tasks reliably. The demand may surge further if the new jobs are more likely to be concentrated in the non-routine and the cognitive and metacognitive categories. Therefore, future workers will need higher-order analytical skills, particularly critical and strategic thinking and decision-making. Today, understanding and using AI technologies (e.g., data analytics, machine learning) combined with higher order cognitive skills is a desired combination for several white-collar professions (Orrell, 2025). *This trend towards higher order cognitive skills may reinforce job polarisation as benefits accrue to high-skill roles* (and some low-skill services), while middle-skill white-collar jobs in high-exposure and low-complementarity tasks face higher displacement risk (IMF, 2026; ILO, 2023).

Increasing demand for digital/ technology skills

Digitalisation has changed the way we learn, the way we work, and the way we communicate and socialise. In this rapidly evolving technological landscape, both generic and specialised digital skills have become crucial in a wide range of occupations. As digitalisation is no longer confined to specific industries, but has become a tool for survival, digital skills are increasingly required in jobs where this was not the case before (ILO, 2021b; EC, 2024; ETF, 2024a). A key milestone of digital acceleration was Covid-19, leading to an upsurge of digital services and digital consumption and expanding e-commerce, logistics, digital media and digital financial services sectors, along with the demand for related skills. This has pushed up the demand for digital content creators, content coordinators, podcasters, social media managers, digital marketing specialists, etc.

On top of these trends, *AI technologies further fuelled the demand for digital skills, both in terms of variety and depth of these skills.* In particular, intermediate and advanced digital skills are increasingly needed to integrate and use AI tools in workflows in several occupations and sectors (OECD, 2023b; ILO 2021b, 2025b; Cedefop, 2023). Based on the second round of the European Skills and Job Survey (ESJS2), Cedefop reports more than 8 in 10 EU jobs (87%) requiring at least basic digital skills. Some four out of ten adult employees had to learn to use new digital technology to do their main

[25] See the source article on the AI World: Why AI Success Stories Mask Workplace Reality / AI World.

job in the (mid-) 2020-21 period (Cedefop, 2022). Accelerated digitalisation has substantially increased training demand by individuals, with affected workers 15.7 percentage points more likely to request general training and 39.7 percentage points more likely to seek IT-specific training (Zhu and Yang, 2026). IMF (2026) notes that every sector demands new IT-related skills, reflecting the general-purpose character of the technology. The demand for digital skills will keep growing in the next decade within the EU, while substantial investment in digital skills training is key for the digital transformation (Cedefop, 2024).

UNESCO (2024a) defines digital skills as ‘the ability to access, manage, understand, integrate, communicate, evaluate and create information safely and appropriately through digital devices and networked technologies for participation in economic and social life’. Several international frameworks have been developed to guide teaching digital skills[26], but the recent update of *the European Digital Competence Framework* is particularly pertinent as it has integrated ‘AI competence’ across all areas and competences in the original framework (DigComp 3.0). This deeper, technical dimension of digital skills, described as ‘technology’ skills by WEF (2025a), are meant for a ‘digital savvy’ workforce which can maintain and manage AI systems. AI is also transforming which digital skills are needed and how they are used. According to WEF (2025c), AI, data and digital skills are the most exposed to transformation; on average, 68% of digital skills are expected to change in how they are applied.

WEF predicts that ‘*technology’ skills are expected to become vital over the next five years, outpacing the growth of all other skill categories* (WEF 2025a). Leading the way are AI and big data, followed by networking, cybersecurity and overall technological literacy. In fact, demand for digital skills learning is soaring (AI and big-data learning now account for one-fifth of all digital learning hours), but employer demand is still concentrated in roles such as cybersecurity and network engineering (representing over half of all digital jobs) (WEF, 2025c). This means that the in-demand digital skills in occupations involve non-routine tasks, problem-solving and the creation of new digital content such as graphic and engineering designs, software products and services and analytical outputs. Whereas office software for administrative purposes is linked to occupations that are predicted to decline (ILO, 2021b). In fact, basic digital skills are often not listed in job vacancies, because they have become so widespread and everyone is assumed to have these skills (e.g. office software is now a core skill) (JRC, 2022b).

This is not to say that basic digital skills are less important for education and training. Skills are aspects of a hierarchically structured learning and capability system, in which advanced skills are built upon a foundation of basic skills. Basic digital skills are indeed necessity for developing more advanced digital skills. From skills development perspective, basic digital skills are closely linked to and a foundation of AI literacy, thus they must be in curricula, frameworks and policy design. This is not only a solid basis for learners to successfully navigate in an increasingly complicated labour market in the age of AI. More importantly, it is critical to enhance inclusion and equity of skills provision, where basic digital skills gap is widening and risk of job polarisation is rising.

The healthcare sector is one example where specialised digital skills have become necessary to understand and control the mechanisms and results of AI-embedded tools (OECD, 2025a; IMF, 2026)[27]. In particular, digital skills for developing and implementing Health Information Management, Telehealth, Advanced Robotics, and Cybersecurity seem to be increasingly in demand. The OECD study (2025a) confirms the increasing presence of AI technologies in both technical and non-technical jobs in healthcare, redefining what constitutes a ‘digitally competent worker’ in the sector. Similarly, the number of digital skills required from workers has increased substantially in many other fields, for example, when a healthcare technician operates AI-driven diagnostic systems; a marketing analyst is expected to use generative AI tools to create campaign content; or a desk clerk uses AI-based chatbots or natural language processing tools to assist customers.

[26] See UNESCO UIS Digital Literacy Global Frameworks (2018); Six pillars for the Digital Transformation of Education (UNESCO, 2024a); Digital Economy and Society Index (DESI); European Digital Competence Framework (DigComp 3.0), which was updated at the end of 2025 to integrate AI competence.

[27] This was based on the analyses of nearly 55.5 million OJVs from Canada, the UK and the USA to track the demand for digital and AI skills in health-related occupations between 2018 and 2023 (OECD, 2025a).

The ILO analyses of OJVs in Brazil, Russia and South Africa found a doubling of demand for advanced digital skills related to AI and ML between 2016–2021 (ILO, 2026). There is also evidence on the rise of 'hybrid roles' that blend traditional expertise roles with computational skills. For example, as AI continues to reshape journalism, journalists are increasingly required to have a deeper understanding of AI's technical capabilities and limitations (ILO, 2025b). Indeed, jobs that are not considered 'AI jobs' increasingly require intermediate digital skills to integrate and use AI tools effectively in the workflows. For instance, many news broadcasting organisations are now actively investing in upskilling their workforce through AI training programmes, responding to the rise of emerging roles that combine traditional journalistic domain expertise with digital skills, such as data management and algorithmic understanding (ILO, 2025b).

The rise of hybrid roles was already evident before the arrival of AI, but AI systems further extend hybrid roles, spreading across occupations and sectors and blurring occupational and industry boundaries. Examples include business and economic journalists, who need to specialise in economics and statistics, possess writing, interviewing and data visualisation skills, and now also use social media and AI tools. Coding skills today are required not only of programmers, but also of artists and designers, engineers and scientists. Possession of such hybrid skill sets will require not only strong initial specialisation in both technical and hard knowledge skills, but also continuous upgrading of skills to master technologies and subject matter expertise that do not yet exist (ILO, 2021b).

However, *there are also differences in the digital skill demand between countries,* even with similar levels of development, and within and across sectors (ILO, 2021b). Those reflect different structures of economies (with some occupations and jobs having low digital skills requirements), technology adoption by businesses, but also the existing supply of digital skills. ETF's (2025) study using the ESJS2 survey results in the Western Balkans confirms the varying needs and use of digital skills in the workplace, while the platform work studies in ETF countries reveal an increasing need for diversified digital skills (ETF 2021b, 2023a, 2024b, 2024c). At the same time, the availability and quality of digital infrastructure influences both the adoption of digital technology and the acquisition of digital skills, and infrastructure bottlenecks and related challenges are most often observed in low and lower middle-income countries (ILO, 2021b).

Strong AI foundations in math, science, engineering and computer science further increase the value of STEM knowledge (Science, Technology, Engineering, Math). While STEM-related skills are required to develop AI systems, even non-technical workers who use AI tools now require a higher-level baseline knowledge in these areas. For example, knowledge of data science is becoming key, as digital literacy and data literacy are prerequisites to function well with AI applications. In fact, scientific and computational literacy overlap and inform AI-related skills. According to IMF (2026), IT skills account for the largest share of 'new skills' sought by employers, followed by business and data analysis skills[28]. To conclude, *the level of cognitive competences required from all workers tends to increase and become broader,* often shifting the occupational structure towards higher skills, even in emerging economies (ETF, 2024a, 2025).

2.2. Changes in demand for socio-emotional skills

Socio-emotional or non-cognitive skills are fundamental to facilitate the development and application of cognitive skills. As such, they are deeply interwoven with cognitive skills. Rising demand for socio-emotional skills in response to technological changes has been evident for some time, but their importance is amplified by their role in managing ethical AI systems, maintaining trust, and enabling collaborative decision-making. Socio-emotional skills are no longer a 'nice to have' supplement to technical expertise, *they are becoming essential for human-centric and fair AI adoption.* They are indispensable assets in AI-driven digital economies, functioning as the human enablers of

[28] IMF study is based on the Lightcast OJV data for Brazil, Denmark, Germany, South Africa, the UK and the US, focusing on the period of 2021-2024, and complemented by the American Community Survey, the German administrative labour market records, US firm-level information, and millions of worker profiles provided by Lightcast (IMF, 2026). '*New skills'* are defined in the paper as those that were barely present in vacancies at the start of the 2010s but have since become more common.

technological advancement while maintaining ethical principles. The presence of socio-emotional skills has become a determining factor of success in the digital and AI transformation of societies.

McKinsey estimated that demand for socio-emotional skills would grow across all industries by 26% in the US and by 22% in Europe between 2016 and 2030. In a study of growth in occupations in the US, the highest growth is found in jobs which require high levels of social skills and strong skills in mathematics (Deming, 2017). Jobs with high social skills but low mathematics skills also saw a significant increase in occupational intensity, suggesting the real driver was the non-cognitive category. And jobs with high mathematics skills but low social skills declined. The rising value of workers who can blend domain knowledge with the 'tacit', subjective, intuitive, and affective aspects of work is observed in the US labour market when unemployment rates for workers with liberal arts degrees were about half that of computer scientists and engineers in 2023 (Deming, 2017). And this increasing demand does not apply only to advanced economies, but also to emerging and middle-income economies (WEF, 2025a; ETF, 2021a).

Human-AI collaboration requires human framing, oversight and contextual understanding. Socio-emotional skills are a core component of what makes us human in an AI world, becoming a prerequisite for effective and ethical implementation. A school principal implementing AI-powered learning platforms must not only understand the tool but also lead change, motivate teachers, and evaluate ethical implications on student data. Or a logistics coordinator overseeing predictive routing software must still respond creatively when supply chains are disrupted, balancing efficiency with local knowledge and human intuition. Design professionals, marketing strategists, and researchers increasingly rely on non-cognitive capabilities to leverage AI tools not as substitutes, but as springboards for innovation. Workers will increasingly focus on higher-order tasks that engage the strategic and creative thought that places a premium on advanced cognitive and non-cognitive abilities such as leadership, decision-making, and team-based work. Personal attributes, social abilities, and emotional capacities underlie effective human interaction in an AI-driven society and economy (Orrell, 2025).

The current generation of AI technologies, at the time of writing, has limited ability to authentically replicate socio-emotional skills. For instance, AI powered tools can certainly deliver media messages; however, since these tools do not yet match the ability of skilled journalists to generate interest and engage audiences, few people would be willing to watch news delivered by a digital avatar (ILO, 2025b). As organisations continue to integrate AI into core business functions, the ability to work alongside AI systems, and to add uniquely human value to their outputs, is likely to become a baseline requirement across the labour market. Human-AI teams also demand new forms of interaction—not just between colleagues, but between humans and machines. Workers must learn to collaborate in hybrid environments, explain AI-driven decisions to clients or supervisors, and maintain ethical standards even when technologies operate behind the scenes. WEF (2025a) and OECD (2024a) confirm that socio-emotional skills are among the fastest-growing requirements in AI-intensive economies.

The limited capability of AI technologies, at the time of writing, to carry out tasks requiring emotional intelligence and complex human interaction is also evident in the ILO's task automation scores and prediction justifications (Gmyrek et al, 2025). For instance, for Primary School Teachers (ISCO-08 2341), the automation scores are relatively higher for tasks that involve data processing and content generation, such as *'Preparing daily and longer term lesson plans in accordance with curriculum guidelines'* (0.465), while scores are much lower for tasks such as *'Maintaining discipline and good working habits in the classroom*' (0.16) which require *stronger skills related to 'human engagement', 'empathy', 'real-time observation', 'judgment and interaction', and 'nuanced interpretation'* (Gmyrek et al, 2025)[29]. Thus, demand shifts toward more complex and creative tasks that require human ingenuity, emotional intelligence, and ethical approach.

The distribution of automation scores across tasks bundles of occupations suggests that GenAI may automate some tasks within occupations, but because other tasks still require human inputs, for now

[29] Task-level scores within the overall hierarchy of ISCO-08 are available here: https://pgmyrek.github.io/2025_GenAI_scores_ISCO08/

most jobs are likely to be transformed rather than fully automated (ILO 2023; Gmyrek et al, 2025). For example, teachers can use AI tools to shorten the time spent on drafting lesson plans and devote more time to one-on-one mentoring of students. Similarly, doctors and nurses might be able to rely on AI technologies for quick diagnostic suggestions or patient monitoring, which they critically examine, and focus more on counselling and explaining treatments through effective communication and demonstration of empathy. A nurse might use AI to track patient vitals, but it is emotional intelligence and empathy that ensure compassionate care.

AI is increasing the value of socio-emotional skills that remain uniquely human. These 'human-centric' abilities are highly valued by employers and the least likely to be automated. Tasks tied to empathy, creativity, leadership and curiosity have just a 13% potential for AI transformation since they depend on human – not machine – judgement, context and lived experience (WEF, 2025b). Effective communication is crucial in building professional relationships, both inside and outside the organisation, while nurturing positive environment and building strong teams. Yet collaboration and communication are cited as major skill gaps by employers in many studies (Eurofound, 2025a). Socio-emotional skills also greatly influence career development in modern society, since they reflect the ability to react to changes, constantly adapt ways of working and improve communication with colleagues. Recent employer surveys with big global companies indicate a significant expected increase in demand over the 2025-2030 period for workers' adaptability, resilience, flexibility and agility, along with curiosity and learning-to-learn (WEF, 2025a).

Several online job vacancy (OJV) analyses confirm higher demand for socio-emotional skills in labour markets (OECD, 2021b, 2023a, 2023b, 2024a; ILO& World Bank, 2024). In a large study covering 10 countries, increasing demand for socio-emotional skills has been persistent in all countries analysed (OECD, 2024a)[30]. A study on OJVs from Brazil, Egypt, Jordan, Russia, South Africa, United Arab Emirates and Uruguay finds that employers tend to bundle different types of socio-emotional skills and combine them with cognitive skills in job advertisements (El Hage Sleiman et al., 2025; ILO, 2026). This bundling shows the complementary nature of socio-emotional skills and the evolving expectations of employers after the automation of predictive tasks by AI – e.g. identifying patterns in consumer behaviour, forecasting sales volumes, or flagging potential risks. Yet these systems continue to rely on human oversight for judgment, strategic framing, and ethical evaluation. As Agrawal et al. (2022) argue, *the declining cost of prediction increases the relative value of complementary human skills such as interpretation, governance, and contextual awareness.* Thus, AI is redefining the comparative advantage of human capabilities.

To sum up, human cognition, emotion, judgment, and creativity form the connective tissue of successful AI-human collaboration. In a world where machines can calculate faster, recognise patterns at scale, and optimise routine decisions, the unique capabilities that humans bring to the workplace lie in the ability to adapt to the unexpected, judge ethical implications, communicate across disciplines, and learn continuously. Creativity, curiosity, and learning-to-learn are vital since AI cannot imagine new paradigms, though it may discover novel solutions that humans have never thought of within the existing paradigm. It takes human ingenuity to ask novel questions and reframe problems. These trends underscore a broader transition in how we value work. It is not just what we do, but how we do it and why: *how we navigate uncertainty, relate to others, integrate meaning and fairness into technology-driven processes.* Thus, *these skills are prerequisite for human-centric and fair AI adoption*.

2.3. Changes in demand for manual skills

Manual skills refer to physical capabilities required to perform jobs, encompassing finger-dexterity, hand-foot-eye coordination, and physical skills related to physical strength. They are often discussed in the context of routine and non-routine tasks (Escudero et al, 2024), and they play an important role

[30] This is based on the analysis of online job vacancy (OJV) database from Lightcast, including English-speaking countries (Canada, the UK and the US) and continental European countries (Austria, Belgium, Czechia, France, Germany, the Netherlands and Sweden) (OECD, 2024a).

in sectors such as manufacturing, construction, agriculture, transportation, mining, and services. The capability of AI technologies to perform tasks requiring manual skills depends on technological advancement in the Physical AI domain. It also depends on the nature of the environment in which AI-enabled robots are expected to operate (i.e. controlled and non-controlled), and the tasks to be carried out (i.e. routine and non-routine).

AI-enabled robots have already entered the workforce in controlled environments with structured, routine and repetitive tasks (e.g. sorting packages and carrying loads in warehouses), causing shifts in job roles, skills requirements, and working conditions. For example, after Amazon introduced Automated Mobile Robots (AMRs), warehouse employees became more occupied by tasks such as maintenance and troubleshooting, instead of constant manual picking (ILO, 2020). This suggests that *the relative importance of physical skills (i.e. physical strength) and some simple finger-dexterity skills for routine tasks among warehouse employees seem to have declined.* However, even in highly automated settings, certain tasks still require human intervention with more sophisticated finger-dexterity skills. In robotic warehouses, tasks such as inventory management are still the domain of humans and workers must handle the items that robots cannot easily grasp due to varied shapes (ILO, 2020). These cases demonstrate the shift in skills requirements for warehouse workers from pure manual skills to more cognitive skills related to overseeing and supporting automated systems by managing exceptions.

Physical AI applications have seen only limited use cases so far in non-controlled real-world dynamic environments with unstructured and non-routine tasks. For example, Level 4 and 5 autonomous driving outside a defined Operational Design Domain is often at a prototype and pilot basis with human intervention, as *it is notoriously difficult to automate non-routine physical tasks in uncontrolled environments.* Indeed, the rate of technological advancement in the Physical AI domain is relatively slow. For example, in the Final Report of the ILO Technical Meeting on the Future of Work in the automotive industry, 'the market for autonomous vehicles was expected to grow by 63.1% each year between 2021 and 2030, outweighing the traditional car market by 2030' (ILO, 2020). However, according to the latest experts' survey, the actual growth has not been as exponential as predicted, especially for high (L4) and full (L5) autonomous vehicles (McKinsey and Company, 2026; Duboz et al., 2025).

Some studies suggest that firms highly exposed to AI can generate spillover effects, increasing employment and wages in complementary occupations, often in lower-skill services (IMF, 2026; OECD, 2024a). By focusing on AI exposure at the firm level, OECD found an increased demand for skills related to production and technology and manual skills in the most AI-exposed firms (OECD, 2024a). These skill groupings with increased demand are found disproportionately in low-exposure occupations and include skills such as maintenance, repair, forklift driving and more fundamental skills such as dexterity, heavy lifting and range of motion. Therefore, AI adoption also affects low-exposure occupations by increasing demand for some blue-collar skills, possibly through a productivity effect that results in higher demand and spills over to these occupations in the firms (OECD, 2024a). This may suggest that *manual skills may see increased demand due to complementarities with AI in production.*

AI technologies can also change the use of manual skills in some high-skilled occupations. One such example is the highly specialised hand skills of surgeons, as robotic surgery practices are increasing due to the growth of less invasive operations that secure faster patient recovery. Robotic surgery is not necessarily better than human surgery, and hand skills may still be necessary to use robots, but it is a different skill. The future of AI in robotic surgery involves advancing autonomy, tailoring surgical methods to individual patients, and improving surgical training through AI-driven simulations and virtual reality technologies. Therefore, surgeons' skills will likely evolve, with AI handling routine tasks and enhancing precision, but with a risk of deskilling if surgeons over-rely on the technology.

AI is also changing skills used in creative arts (painters, sculptors, and musicians) by becoming a new tool, potentially increasing competition for entry-level and certain commercial art jobs, while pushing human artists to emphasise process, storytelling, and unique human creativity as a form of value. Artists will still need their *manual* skills in human creations, with higher focus on unique physical craftsmanship and human storytelling. The value of handmade art and physical crafts work could increase to distinguish it from mass-produced AI content. Similarly, AI has already automated some musical tasks, but as AI-generated music becomes more prevalent, live in-person performances may become more valuable due to their authenticity and human element.

In summary, *manual skills for routine tasks are losing their relative importance due to the increasing capability of Physical AI to take over simple manual tasks,* while finger-dexterity skills and hand-foot-eye coordination skills for non-routine tasks are still relatively less affected. In the future, low-skilled workers in factories themselves may contribute to the collection of 'real world data' on their manual tasks, and companies may look to replace factory workers by making breakthrough on physical AI. The employer survey conducted by the World Economic Forum also confirms a net decline of the importance and demand for manual dexterity, endurance and precision in routine tasks (WEF, 2025a). At the same time, *physical AI have seen limited use cases so far in non-controlled environments with unstructured and non-routine tasks.* A typical example is caring for a child or an elderly person. It is hard to replicate manual skills required in such care professions for now, and future developments may lead to a higher valuation of these jobs and tasks given that no machine can do them as well yet.

The overall conclusion of the chapter indicates the possible increase in the demand for higher-order skills, particularly in cognitive and socio-emotional fields due to AI adoption. However, this increased demand does not automatically translate into improved job quality. In some contexts, AI-driven task reorganisation may intensify work, increase cognitive and emotional demands, or place more responsibility for oversight and judgement on workers without sufficient autonomy, training or pay. For this reason, analysing changes in skills demand also requires attention to job quality, working conditions and worker protection. This is especially important for vulnerable groups, such as mid-skilled youth who are looking for entry-level jobs and older workers who hold clerical work (many of whom are women). The benefits of AI are and will be unequally distributed, pushing the polarisation further, so there is a need for policies and programmes to support these groups.

CHAPTER 3: EMERGING DEMAND FOR TECHNICAL AI SKILLS

Perhaps the most immediate impact of AI has been the emergence of new demand for AI-specific technical skills and consequently a *'technical AI workforce'* to develop, maintain and implement AI systems and tools. The *'AI workforce'* includes differing degrees of competency, varying from highly technical AI researchers and engineers to professional users of AI as part of their job. This chapter looks at studies focused on the size and characteristics of the existing AI workforce, which, although representing a relatively small segment of the workforce, is experiencing rapidly growing demand for its skills. It also reviews available evidence about variations of their technical proficiency levels, and some trends in hiring AI talent.

Up until recently, there was no 'AI occupation' or a taxonomy for classifying AI workers. Occupational classifications used in labour force surveys are not yet detailed enough to capture the niche skills required to develop AI systems. Thus, AI workers appear in various occupations to different extents, and they are classified with other similar, technical workers, who may not be actively developing AI or possess the requisite skills to do so[31]. Different methods and data sources are employed to overcome this problem and estimate the size of the AI workforce, e.g. case studies, administrative data, representative firm- or worker-level surveys, web-based big data. Despite their limitations, online job vacancies (OJVs) and CVs are often used for identifying or proxying such workers[32]. It is not the aim of this report to discuss the benefits and limitations of different methods and data sources to identify the AI workforce, but to provide a glimpse of practices to help understand discrepancies in reported shares of AI workers in the labour force, even for the same country and same year.

In the absence of a clear definition of 'AI skills', commonly a list of AI-related keywords is drawn to categorise AI-related tasks, technologies and skills (Lightcast, 2024; OECD, 2021b, 2023b, 2024b). These keywords are then sometimes cross-checked with experts, industry stakeholders and occupational databases. For example, keywords like 'artificial intelligence' (AI) and 'machine learning' (ML) are largely used to proxy AI skills, as well as required programming languages such as Python, or the ability to work with and manage big data. As a new domain with constant advances, AI-related skills are evolving quickly. As the domain matures, some keywords have become more generic, umbrella terms, and others more specific sub-categories. This has led to differentiation between 'generic' versus 'specific' AI skills and several AI sub-domains. More generic AI skills involve terms like AI, ML, computer vision and machine translation, while specific AI skills require knowledge of AI models (e.g. decision trees, deep learning, neural network, random forest, etc), AI tools (e.g. TensorFlow, PyTorch, etc.) and AI software (e.g. Java, Gradle, galaxy cluster, etc.) (OECD, 2023b).

When OJVs and CVs are used to identify AI skills, the number of skills included and their added value in executing jobs determine their relevance. For example, Lightcast classifies an OJV as 'AI-related' if it includes at least one skill from the pre-defined list of AI keywords (Lightcast, 2024). Others apply stricter criteria, requiring vacancies to contain at least two AI skills belonging to different concepts or methodologies, only one of which may be a software-related skill (OECD, 2021b). Stricter criteria prevent accidentally picking up non-AI vacancies. For example, even if a vacancy contains the words 'deep neural networks' and 'convolutional neural networks', it is not considered to be 'AI-related' unless it contains another keyword, such as 'computer vision' (OECD, 2023b)[33]. In a related approach, Acemoglu et al. (2022) distinguish between a 'narrow' and a 'broad' definition of AI vacancies, where

[31] For example, the ISCO-08 (212) occupation Mathematicians, Actuaries and Statisticians includes the sub-occupation Statisticians, many of whom will have AI skills, although some will not (OECD 2023d).
[32] For challenges and limitations of web-based big data, please see Cedefop/European Commission/ETF/ILO/OECD/UNESCO (2021) and JRC, 2021c.
[33] Software-related skill 'Python' is used in many domains worldwide and not only for AI-related purposes. If the criteria are at least two keywords for the identification of AI-jobs, then it excludes jobs requiring software skills related to the use or development of Python in other domains (OECD, 2021b). In another example, an economist is not (yet) an AI-related job just because by using a 'random forest estimator' in their analysis.

the narrow list of skills is limited to strictly technical AI, while the broader one also includes data science.

With the evolution of AI technologies in the last decade, the number of AI skills and AI sub-domains have gradually increased and diversified. Although generic terms like AI and ML are still most widely used to express demand for AI skills, more specific terms/ domains appeared recently such as natural language processing (NLP) or Generative AI[34]. For example, in an analysis of OJVs in 2019-2022 for 14 member countries, OECD (2023b) categorised AI skills under seven sub-domains: *AI, ML, NLP, Neural Networks; Autonomous Driving; Visual Image Recognition; Robotics.* Later, the seven AI sub-domains were expanded to nine to reflect new developments, adding *Generative AI* and *AI Ethics, Governance and Regulations* (Lightcast, 2024). The number of AI skills has also increased significantly to over 300 keywords. These AI skill categories are likely to continue to change requiring regular updates and tracing of new developments in the AI field before its consolidation (Napierała, 2024).

3.1. The size of AI workforce

Despite the differences in results for the reasons explained above, *all studies point to a very small group of people involved in the development and professional use of AI technologies*. Yet the demand for AI skills has been rapidly expanding over the past decade in both advanced and emerging economies, driven by the growing need to design, apply, and manage these systems. As mentioned before, AI workforce varies from highly technical AI researchers and engineers to professional users of AI as part of their job. Depending on the type of analytical methods and definitions used, the share of AI workforce accounts for between 0.3% and up to 5% of total employment, with varying degrees across time and countries (Cedefop, 2022, 2025; Alekseeva, 2021; Acemoglu et al., 2022; Gehlhaus and Mutis, 2021; OECD 2021b, 2023b, 2023d; Pal et al., 2025; IMF, 2026).

Table 2 provides a quick overview of comparative findings of selected studies on the size of the AI workforce. The share was found to be around 0.8% of employment in 2018 in the studies of Alekseeva et al. and Acemoglu et al., both of which identify a significant increase from 2012. An OECD analysis using data from the labour force survey, population survey and OJVs in 24 OECD countries found similar results: the AI workforce represented 0.34% of employment in 2019, almost tripling from its share of 0.1% in 2012 (OECD, 2023d)[35]. There is significant variation in the size of the AI workforce across 24 countries. The largest share of employment with AI skills is found in the UK, Finland, Sweden and the Netherlands, while Southern European countries have smaller shares. The AI workforce was tightly clustered in a small set of high-skilled technical occupations, including software engineers and statisticians (OECD, 2023d).

Table 2: Comparative findings of selected studies on the size of AI workforce

Study and timeframe	Main data source and countries	The size of AI workforce found
Alekseeva et al., 2021 *(the 2010-2018 period)*	OJVs from Burning Glass including at least one AI skill from the list of keywords – covering the US labour market.	Demand for AI skills grew 4 times over the period from 2010 to 2018 in the US – with AI vacancies from 20.6 thousand in 2010 to 180.9 thousand in 2018. The share of job postings demanding AI skills was 0.8% in 2018.
Acemoglu et al., 2022	Establishment-level dataset based on OJVs from Burning Glass that include at least one AI skill from	Difference between 'narrow AI' with strictly technical skills and 'broad AI' including data science skills. The share of AI vacancies in 2010 was below 0.2% for both

[34] For some examples of classifications on AI sub-domains, see JRC 2020; OECD 2021b; JRC 2025c; OECD 2023b; Lightcast 2024, 2025.
[35] The study used the share of vacancies within each occupation demanding AI skills as a proxy for the within-occupation share of the AI workforce. The skills demanded in a vacancy are used to classify vacancies as demanding AI skills, or not.

Study and timeframe	Main data source and countries	The size of AI workforce found
(the 2010-2018 period)	the list of keywords – covering the US labour market.	categories. By 2018, 'broad AI' reached to 0.7%, while 'narrow AI' to 0.5% of job vacancies.
OECD, 2021b *(the 2012-2018 period)*	OJVs demanding at least two AI skills in their skill requirements, covering Canada, Singapore, the UK and the US.	The number of job postings demanding AI skills increased from 5.7 million to 8.1 million in the UK and from 14 million to 29 million in the US in the 2012-2018 period.
OECD, 2023d *(the 2012-2019 period)*	OJVs, data from the labour force survey and population survey in 24 OECD countries.	The AI workforce has tripled from 0.1% in 2012 to 0.34% of employment in 2019. Large variation between the countries, from the lowest share of <0.27% in Greece, Italy, Spain to the highest one of 0.45% in the UK, Finland, Sweden in 2019.
OECD, 2023b *(the 2019-2022 period)*	OJVs including at least two AI skills in 14 countries: Australia, Canada, New Zealand, the US, the UK, Austria, Belgium, France, Germany, Italy, the Netherlands, Spain, Sweden, Switzerland	The share of job postings increased on average from 0.3% in 2019 to 0.4% in 2022. Large variation between the countries: in 2022 the lowest share of 0.14% in Belgium, Italy and New Zealand, while the highest shares were in the US (0.84%), Canada (0.54) and the UK (0.51).
Gehlhaus and Mutis, 2021 *(the year 2018)*	The data from the US Census Bureau and other datasets from Burning Glass, focusing on the US labour market	3% of occupations were found 'technical AI' or related to AI development, while this number becomes 9% when other occupations that 'could' become AI or which support AI technical occupations in product development or marketing are added as well.
Cedefop, 2022 *(the year 2021)* Cedefop, 2025 *(the year 2024)*	Second European Skills and Jobs Survey (ESJS2) conducted with 46 213 adult workers in 27 EU Member States + Iceland and Norway	Only a minority of adults working with AI (about 4-5%) are AI developers. 7% of European employees were writing programmes or code using a computer language as part of their main job, but only 18% of these computer programmers write code using AI methods.
Pal et al., 2025 *(the 2023-2024 period)*	OJVs from Lightcast and workforce profile data from Revelio Labs included the EU-27, the UK, Norway and Switzerland	The number of job postings demanding AI skills in 2024: 168.000 in the UK, 102.000 in Germany, 88.000 in France (together 57% of all postings). In terms of share, the EU-average is 1%, going up to 3% in countries like Portugal, Luxembourg, Ireland.
Lightcast, 2024 *(the 2019-2024 period)*	Global AI skills outlook based on the OJVs including at least one AI skill in advanced economies	The share of job postings increased from less than 1% of total OJVs in 2019 to around 2% or more in 2024 in digitally advanced economies.
IMF, 2026 *(the 2015-2025 period)*	Long series of OJVs from Lightcast in the US, the American Community Survey, US firm-level information - the US labour market	Difference between 'AI developer' and 'AI user' skills. AI skills appeared in fewer than 1% of postings before 2015 but in almost 5% by 2025 in the US. In 2025 half of them demand only AI-user skills, one-fourth demand AI-developer skills, and one-fourth both types of AI skills.

Note: Different methodological approaches, mostly relying on online job postings from Lightcast, have been adopted to identify AI jobs, often based on a list of AI-related keywords.

Another analysis of OJVs in 14 OECD countries reflects a similar increase of relevant job postings demanding AI skills, although their share did not exceed 1% of all vacancies in any country or any year covered by the study. Its average across countries increased from 0.3% in 2019 to 0.4% in 2022. There was a large variation across countries, and the shares changed over time. In 2022, the share of job postings demanding AI skills varied from the lowest share of 0.14% in Belgium to the highest one of 0.84% in the US. Besides the US, higher demand was noted in Canada, the UK, Switzerland and Sweden (OECD, 2023b). Despite some differences in results, all studies note a rapid growth of job postings demanding AI skills as well as increasing number of AI skills demanded in each job posting (OECD, 2021b).

In the second European Skills and Jobs Survey conducted in 2021, Cedefop found that overall, 7% of European employees were writing programmes or code using a computer language as part of their main job, but only 18% of these computer programmers write code using AI methods (machine- or deep-learning algorithms) (Cedefop, 2022). The share of the AI programmer workforce was more widely dispersed across sectors and less concentrated in the ICT sector than the conventional workforce of ICT programmers not coding using AI (Pouliakas et al., 2025). Moreover, Cedefop's 2024 AI skills survey shows that even though close to one in three European workers use AI tools or technologies as part of their regular work, only a minority of adults working with AI (about 4-5%) are AI developers (Cedefop, 2025).

Another study covering 30 European countries indicates that the absolute number of job postings demanding AI skills is dominated by large economies (Pal et al., 2025). In the period from 2023 to 2024, about 168 thousand 'AI vacancies' were posted in the UK, followed by 102 thousand in Germany and 88 thousand in France. Together, these countries account for 57% of all AI vacancies in Europe. Spain, Portugal, the Netherlands and Poland also register non-negligible AI skill demand, each showing over 25 thousand AI job postings. When it comes to the relative share of these AI job postings in total OJVs, however, the average is around 1% with countries like Portugal, Ireland and Luxembourg toping the ranking with 2-3% of total OJVs (Pal et al., 2025).

A comparison of several studies of AI workforce in the US illustrates well the different findings coming from the use of different methods, data sources and definitions (Table 2). In 2019, the share of AI workforce in the US ranges from 0.7% (Acemoglu et al., 2022) and 0.8% (Alekseeva et al., 2021) to 1% (IMF, 2026) and 9% (Gehlhaus and Mutis, 2021). Gehlhaus and Mutis (2021) used a model of the AI development process as a framework to define AI workforce, and based on their definition, 3% of occupations were found to be 'technical AI' jobs, while this number goes up to 9% when other occupations that 'could' become AI or which support AI technical occupations in product development or marketing are added.

The growth trajectory of demand for AI skills is best exemplified in the US, as the country with a highly developed digital economy and AI investments. IMF (2026) found that AI skills in the US appeared in almost 5% of job postings in 2025, up from less than 1% before 2015. The Stanford Institute for Human-Centered AI notes that the global share of job postings demanding AI skills has grown more than sevenfold since 2014, signalling a widespread integration of AI technologies into sectors (Maslej et al., 2025). Data from the Global AI Skills Outlook supports this trend (Lightcast, 2024): in 2019 job postings demanding AI skills accounted for less than 1% of total OJVs in digitally advanced economies, but it increased to around 2% or more in 2024. In conclusion, the share of the AI workforce in total employment remains small, but demand for AI skills is rising quickly as the need to deploy and integrate AI technologies across industries grows.

3.2. The characteristics of AI workforce

Research on the AI workforce consistently shows that most of them are highly educated white men in their prime working age (OECD, 2023d; Lazzaroni and Pal, 2024; Eurofound, 2025a). This is particularly true for the technical AI workforce, while some with upper secondary qualification were also found among other professional AI users (Pouliakas et al., 2025). According to OECD (2023d), on average, over 60% of the AI workforce has at least a tertiary degree across 24 OECD countries analysed, and less than 40% are women. Highly specialised 'AI developers' show a particularly high imbalance by race, gender and socio-economic background (Lazzaroni and Pal, 2024). The example provided by Nurski from the US tech industry is striking, e.g. women account for only 15% of AI research staff at Facebook and 10% at Google; while black workers represent just 2.5% of Google's workforce, and 4% at both Facebook and Microsoft (Eurofound, 2025a, p. 44).

In terms of studies, specialised AI knowledge and skills lie at the intersection between mathematics (statistics, calculus, algebra, algorithms, probability), science (physics, cognitive learning theory, language processing) and computer science (data structures, programming) (Verma et al., 2021). According to Magrini and Milde (2025), most AI workers in tech roles have studied adjacent fields such as computer science and other STEM disciplines (80%), with the remaining workers holding qualifications entirely outside STEM. Thus, education pathways of AI developers tend to be broader than the typical ICT workforce as they are not ready-made or resulting from standardised programmes (Pouliakas et al., 2025). Part of this reflects the newness of the field—in many ways, AI builds on computer science and ICTbut it also shows that people are acquiring AI skills on-the-job or through alternative routes such as digital portfolios, bootcamps, or (micro-)certifications.

The transformational potential of AI has been most visible in STEM jobs. Since AI adoption workers with specialised AI skills are concentrated in a few high-skilled occupations in the 24 OECD countries: mathematicians, actuaries and statisticians, software and application developers, ICT managers, database and network professionals, and electrotechnology engineers (OECD, 2023d). Therefore, AI skills are most relevant for occupations like computer scientists, IT directors and data scientists, including roles such as computer programmers, mathematicians, software developers/engineers, network and hardware engineers, data mining analysts and database architects (OECD, 2023a). Similar findings are also found in the UK, where professions such as data scientist, computer scientist, hardware engineer and robotics engineer were the most AI-hiring intense occupations in 2022 (OECD, 2024b).

Finally, in European countries, JRC (2025c) analysed OJVs only for ICT specialists from 2020 to 2023 and found that AI-related job postings within the ICT field are dominated by software and applications developers and analysts (62%) and database and network professionals (16%). And three ICT occupations show a higher level of AI specialisation: 'Systems Analysts'; 'Database and Network Professionals'; and 'Software and Applications Developers and Analysts' (JRC, 2025c).

***In terms of professional groups**, the highest share of AI workforce is found among 'professionals and associate professionals' in the ICT, finance and professional services*, but an increase was detected across almost all occupational groups between 2012-2018 by OECD (2021b). In another OECD study for the period 2019-2022, around 73% of OJVs requiring AI skills in European countries advertise positions for 'professionals', 9% for 'managers', 8% for 'technicians and associate professionals', and the remaining 10% for the other occupations (OECD, 2023b).

The study of 30 European countries for the 2023-2024 period split the OJVs demanding AI skills into two groups: vacancies for ICT professions versus vacancies for 'other occupations' (Pal et al., 2025). Overall, almost two-thirds of vacancies analysed were in the group of 'other occupations', while the remaining third were in the group of ICT professions. Obviously, the share of these vacancies within the group of ICT professions is much higher (4.3%) than their share within the group of other occupations (0.6%), possibly implying that AI skills are on their way to becoming a 'core skill' for ICT professions, and slowly spreading into other occupations (Pal et al., 2025).

Indeed, recent Cedefop analysis from 32 European countries, relying on Cedefop-Eurostat online job adverts (OJA) from the Web Intelligence Hub, classifies occupations according to their growth in frequency of AI-related terms over the 2021-2024 period. Occupations that increasingly mention AI in OJAs are categorised by function into three groups: 'build', 'redesign' and 'improve' (see Table 3). This categorisation reflects the gradual integration of AI towards a wider set of jobs in which AI technology is being used for the purposes of product or task optimisation, design or promotion, in addition to strict technology development as part of technical ICT professions.

Table 3: Jobs with the highest concentration of AI related tasks in 2024

Build	Redesign	Improve
Mathematicians, actuaries and statisticians Systems analysts Database and network professionals Software and app developers and analysts Software developers Website and multimedia developers Applications programmers Computer network& systems technicians Database administrators	Electronics/ electrical engineers Civil engineers Mechanical engineering technicians Manufacturing/ production managers Product and garment designers	Translators, interpreters, other linguists Broadcasting and audiovisual technicians Journalists Authors and related writers Film, stage and related directors & producers Advertising & marketing professionals Public relations professionals

Source: Cedefop analysis of WIH-OJA data from 32 European countries.
Note: Trends in keywords of unique job titles of AI-related online job adverts (2021-2024).

In terms of economic sectors, the AI workforce is found most heavily concentrated in three sectors: ICT; Finance and Insurance; and Professional, Scientific and Technical Activities. OECD (2023b) reports that in 2022 across 14 OECD countries, most job postings requiring AI skills are in the ICT sector (24%), Professional Services (25%), and Manufacturing (13%). There are some cross-country heterogeneities, possibly reflecting differences in the sectoral composition of labour markets. For example, another study focused on the UK found that most demand was concentrated in ICT and Finance and Insurance sectors (OECD, 2024b). Based on the OJVs from Canada, Singapore, the UK and the US in the period 2012-2018, job postings asking for AI skills were also considerable in Wholesale and Retail Trade (OECD, 2021b).

Recent evidence confirms a gradual diffusion of demand for AI skills across a range of sectors and occupations, albeit with varying degrees and in different countries. Although AI skills are still more heavily required for ICT specialists, where on average 15% of OJVs included at least one AI skill compared to only 3% in non-IT roles (Cedefop, 2023), the WEF (2025a) highlights growing demand for AI skills in finance, logistics, manufacturing, education, and healthcare. Some sectors, though, still lag behind when it comes to the share of OJVs for non-IT workers requiring at least one AI skill, such as education, water supply, and waste management sectors (Cedefop, 2023).

In conclusion, demand for AI skills is no longer confined to the ICT sector. In another recent analysis of global OJVs, Lightcast (2025) argues that *'AI job' is not necessarily a 'tech job' anymore;* using a less strict criteria, as large as 51% of AI-related job postings were found outside IT and Computer Science in 2024, compared to 39% in 2019. The Lightcast report points to five sectors where demand for AI skills grew fastest from 2023 to 2024: HR, Marketing & PR, Finance, Education & Training, and Science & Research. Since ChatGPT's launch in late 2022, global job postings mentioning generative AI skills are up 800% for jobs outside IT and Computer Science. Out of 80,000 global job postings demanding generative AI skills in 2024, 29,050 of them were in non-IT roles (Lightcast, 2025).

3.3. AI workforce by proficiency level

Technical AI skills can be conceptualised along a hierarchical spectrum, ranging from minimal task-based familiarity with AI tools to sophisticated AI development and engineering competencies. Thus, a simple binary classification (AI versus non-AI profiles) does not reflect this complexity. Another classification of technical AI skills is done by IMF (2026): it distinguishes between *AI-user skills*—use of generative-AI applications integrated into work processes (for example, ChatGPT, GitHub or Copilot)—and *AI-developer skills*—competencies related to building and deploying models (for example, Python for machine learning, TensorFlow/PyTorch, model evaluation and ML-Ops). This approach allows a separation of AI adoption and creation patterns. Accordingly, in 2024 roughly half of job postings in the US demand only AI-user skills, one-fourth refer to only AI-developer skills, and one-fourth both types of AI skills (IMF, 2026).

Perhaps *'AI-developer' profile is the most easily identifiable category, where advanced technical competencies are necessary to design, build, and improve AI systems* (Sayem et al., 2024; Babashahi et al., 2024; Maslej et al., 2025). However, 'AI-user' profile is not straight forward, varying between those with some technical skills to redesign/ implement AI tools and those non-specialist users engaging with AI-enhanced systems and tools. A logical framework for capturing this diversity is a three-tier model of AI roles, each one consisting of coherent bundles of AI-related skills categorised from basic to intermediate and advanced proficiency levels (Pal et al., 2025). The underlying idea is that skills are not independent units but aspects of a hierarchically structured learning and capability system, in which advanced skills are often built upon a foundation of more basic skills[36]. It is similar to the three categories of AI jobs made by functions of 'build', 'redesign' and 'improve' (see Table 3 in section 3.2).

A study of 30 European countries developed and applied this three-tier model to classify AI skills demand and supply in Europe (Pal et al., 2025)[37]. AI skills are stratified in a hierarchical structure, from *basic* skills towards *intermediate* and *more advanced* competences, each level built upon the previous level's existing skills. Thus, each tier consists of a coherent bundle of AI skills assigned, following the approach of a 'nested structure' of skill portfolios (Hosseinioun et al, 2025). Both individuals and vacancies are classified based on their level of involvement with AI technologies, technical expertise, and professional roles. The three categories are defined as *Tier 0 (Basic level)*, *Tier 1 (Intermediate level)*, and *Tier 2 (Advanced level)* (see Box 2).

Box 2: Demand and supply for AI skills by three proficiency levels

Advanced (AI research& engineering): This category includes individuals employed in or studying for roles or demonstrating skills directly involving developing, applying, or researching deep learning techniques and other advanced AI applications. They work with complex neural network architectures and cutting-edge AI systems, e.g. a ML engineer developing custom neural network architectures, optimising graphics processing unit performance, and implementing state-of-the-art algorithms. Typical skills are deep learning frameworks, neural architecture design, ML operations, and reinforcement learning.

Intermediate (Software& data proficiency): This category includes individuals employed in or studying for technical roles or demonstrating skills involving software development or data science that may employ basic machine learning techniques – e.g. data scientists who work with traditional statistical methods and fundamental ML algorithms but not advanced deep learning. Typical skills are data analytics, database management, basic machine learning algorithms, and data preprocessing.

Basic (AI literate& curious): This category includes individuals employed in or studying for roles requiring familiarity with AI but not directly working with technical AI applications, and who do not fit in the other two tiers. They are workers in non-technical roles or unrelated study fields but with basic familiarity with AI concepts and usage of AI tools as end-users, e.g. a business analyst with a basic understanding of AI applications who is familiar with AI terminology and uses pre-built AI tools for reporting. Typical skills are basic AI literacy, familiarity with business intelligence tools, and prompt engineering.

Source: Pal et al., 2025.

[36] According to Hosseinioun et al (2025), modern economies require increasingly diverse and specialized skills, many of which depend on the acquisition of other more fundamental skills first, so-called 'nested structure' of skill portfolios. Human capital development and career progression follow this structured pathway in which skills more aligned with this nested structure command higher wage premiums, require longer education and are less likely to be automated. This nested structure has become even more pronounced over the past two decades, indicating increased barriers to upward job mobility.

[37] The study is based on based on the OJV data from Lightcast and workforce profile data from Revelio Labs, covering EU-27, plus the UK, Norway and Switzerland. To classify AI-related supply accurately across the three proficiency tiers, the study employed a large language model (LLM), Llama 3.1 70B, using chain-of-thought prompting techniques. To classify AI skill demand, they used the Lightcast AI Skills Dictionary containing 251 specific AI skills and manually extended this dictionary by assigning each AI skill to one of the three proficiency levels (Tier 0, 1, or 2) (Pal et al., 2025).

The study of Pal et al. shows that intermediate level AI skills are currently the backbone of AI demand and supply in Europe, with a broadly balanced match between the two. On average, 47% of vacancies and 63% of CVs mentioning AI skills belong to this mid-level tier. On the other hand, both basic level and advanced AI skills are in short supply. Basic AI skills are sought in 29% of vacancies but appear only in 22% of CVs on average. Similarly, advanced AI skills are required in 24% of vacancies but appear only in 15% of CVs. This creates a visible imbalance at both the expert and novice levels in Europe: relatively fewer AI-skilled candidates have an advanced or basic degree of AI proficiency compared to demand expressed in job postings in 2023-24 (Pal et al., 2025).

The three-tier hierarchical model of AI roles (basic, intermediate, advanced) reflects a triangle structure in which the number of workers with advanced AI skills remains quite small at the very top, while the volume of workers gradually increasing at each level going down. This means a relatively larger group of workers with intermediate technical skills who need to apply/integrate AI systems into new areas, while the need for workers with basic AI skills would be the largest (almost covering the whole workforce). The workers with basic AI skills would often be in non-technical roles or unrelated study fields, but with basic familiarity with AI concepts and usage of AI tools as end-users, e.g. the use of ChatGPT tool for basic tasks.

The basic user profile at the bottom may not necessarily belong to the technical AI workforce, but rather constitute a new literacy required from most workers. As discussed in CHAPTER 2: CHANGING SKILLS DEMAND IN WORKPLACES ADOPTING AI, these would be needed at AI-adopted workplaces where skills requirements are gradually evolving, and additional skills are needed to use existing AI applications. It results from expanding AI technologies across economic sectors, which are no longer confined to technical AI fields but are spreading to many occupations and fields – from warehouse operators and customer service representatives to educators and managers.

3.4. Trends in hiring AI talent

Job postings demanding AI skills often stress complementary non-technical abilities. In settings where humans and machines increasingly interact, social and ethical capabilities complement AI tasks and ensure responsible, context-sensitive, and human-centred implementation (OECD, 2021a, 2024b; Bone et al., 2024; WEF, 2025a). Increasing importance of 'softer', non-technical skills has been long highlighted in many employer surveys and academic reviews (Mäkelä & Stephany, 2025); 'AI jobs' may simply mirror or increase such pre-existing trends in labour markets (see CHAPTER 2: CHANGING SKILLS DEMAND IN WORKPLACES ADOPTING AI). Moreover, job postings demanding AI skills also necessitate high-level cognitive skills and business and management skills (OECD 2023a, 2023b).

Wage premium to AI skills. With accelerating digital transformation and technological advances at a rapid pace, widening talent and skills gaps have become a challenge for many firms, especially for emerging roles with a limited pool of talent. As a result, several studies have shown a wage premium for technical AI skills in labour markets, typically based on data from web-based sources (OECD, 2023a; Bone et al., 2025; JRC, 2022b; PwC, 2025). However, the magnitude and consistency of this premium vary significantly across studies, occupations, sectors, and countries. Besides increasing demand for people with technical AI skills, wage premium may also arise due to complementarities with other cognitive and non-cognitive skills. Stephany and Teutloff (2024) have found that AI skills are particularly valuable due to rising demand and strong complementarities, increasing worker wages by 21% on average.

The findings from the Cedefop second European skills and jobs survey data on adult workers also confirm a similar reward for AI developer skills in the European job market. Such workers enjoy a wage premium of 4-8% depending on specification, relative to comparable non-AI programmers, and 12-24% relative to similarly educated employees (Pouliakas et al, 2025)[38]. AI wage returns are in

[38] This is the representative data from the second European skills and jobs survey conducted in 29 European countries by Cedefop in 2021 (ESJS2).

general higher among females and tertiary-educated employees, which is indicative of a relative scarcity of such workers with knowledge of AI methods. The data reveals a higher dispersion of AI programmers into diverse economic sectors, occupations, and fields of study, compared to other programmers who do not use AI at work.

In many cases, *AI wage premium seems closely linked to advanced digital skills.* Based on OJV data from the UK, JRC (2022b) found a 16% wage premium for software development, 11% for big data and AI, and 6% for ICT support in 2012-2020. In another study in the UK, advanced digital skills are associated with 9% higher wages, with AI and cybersecurity skills yielding the highest returns in job postings (Garcia-Lazaro et al., 2025). Combining advanced digital skills with domain expertise has emerged as a key differentiator for the results. Bone et al. (2025) found that AI skills command a wage premium of 23% in the UK, exceeding the value of degrees up to the Doctorate level[39]. This is because emerging professions in the AI field are experiencing labour shortages, as industry demand outpaces labour supply in the UK. In occupations with high demand for AI skills, the premium for skills is high, while the reward for degrees is relatively lower (Bone et al., 2025).

Other evidence comes from emerging economies, where the ILO has conducted OJV analyses in Brazil, Egypt, Jordan, Russia, South Africa, the United Arab Emirates (UAE) and Uruguay (ILO Forthcoming). This study shows that AI and ML skills are associated with substantial wage premiums even after controlling for occupation specific factors. In the UAE, AI and ML skills are associated with a wage premium of 18%, while it is 5.4% in Russia. The analysis also points out that skills are required as bundles in OJVs. In the UAE, AI and ML skills are required together with socio-emotional and cognitive skills (e.g. planning, designing, problem solving, strategic thinking, analysis) and customer service skills. In Russia, the most demanded skills, together with AI and ML are sophisticated cognitive skills (e.g. research, statistics, data analysis, etc), socio-emotional skills and customer service skills. These suggest that development of AI and ML skills should not be treated as a stand-alone technical skills development, but rather as a driver of positive labour market outcomes within a broader skills mix.

The emergence of demand for 'new skills' and a related wage premium is not limited to AI skills only. According to a recent IMF report (2026)[40], most of the new skills are IT-related, partly reflecting the rapid pace of technological innovation with continuous updating of software, tools, and digital platforms. AI-related skills have been gaining prominence as well, accounting for nearly one-third of all new IT skills. Yet not all emerging skills are IT-related: postings also point to rising demand for business and data analysis, social and administrative skills and new health care skills. What is more important is how new skills affect employment and wages, since these trends may diverge. IMF (2026) found that job postings requiring new skills pay around 3–3.4% more in the US and UK, while also raising local wages and employment. However, AI-specific skill demand yields wage premiums without broad employment gains and lowers employment in high-exposure and low-complementarity occupations (IMF, 2026).

AI talent shortages. Several studies point to a growing talent gap with concentrated AI expertise in advanced economies (UN and ILO, 2024; Maslej et al., 2025; Lazaroni and Pal, 2024). An AI asymmetry is visible across countries based on their volume of AI research, patents, investments and talent, despite the global discourse on AI as a shared frontier[41], China and India are exceptions regarding the role of emerging economies in AI development. The study from Lazaroni and Pal (2024) lists the countries with the highest concentration of AI talent per capita, such as Singapore, Luxembourg, Switzerland, Israel, the Netherlands, Ireland, Sweden, the US, Canada, Finland, Denmark, and the UK[42]. If the absolute number of AI talent is taken by country, however, the US tops

[39] This is a study based on 11 million OJVs in the UK from 2018 to 2023.
[40] The IMF (2026) study defines 'new skills' as those that were barely present in vacancies at the start of the 2010s but have since become more common. The study combined several datasets in its analysis: long series of job postings from Lightcast datasets for Brazil, Denmark, Germany, South Africa, the UK and the US in the period of 2021-2024; the American Community Survey; the German administrative labour market records; US firm-level information; and millions of worker profiles provided by Lightcast.
[41] See the country page at AI World / Artificial Intelligence in Data
[42] This is calculated as the number of AI talent per 1000 people in a given country. The ranking changes when the absolute number of AI talent is taken by country.

the list with around 450 thousand AI professionals. This is followed by India (~220K), the UK (~60K), Germany (~50K), etc. Only some emerging economies, such as Brazil, Türkiye, Indonesia, Iran and Pakistan feature in that list (Lazaroni& Pal, 2024).

Indeed, *the AI talent by country of origin indicates significant immigration from the Global South to advanced economies.* For example, within the EU, India is the largest country of origin (12%), followed by China (11%), among the AI workforce (Lazaroni and Pal, 2024). There is also talent coming from the US and the UK to the EU (10% from each), probably reflecting the mobility of EU nationals. The diversity of countries from which AI professionals migrate to the EU include Iran (7.6%), Russia (5%), and other emerging nations like Brazil, Egypt, Pakistan and Argentina, highlighting its appeal as a destination for the AI workforce (ibid). For developing and emerging economies, the wage premium for AI technical skills may exacerbate wider societal challenges, such as talent emigration and 'brain drain'. Without competitive conditions in local labour markets, high-skilled individuals may increasingly emigrate to advanced economies offering higher wages and career development opportunities.

CHAPTER 4: POLICY IMPLICATIONS FOR SKILLS DEVELOPMENT

The earlier chapters showed how AI technologies are reshaping both the variety and depth of skills demand across sectors and occupations, while simultaneously increasing the need for a range of technical AI skills from basic to advanced levels. This chapter reflects on what these trends mean for skills policies. Firstly, it introduces AI literacy as a new transversal skill, outlining its definition and main components, and it argues that it is essential not only for workers in AI-enhanced workplaces, but also for citizens to access services, information, and rights. Besides incorporating AI literacy into educational curricula, the report argues for widespread AI upskilling of adults and workers, and a shift from specific 'skill sets' to broader 'capabilities' and human agency. The growing use of AI technologies in education and the workplace also requires the revision of occupational standards, qualifications and curricula, and the adaptation of assessment, certification and quality assurance systems in education.

4.1. AI Literacy as a foundational capability

AI's impact on life and work means that there is a new 'basic' skill that all students, job seekers and workers need: the ability to use AI tools. AI literacy is increasingly recognised as a foundational skill for the new digitalisation phase – an essential enabler of human agency and inclusion in AI-augmented environments. It refers to the ability to understand, use, monitor, and critically reflect on AI systems. More than technical familiarity, AI literacy encompasses awareness of how AI works, its potential and limitations, and its social, ethical, and economic implications. In this sense, it builds on and extends existing notions of digital, data, and media literacy.

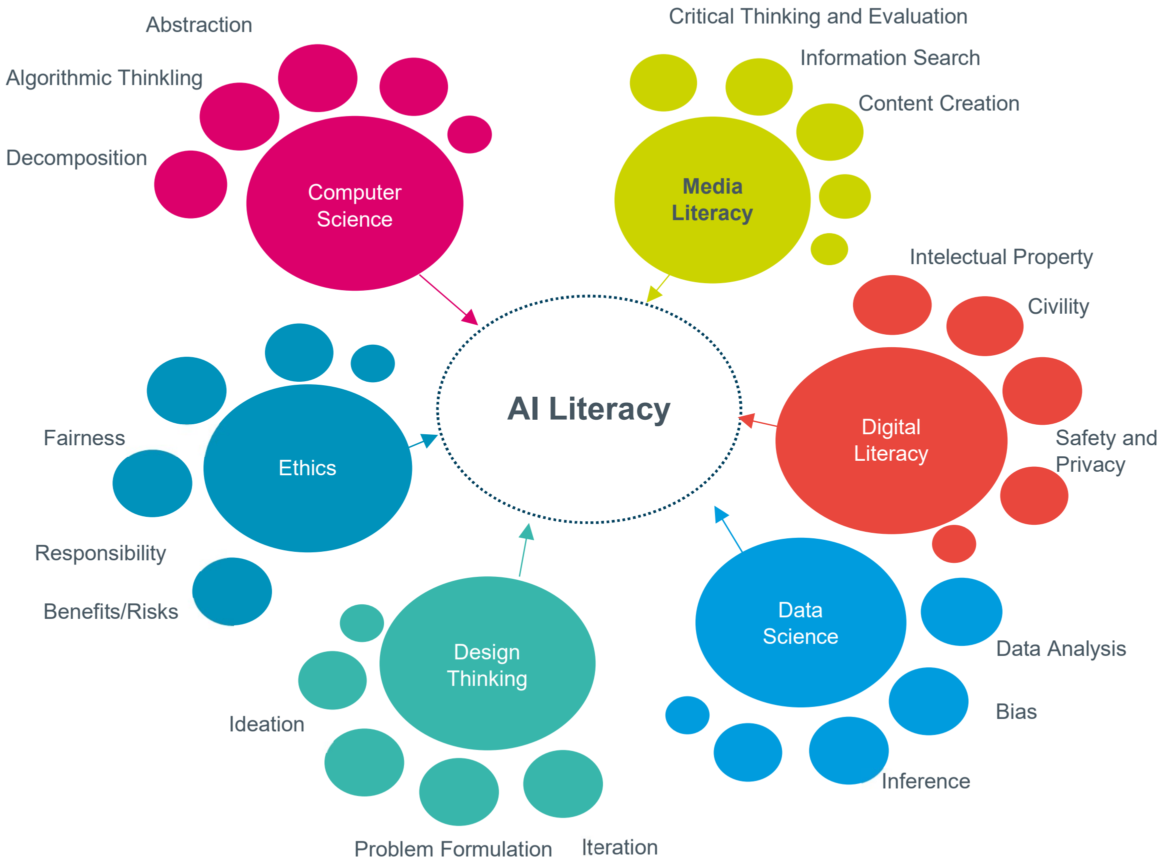
At its foundation, AI literacy includes a mix of knowledge, skills and attitudes that are technical, social and ethical in nature. It enables individuals to critically evaluate AI technologies, communicate and collaborate effectively with AI, and use AI as a tool online, at home, and in the workplace (Long and Magerko, 2020). Developing AI literacy starts with the recognition that it is not just about technology: people also need to grasp the social and ethical components of the technology, which relates to socio-emotional skills. AI literacy is not simply programming or the mechanics of neural networks, and it is certainly not just prompt engineering; it goes beyond knowledge about the latest AI tools.

Given its crucial importance, acquiring AI literacy is not just an individual's responsibility. Both businesses and public authorities have a shared obligation to provide individuals with adequate training, time and support to develop AI-related competences needed by labour markets. Social dialogue plays a critical role in shaping effective responses to AI-related skills challenges. Engagement with workers' and employers' organisations can help anticipate skills needs, negotiate training arrangements, and ensure that AI deployment supports productivity while safeguarding workers' rights, job quality and inclusion. Thus, skills policies for the AI transition are most effective when embedded in broader governance frameworks that include worker voice.

In practice, *AI literacy comprises three interrelated domains.* The first is *technical literacy*: basic knowledge of how AI systems operate, including familiarity with ML, algorithms, and data-driven technologies. While not all workers will develop or train models, a basic understanding of how AI applications function is increasingly required across professions, from customer service to legal advice and public administration. The second domain is *analytical and data literacy*, or the ability to interpret and evaluate AI outputs in real-world settings. This includes using AI-generated insights to support decision-making, validating data sources, and recognising when human oversight is necessary. For example, a procurement officer assessing supplier risk through an AI tool must be able to question anomalies or investigate flagged results before acting on recommendations.

The third domain is *ethical and societal literacy*. As AI becomes embedded in everyday life, workers need to be aware of issues related to data privacy, algorithmic bias, transparency, accountability, fairness, and sustainability. Awareness and knowledge of the environmental impact of AI (energy usage, water usage, etc.) is a good example, as people must be able to weigh pros and cons of AI use and comprehend long-term environmental impact, e.g. no need for huge models for very simple tasks. People must also understand the role of AI in shaping human behaviour, influencing public discourse, or reinforcing existing inequalities. Cultivating this form of literacy empowers individuals not just to comply with AI systems, but to question and shape them. **Error! Reference source not found.** illustrates the relationship between AI literacy and other disciplines.

Figure 1: Relationships between AI Literacy and other topics/ disciplines



Source: Taken from the Draft Framework on the role of AI in Teaching and Learning (OECD& EC, 2025).

Everyone needs AI literacy, including the employees and workers using it, and the citizens navigating its growing effects. As AI has spread to more sectors and areas of life, the implications of AI literacy, or its absence, are far-reaching. They extend beyond preparing an AI-skilled workforce. Without basic literacy, citizens and consumers are not well equipped to understand the algorithmic platforms and decisions that affect so many domains of their lives: government services, privacy, lending, health care, education and more. And the lack of AI literacy risks ceding important aspects of society's future to a handful of multinational companies (The Conversation, 2025). Institutions need to help people understand and use – or resist – AI as individuals, workers, parents, innovators, job seekers, students, employers and citizens.

Therefore, AI literacy functions both as a practical competence and a civic capability. It prepares people to work safely and confidently in AI-enhanced workplaces and to make informed choices in a society where automated systems influence access to services, information, and rights. Thus, AI literacy is also about empowerment: it concerns how societies educate citizens to engage with the future of technology and how education systems equip learners not only to operate machines, but to question their design, governance, and implications. For this reason, several experts have likened AI literacy to a new kind of *'AI driving licence'* – a minimal and necessary condition for safe and responsible participation in the digital economy.

With AI becoming a new transversal skill, embedding an AI competence framework into initial education and training becomes a necessity to prepare new learners for an AI-driven future. Many experts propose AI literacy to be systematically integrated across the curricula, from social studies to science and from primary to higher education, adult learning programmes and workplace training. As a result, several countries introduced AI literacy modules into education, training and civil services to ensure confident, critical and ethical interaction with AI. Early examples include countries like China, which requires at least eight hours of AI education annually as early as elementary school, or Estonia, which partners with Anthropic and OpenAI to provide access to AI tools for students and teachers.

Recent national and international efforts have increasingly focused on operationalising AI literacy, not only as an abstract aspiration, but as a structured, teachable, and measurable competence that can be integrated into mainstream education systems. This underlines the growing recognition that individuals must not only use AI tools but also understand, evaluate, and shape them critically and ethically from an early age. Thus, several frameworks have been developed to teach and learn AI to students, teachers and adults (see Box 3). They aim to provide a shared reference for curriculum designers, educators, and policymakers to ensure that all learners acquire the knowledge, skills, and attitudes needed to function in a world increasingly mediated by AI. In addition, various universities have launched new master's in AI programmes at the university level.

Box 3: Example frameworks to guide teaching and learning AI Literacy

- The European Digital Competence Framework for Citizens (DigComp): describes knowledge, skills and attitudes that are needed to be digitally competent for daily life, participation in society, working and learning. It was updated in November 2025, to among other things, integrate AI competence in a new version called 'DigComp 3.0'[43].
- UNESCO's AI Competences for Students and AI Competences for Teachers: global relevance, distinction between learner and educator perspectives[44].
- Draft Framework on the role of AI in Teaching and Learning (AILit): three key pillars: technical knowledge on how AI works; human skills needed to collaborate effectively with AI; and ethical considerations[45].
- The US Digital Promise's AI Literacy Framework: interconnected modes of engagement – understand, evaluate, use AI tools responsibly and safely – targeting adults[46].
- The US 'AI4K12's 5 Big Ideas in AI: five core technical aspects, including the nature of AI and the role of data in the AI training process for primary and secondary education[47].
- The EC has a living repository to provide examples on ongoing AI literacy practices and foster learning and exchanges across countries[48].

UNESCO (2023a) notes that AI literacy should begin in primary school, building progressively through STEM education, interdisciplinary learning, and lifelong learning opportunities. To understand the key elements of these frameworks listed in Box 3, attention can be given to UNESCO's AI competency frameworks which have been created to guide public education systems. Promoting a human-centred approach to AI education, the *AI competency framework for students (AI CFS)* outlines twelve competencies across two dimensions for students (see Table 4). The first dimension comprises four competency aspects: human-centred mindset, ethics of AI, AI techniques and application, and AI system design. The second dimension consists of three proficiency levels (understand, apply or create) that students are expected to engage with iteratively.

[43] See DigComp 3.0 - Joint Research Centre - European Commission
[44] See AI competency framework for students | UNESCO and AI competency framework for teachers | UNESCO
[45] See home | ailit framework. It is a joint initiative of European Commission, OECD, and Code.org.
[46] For more info, see AI Literacy – Digital Promise, a US based global nonprofit initiative.
[47] For more info, see AI4K12 – Sparking Curiosity in AI, the US-based initiative of K-12 elementary education.
[48] See Living repository to foster learning and exchange on AI literacy | Shaping Europe's digital future

Table 4: UNESCO's AI competency framework for students (AI CFS)

COMPETENCY ASPECTS	PROGRESSION LEVELS		
	UNDERSTAND	APPLY	CREATE
1. Human-centred mindset	Human agency	Human accountability	Citizenship in the AI era
2. Ethics of AI	Embodied ethics	Safe and responsible use	Ethics by design
3. AI techniques and application	AI foundations	Application skills	Creating AI tools
4. AI system design	Problem scoping	Architecture design	Iteration and feedback loops

Source: UNESCO, 2024a.

The *AI Competency Framework for Teachers (AI CFT)* is designed for teachers who integrate AI to enhance learning in core subject areas, rather than for those specialising in advanced AI instruction (Table 5). Keeping a human-centred approach, it provides a practical tool for teachers to design and implement AI-focused training courses and supports teachers' ongoing professional development. The AI CFT is structured as a two-dimensional matrix: five competency aspects are developed across three progression levels (acquire, deepen, and create), resulting in fifteen blocks. They are designed to support schools and teachers, while serving as a reference for the development of national AI competency frameworks (UNESCO, 2024b).

Table 5: UNESCO's AI competency framework for teachers (AI CFT)

COMPETENCY ASPECTS	PROGRESSION LEVELS		
	ACQUIRE	DEEPEN	CREATE
1. Human-centred mindset	Human agency	Human accountability	Social responsibility
2. Ethics of AI	Ethical principles	Safe and responsible use	Co-creating ethical rules
3. AI foundations and applications	Basic AI techniques and applications	Application skills	Creating with AI
4. AI pedagogy	AI-assisted teaching	AI-pedagogy integration	AI-enhanced pedagogical transformation
5. AI for professional development	AI enabling lifelong professional learning	AI to enhance organisational learning	AI to support professional transformation

Source: UNESCO, 2024b.

The *Draft Framework on the role of AI in Teaching and Learning (AILit),* launched in 2025 by the European Commission, OECD, and Code.org, is the latest initiative to support the development of AI literacy in education systems. Designed for teachers, education leaders, education policymakers, and learning designers, the framework outlines competences and learning scenarios to inform learning materials, standards, school-wide initiatives, and responsible AI policies for primary and secondary education settings. It has three learning outcomes: technical knowledge on how AI works; human skills needed to collaborate effectively with AI; and ethical considerations. The outcomes are a blend of conceptual knowledge, practical skills, and future-ready attitudes, such as curiosity, adaptability, and ethical reasoning. Its teaching is organised around four domains of interaction with AI: Engaging with AI, Creating with AI, Managing AI, and Designing AI (OECD& EC, 2025).

These examples of frameworks are very relevant at a time of widening AI skills gap. As recent surveys show, young people are increasingly exposed to and experimenting with AI in informal settings—often without sufficient support or critical guidance. Only 46% of students feel their schools prepare them adequately for AI (Vodafone Foundation, 2024), and 49% of learners aged 17-27 struggle to critically assess AI-generated content (Merriman & Sanz Sáiz, 2024). Another study from Eurofound based on Eurostat's survey on the use of ICT in households provides an even more compelling picture on the use of Generative AI across EU27 Member States in 2025. Overall, the use of GenAI by students (72%) far exceeds that of employed (36.4%), unemployed (28.3%), and retired/inactive populations (12.9%) (Eurofound, 2026b). Private use systematically exceeds professional use, with almost 64% of those aged 16-24 having used generative AI in the past three months compared to just 6.5% of those aged 65 and above.

Regarding teachers, Cedefop's 2025 pilot European VET Teacher Survey (EVTS) has revealed that 29% of those in initial vocational schools regularly use AI tools or technologies as part of their work. However, about one third feel that they need additional professional development in learning how to best use such technology in a safe and ethical manner (Psifidou et al., 2026). The frameworks, hence, represent a major step forward in rethinking education for the age of AI. By embedding AI literacy in compulsory education, it reframes it not only as a digital skill but as a civic competence, necessary to participate meaningfully in democratic societies and future labour markets.

4.2. Curriculum and qualification reforms

The growing integration of AI into workplaces requires education and training systems to translate evolving skills requirements into occupational standards, qualifications and curricula. As AI increasingly performs routine and low-complexity cognitive tasks, including those traditionally used to define occupations and entry-level roles, qualifications anchored narrowly in task performance risk becoming obsolete more quickly. The importance of work-based learning becomes even more vital than ever, given the falling numbers of entry-level jobs that had long provided solid work experience for beginners. Qualifications systems need to reduce over-reliance on narrowly defined occupational tasks that AI can rapidly substitute, while placing greater emphasis on transferable capabilities, such as analytical reasoning, problem-solving, and socio-emotional skills.

While previous sections discussed the increasing importance of AI literacy and digital skills, the challenge for skills systems is how to operationalise these requirements within learning pathways, certification systems and occupational programmes (UNESCO, 2024c). It is useful to distinguish between different levels of AI-related competences: foundational AI literacy for all, occupation- and sector-specific AI competences, and advanced technical AI skills for specialist roles. In all cases, qualifications systems and curricula should move beyond treating AI as a specialised technical subject confined to ICT-related fields and treat AI literacy as a generic learning outcome and transversal competence applicable across levels and sectors and integrate AI literacy horizontally across qualifications. This includes not only the ability to use AI tools, but also critical understanding of AI outputs, data literacy, ethical awareness, bias, transparency, privacy, environmental implications and human oversight (OECD, 2024a).

For TVET and adult learning, learners and workers not only need general AI literacy, but also sector- and occupation-specific guidance on how AI changes tasks, work organisation and required skills. In practice, this implies revising occupational standards and learning outcomes to reflect changing workplace realities, through structured engagement with employers' and workers' organisations, sector skills bodies and training providers. For example, learners in the manufacturing sector may need to interact with AI-supported predictive maintenance systems; healthcare workers may need to interpret AI-assisted diagnostic outputs; logistics workers may increasingly rely on AI-supported planning tools; while media professionals may need to critically review AI-generated content. The objective is not simply to teach the use of AI tools, but to ensure that learners can apply occupational expertise alongside digital, analytical and ethical judgement (ILO, 2025b).

AI-related competences need to be embedded within occupational curricula throughout TVET, higher education and adult learning systems (European Commission, 2025). This includes identifying how AI tools are changing workflows, decision-making processes, quality standards and human interaction within specific occupations and sectors. Given the growing emergence of hybrid occupational profiles that combine sector-specific expertise with digital and data-related skills, qualification systems must recognise combinations of technical, cognitive and socio-emotional competences rather than narrowly defined occupational tasks (OECD, 2024a). In many occupations, workers are increasingly expected to combine domain expertise with the ability to interpret AI outputs, work with data, solve non-routine problems and collaborate effectively in technology-rich environments.

This evolution also requires greater flexibility within qualification systems. Qualification frameworks could recognise AI-related skills acquired via informal and non-formal education, adapt flexible learning methods, and build a pathway for learners to navigate in different education and training scenarios, which would serve as a basis for succeeding in the increasingly complicated labour market in the age of AI. Indeed, short learning programmes, modular pathways and micro-credentials are increasingly used to respond to rapidly evolving skills needs, particularly for adult learners and workers already in employment. However, fragmented certification risks reducing transparency and quality. AI-related micro-credentials should therefore be linked to national qualifications frameworks, occupational standards and quality assurance systems to ensure comparability, recognition and progression opportunities (Council of the European Union, 2022; OECD, 2023e; ETF, 2023b).

In summary, curriculum and qualification reforms should integrate new AI developments as learning outcomes, avoid excessive focus on rapidly changing technical tools alone, and have greater flexibility without losing quality assurance. They must also place more emphasis on work-based learning and ensure that micro-credentials are stackable, quality-assured, and linked to qualifications frameworks and recognition of prior learning. Given the speed of technological change, curricula need to strengthen transferable foundations that support long-term adaptability, including problem-solving, digital and data literacy, communication, collaboration and learning-to-learn competences (WEF, 2025a; OECD, 2025h). The objective is to prepare learners not only for current AI applications, but also for continued technological changes throughout their working life.

4.3. Teachers, trainers and institutional capacity

The successful integration of AI-related competences into education and training systems depends heavily on the preparedness of teachers, trainers and institutions, whose capacity is essential for implementation. Teachers and trainers need protected time, incentives and institutional support to experiment with AI tools and redesign learning activities. Curriculum reform alone is insufficient if education providers lack the human and institutional capacity required to implement new approaches effectively, including guidance on the responsible use of AI in teaching, assessment and learning support (UNESCO, 2023b).

Teachers and trainers need time and effort to develop the capacity to integrate AI-related tools and approaches into teaching, learning and assessment practices. Their capacity must include understanding the opportunities, limitations and risks of AI applications within their professional fields, selecting appropriate pedagogical uses of AI tools, and guiding learners in critically interpreting AI-generated outputs (UNESCO, 2024d). In TVET systems in particular, teachers and trainers require familiarity with the evolving use of AI technologies in workplaces and occupations relevant to their sectors, through industry placements, joint curriculum development and sectoral communities of practice (OECD, 2021c).

This creates growing demand for continuous professional development systems that move beyond one-off awareness-raising activities. Effective professional development increasingly requires sustained approaches that include practical experimentation, peer learning, mentoring, collaborative lesson design and opportunities to adapt teaching materials and assessment methods (OECD, 2024e; 2026). Institutional support structures are therefore critical to allow teachers and trainers sufficient time, resources and professional autonomy to redesign learning activities and integrate new technologies meaningfully.

For TVET teachers, maintaining strong links with industry becomes even more important in the context of AI adoption. Rapid technological change requires regular updating of occupational knowledge and exposure to changing workplace practices. Partnerships between training institutions and employers can therefore support teacher industry placements, workplace learning opportunities and joint curriculum development activities (Gmyrek et al., 2023).

Institutional leadership and AI governance also play a crucial role. Education and training institutions increasingly require clear strategies, rules and code of conduct regarding the adoption and use of AI tools in their services, including policies related to ethics, data privacy, transparency and academic integrity (UNESCO, 2023b). Educational institutions must have clear guidance on responsible use, data protection, bias, copyright, academic integrity and accessibility. Without institutional guidance, access to AI-related learning opportunities may become uneven across institutions and learner groups, reinforcing existing inequalities in digital access and educational quality.

Infrastructure and resource gaps remain major constraints in many countries, particularly in low- and middle-income contexts. Reliable connectivity, access to digital devices, appropriate software and technical support remain unevenly distributed across institutions and regions (UNESCO, 2023c). As a result, policy responses should not only focus on advanced AI adoption, but also on ensuring the foundational digital infrastructure and institutional conditions necessary for equitable participation in AI-enhanced learning environments.

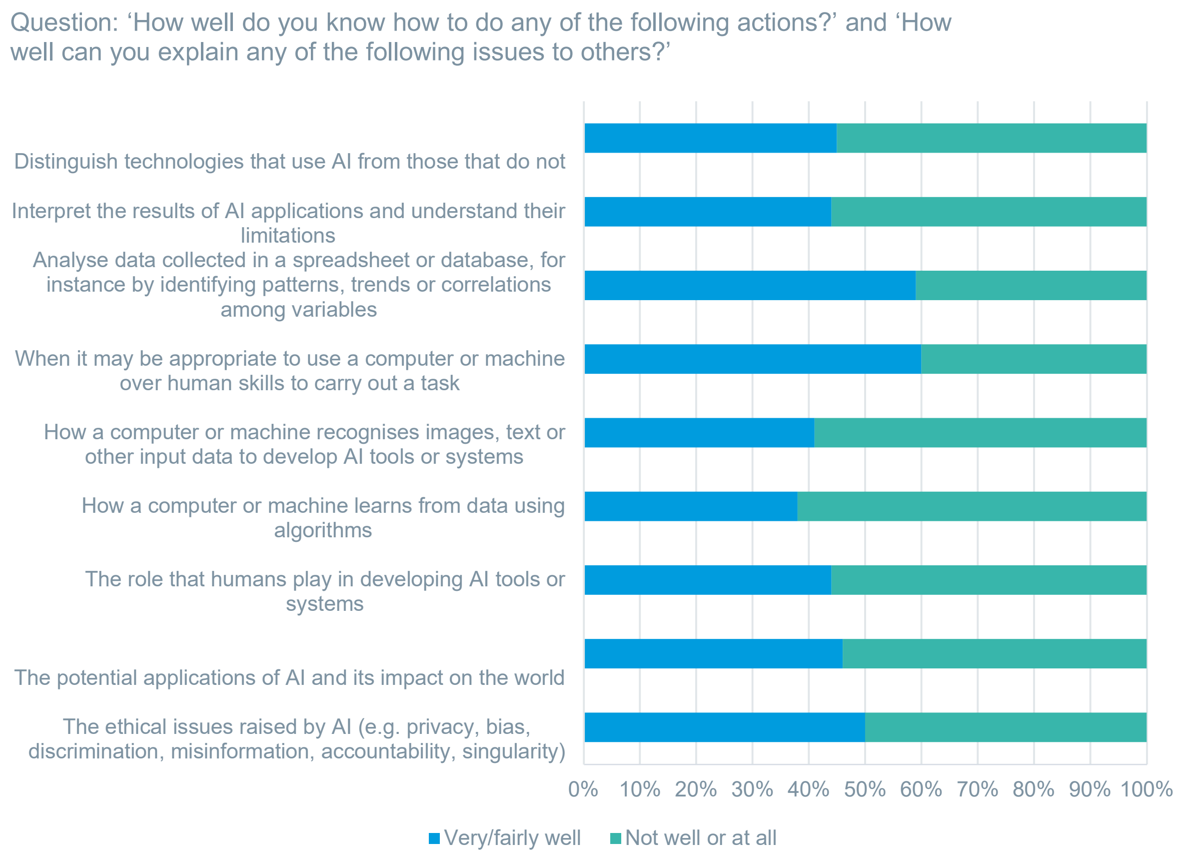
4.4. AI upskilling for adults and workers

The relevance of AI literacy for the workplace is evident across sectors and occupations. Although highly qualified workers are more inclined to use AI technology in their jobs, the need for AI upskilling spans across all skill levels. For example, in education, teachers are expected to evaluate and adapt content generated by AI tutoring platforms. In healthcare, nurses and technicians must understand how diagnostic algorithms support (but do not replace) clinical judgement. In logistics and manufacturing, workers interact with robots and wearables that require basic familiarity with automation protocols and safety rules. These tasks do not always require advanced technical training but depend on the situational awareness and ethical discernment that AI literacy enables (OECD, 2024f). Furthermore, improving AI literacy transversally can stimulate bottom-up use of AI technology in work environments and help with its mainstreaming.

In spite of the wide consensus on its importance, existing evidence suggests a relatively low level of AI literacy among workers, even in advanced economies. Despite the increasing need for both specialised AI professionals alongside workers with a more general understanding of AI, according to Orrell (2025), AI literacy is low in the US, for instance, as only 25% of workers are deploying AI on the job, compared with 60% of workers in China and India in 2024. This skills gap is also reinforced by a trust gap. According to the 2025 Edelman Trust Barometer, 77% of Chinese and 75% of Indian respondents are reported to trust AI, compared to only 47% of Americans (Orrell, 2025). These figures suggest that AI literacy is not only a matter of technical training but also of technological trust building, especially among worker groups most vulnerable to AI-driven changes.

Cedefop's AI skills survey carried out in 2024 included a specific AI literacy scale covering different meta-aspects of it, ranging from whether workers can recognise an AI technology and its limits, to understanding of the way in which AI systems and machines represent and learn from the world, and awareness of the socioeconomic and ethical challenges implied by AI systems (Figure 2). The findings of the survey show the low AI literacy in the European adult workforce, with between 40-60% of adult workers surveyed possessing a relatively limited understanding of the diverse pillars of AI literacy (Cedefop, 2025). This is important, since European workers with high AI literacy are found to have a higher incidence of AI use and are, in general, more likely to enjoy positive labour market outcomes. Cedefop's evidence further shows that between 2023-24 only about 15% of employees participated in education or training activities aimed at further improving their knowledge and skills in using AI technology (ibid., 2025).

Figure 2: Pillars of AI literacy in the AI skills survey



Source: Taken from Cedefop 2025, p.20.
Notes: (1) The survey was conducted in 2024 among 5342 adult employees from 11 Member States: Belgium, Czechia, Germany, Ireland, Greece, Spain, France, Luxembourg, Poland, Portugal, and Slovakia.
(2) Cedefop has operationalised the definition of AI literacy from Long and Magerko (2020) and used it in its AI skills survey with a wide range of different AI literacy aspects as listed in the figure.

Within this context, several countries have included AI skilling in national AI strategies and actions. For example, Finland was one of the pioneers when it launched the Elements of AI series in 2018 for public education on AI. Singapore's AI for Everyone (AI4E) is another open-access foundational course made up of six modules designed to demystify AI, dispel misconceptions, and show its practical uses[49]. Germany's AI Competences (AIComp) is also for the general public, focusing on AI skills that are important for a broad spectrum of individuals[50]. Another example is a transnational project funded by the EU Erasmus+ programme: ARISA – Artificial Intelligence Skills Alliance. It aims to develop AI knowledge and skills programmes in Europe so people can understand, design, and make use of human-centred, trustworthy AI-based solutions[51].

Based on a policy questionnaire with replies from 21 OECD countries in 2024, an OECD report (2025d) has mapped the current supply of training and the readiness of adult learning systems for the AI transition. Accordingly, 14 countries have invested in publicly funded AI training programmes. Nine programmes focus on developing AI professionals, while seven provide training in AI literacy for the general public. Moreover, numerous countries have introduced incentives to support employers in

[49] See AI For Everyone - AI Singapore Community. It targets a broad audience including students, professionals, and retirees. There is also AI for Kids.
[50] See AI Campus | The learning platform for artificial intelligence. Developed as part of two projects by AI Campus Hub Baden-Wuerttemberg, it focuses on AI skills requirements for the world of work and life.
[51] See Home - Arisa

providing training for their employees, typically through subsidies or tax deductions. However, these financial incentives rarely target AI skills, with support more commonly directed towards general digital skills training without an explicit focus on AI (OECD, 2025d).

In the same OECD study, a more in-depth quantitative analysis focused on Australia, Germany, Singapore and the US found that only between 0.3% and 5.5% of analysed training courses deliver AI content (OECD, 2025d). This could be content related to the development of both advanced AI skills and more general AI literacy. Whilst these figures may be underestimated (learning can also happen informally or in the workplace), this result suggests current training supply may not be sufficient to meet demand, especially the growing demand for AI literacy. Moreover, most countries analysed place a bigger focus on developing AI professionals than expanding general AI literacy. Policymakers should consider ways to expand general AI literacy programmes for a wider population, as most workers will require skills for using and interacting with AI systems, including general AI literacy skills (OECD, 2025d).

Several short and diverse learning pathways exist regarding the AI skilling of the workforce, from employer-led training and academic-industry hybrids to bootcamps and massive open online courses (MOOCs). These are often for highly educated workers in more tech-savvy fields like ICT, who are acquiring most AI skills on-the-job or through alternative routes such as digital portfolios, certifications, or bootcamps as a result of new learning needs (see some examples in Table 6). Employers in public administration, finance, and health are also beginning to offer AI awareness courses, often as part of broader digital upskilling initiatives. These are useful initiatives, especially for quick fixes. However, more system-wide initiatives could be introduced as systems for verifying and recognising skills acquired outside traditional frameworks remain underdeveloped.

Table 6: Examples of short and diverse learning pathways for AI skilling

Examples	Providers of training	Geographical reach	Outcomes and benefits
Bootcamps	Le Wagon, General Assembly, Ironhack, 4Geeks, DataCamp	Global (urban, hybrid/ remote)	Intensive, job-ready training; high placement rates; strong portfolio and peer support.
MOOCs	Coursera, edX, Udacity	Global, open access	Scalable and low-cost; self-paced; certificates recognised by many employers.
Employer-led training	IBM SkillsBuild[52], Google AI, Microsoft Learn, Amazon AWS AI, PwC Digital Fitness app, Microsoft AI Business School, Google ML Crash Course, Accenture Responsible AI Toolkit	Global (focused on local markets)	Industry-aligned; direct pipeline to hiring; useful for internal mobility and reskilling.
Academic-industry hybrids	MIT xPro, Harvard Extension, African Master's in Machine Intelligence (AMMI)	Regional/ global	Combines rigour of academia with practical AI application; often includes mentorship.

Source: Based on a review of internet sources.

Low-skilled workers often seem to be the least likely to access and participate in AI literacy training, although they may be in jobs with a higher risk of automation and thus require extra support (OECD, 2025d; Bertoni et al., 2024). Cedefop's 2024 AI skills survey found that the probability of participating in AI training is higher among younger workers, managers, workers with higher AI competence, in jobs with continuing (digital) learning needs, and those with permanent contracts. They tend to be concentrated in the ICT, professional and scientific services, utilities and education sectors (Cedefop, 2025). Therefore, offering a broader range of courses to promote general AI literacy with inclusive and flexible training options is key to broadening access to training and managing the unequal impacts of AI across different groups. Expanding and better targeting initiatives must include using financial and

[52] See https://skillsbuild.org/

non-financial incentives, collaboration with industry, and the development of more inclusive learning pathways (OECD, 2025d).

Considering the persistent 'digital divide' among social groups and countries, inclusion, equity and linguistic diversity must be at the centre of education and training systems. Within countries, low-skilled individuals face greater challenges, so access to AI-related training must be designed to meet their needs. AI upskilling should complement rather than replace investments in foundational skills, given growing concerns regarding literacy, numeracy and basic digital skills. Whereas continuous lifelong learning becomes a must against rapidly changing skills demands for the AI era.

In low- and middle-income countries, poor internet connectivity is the single most important factor preventing the use of AI, which requires significant investment in digital infrastructures (ETF, 2026). Constraints related to informality, firm size, limited training provision and digital infrastructure mean that AI skills policies need to prioritise accessible, work-based and publicly supported learning pathways, rather than relying primarily on employer-led or market-based training solutions. Moreover, promoting first-language-based multilingual education becomes even more important given that most LLMs are designed in just a few languages. As well as affecting the AI model first, it can negatively influence users in terms of access to and development of AI-related skills (ETF, 2026)[53].

4.5. Assessment, certification and quality assurance systems

The growing use of AI technologies in education and workplaces also requires significant adaptation of assessment, certification and quality assurance systems. It is important to distinguish between using AI to support assessment processes and assessing AI-related competences themselves. Traditional assessment approaches may become less effective in contexts where learners can use generative AI tools to produce sophisticated outputs with limited demonstration of underlying understanding or competence (UNESCO, 2023b).

Assessment systems increasingly need to emphasise not only final outputs, but also learners' reasoning processes, problem-solving approaches, critical judgement, and ability to apply knowledge in authentic contexts. The assessment itself could focus more on process, reasoning, verification, occupational judgement and the ability to identify errors or bias in AI outputs. This is particularly important in AI-enhanced environments where the capacity to interpret, validate and improve AI-generated outputs becomes as important as producing content independently (OECD, 2023f, 2025e).

As a result, greater emphasis may be placed on performance-based and authentic forms of assessment, including practical projects, workplace simulations, portfolios, oral examinations, supervised problem-solving exercises and collaborative tasks. Such approaches can help assess whether learners are able to apply occupational knowledge, exercise judgement and interact responsibly with AI-supported tools in realistic settings (European Commission, 2025).

Recognition systems also need to evolve to reflect increasingly diverse forms of learning. Many AI-related competences are acquired through workplace experience, online learning, short courses, vendor certifications or non-formal training pathways. Recognition of prior learning and modular certification systems can help make these competences more visible and portable within labour markets. However, maintaining trust and transparency requires robust quality assurance arrangements and clear descriptions of learning outcomes, assessment methods and qualification levels (Council of the European Union, 2022).

Quality assurance systems therefore need to adapt to rapidly evolving AI-related programmes and credentials, and they can be further strengthened by including equity considerations, since AI-supported assessment may disadvantage learners with weaker access to digital tools, connectivity, language support or prior exposure to AI. Overall, they must ensure the relevance of learning content to labour market developments, the credibility of assessment practices, the preparedness of teaching staff and the ethical use of AI within teaching and assessment processes (OECD, 2024e). Regular

[53] For a detailed discussion on the impact of AI in developing countries, see the chapter 5 in ETF 2026, pp.69-78.

review and updating mechanisms become particularly important in AI-related fields given the speed of technological change.

Finally, assessment reform should recognise that AI-related competences extend beyond technical proficiency alone. Effective participation in AI-enhanced workplaces increasingly requires the ability to combine occupational expertise with critical thinking, ethical judgement, communication and responsible use of technology (WEF, 2025a). Assessment and certification systems therefore need to capture broader combinations of competences that reflect the realities of human-AI interaction in work and society.

4.6. Shifting focus from specific ‘skills’ to broader ‘capabilities’

It is important to note that AI is not the only factor changing labour markets, and other simultaneous disruptions are occurring as well, such as demographic transitions, climate change, geopolitical/ economic tensions, to name a few. These concurrent changes happen at different speeds in every region and from different starting points across geographies. The ways these trends coexist and overlap ultimately determine the type and size of their ultimate effects. It is probably their combined effects that will shape the eventual future skills demand. In the context of multiple disruptions and high uncertainty, individuals will have to be agile with a broader set of skills beyond digital and technology-related skills, such as skills for sustainability, entrepreneurial skills, career management skills, etc.

Some experts refer to *‘future-ready skills’* that enable individuals to adapt to a rapidly changing world, remaining resilient and excelling in the 21st-century workplace (see OECD/Cedefop/European Commission/ETF/ILO/ UNESCO, 2024). They often imply much stronger foundational skills and socio-emotional skills that enable people to adapt, interact well, and be attuned to their own emotional states. Within stronger cognitive and socio-emotional skills, future-ready skills emphasise, in particular, *digital and tech-savviness* (understanding and utilising technology), *proactivity and adaptability* (continuous professional development), and *entrepreneurial mindset* (risk-taking and open-minded approach to new ideas). These transversal abilities and mindset for readiness, agility and resilience are crucial in solving complex problems and working with people in an uncertain future. They help to increase adaptability, encourage innovation and complement technology with human skills.

Others use the terms *‘21st century skills’ or ‘core skills’,* emphasising the *generic or transversal nature of skills across sectors and occupations* – different names with similar underlying abilities. Despite the confusion with the terms, the critical importance of future-readiness and socio-emotional maturity is widely recognised, alongside technical skills and academic knowledge. These are the glue of all skills, essential in adapting to new developments and required at some level from every worker. Moreover, the need for expanded digital and technology-related skills is growing beyond workplaces, becoming key to access to public services, information, and rights.

Due to their high importance, some international frameworks provide a taxonomy for these skills, such as ‘Global Framework on Core Skills for Life and Work in the 21st Century’ (ILO, 2021a) and ‘Global Framework on Transferable Skills’ (UNICEF, 2019). The European Commission has also developed several EU frameworks that provide guidance for teaching similar qualities. Examples include the European Key Competences for Lifelong Learning, the European Framework for Entrepreneurial Competencies (EntreComp), the European Sustainability Competence Framework (GreenComp), the European Framework for Personal, Social and Learning to Learn Key Competence (LifeComp), alongside the European Digital Competence Framework for Citizens (DigComp 3.0).

There is a close connection between robust foundational skills, socio-emotional maturity, and future-readiness, often fostered by access to good quality education. These broader skillsets are now essential not only for handling more complex workplace tasks, but also for empowering citizens in an uncertain future. *The vital importance of foundational learning/ skills could not be overstated.* As PIAAC results reveal, there is a tendency of decreased ‘functional’ literacy and numeracy in many countries. Literacy, numeracy and basic digital skills cannot be neglected in any discussion about the skills landscape in the age of AI. Learners must be equipped with stronger, and more solid foundational skills so that they can succeed in skills programmes and workplaces.

With the advent of AI technologies, the demand for higher-order cognitive and metacognitive skills is increasing beyond highly skilled professions; citizens increasingly need to use analytical and critical thinking, problem-solving and decision-making or self-reflection in their work and lives alike. Similarly, an enhanced level of socio-emotional skills becomes crucial in regulating thoughts, emotions and behaviours and fostering endurance in uncertain times with big changes. Socio-emotional intelligence can also provide safeguards for ethical and human-centred AI ensuring inclusivity, agency and wellbeing (see Box 4). Hence, investing in socio-emotional learning is not just for learners' personal growth, but a strategic imperative for safe, effective, and equitable AI adoption (UNESCO, 2024b).

Box 4: Teaching socio-emotional skills for ethical and human-centred AI

Despite their increasing importance, teaching socio-emotional skills is less visible in education and training. UNESCO defines 'socio-emotional learning' (SEL) as the process of acquiring competencies to recognise and manage emotions, show care and concern for others, establish positive relationships, make responsible decisions, and handle challenging situations effectively. Recently, it developed a policy guide on how to mainstream SEL in education systems (UNESCO, 2024b). According to UNESCO, SEL integrates cognitive, emotional, and relational dimensions to foster learners' wellbeing, academic attainment, and active global citizenship oriented towards positive social transformation. Capacities such as self-control, critical reflection and social awareness are hallmarks of SEL (ibid).

Effective human–AI interaction depends on socio-emotional dispositions. Research shows that people often either over-rely on AI outputs (automation bias) or under-use them (algorithm aversion). Avoiding both extremes requires metacognition, reflective judgment, and emotional regulation, which are core SEL competencies (ibid). SEL equips learners to calibrate trust in AI systems, question outputs critically, recognise potential harm to others, manage uncertainty and act responsibly.

These higher-order and broadened skillsets have become essential to empower citizens, so that they get the most out of changing labour markets and perform effectively in different work-related settings as employees, self-employed and entrepreneurs. It is not only AI adoption shifting humans toward cognitively and emotionally more demanding tasks; the shift from 'curator' to 'editor' is making AI's impact less visible, because AI can massively influence public discourse and the way people think through algorithms and AI chatbots, often without independent oversight[54]. The surge in the new forms of work and evolving employment structures also requires people to be more resourceful to manage greater uncertainty and the prospect of multiple careers in one's life. Coping with new forms of work is a case in point for the increased importance of digital, self-management, and learning-to-learn skills, especially in many developing countries (see ETF 2021a, 2021b, 2023a, 2024a, 2024b, 2024c).

This context calls for a shift from teaching narrow skill-sets to the cultivation of broader human 'capabilities' for citizens with higher agility, resilience and adaptability[55]. Human capabilities transcend specific skill domains; they underlie the *'human agency'* and ability to learn, apply and effectively adapt knowledge and skills for meeting one's own future needs[56]. New studies of human wellbeing increasingly emphasise the importance of 'subjective capacity', with dimensions of agency, resilience, optimism, and a sense of purpose (Lehmus-Sun, 2026). *Agency* reflects an individual's capacity to act, *resilience* pertains to their capacity to bounce back from challenges, *optimism* measures capacity to have a positive outlook, and *purpose* captures the capacity to feel a sense of meaning in life.

[54] As argued by Marc Faddoul, 'algorithms are not value neutral. AI chatbots do not simply curate existing information, they generate and frame it. Whereas Facebook and Google decided which news articles to show you, tools like ChatGPT, Claude, and Gemini synthesise that information into authoritative-sounding answers', see [Who's Whispering in Your Chatbot's Ear? by Marc Faddoul - Project Syndicate]

[55] For a good discussion of skills policies for resilient labour markets and societies, please see OECD/Cedefop/European Commission/ETF/ILO/UNESCO, 2024.

[56] This reminds the 'capability approach' promoted by the economist and philosopher Amartya Sen in the 1980s as an alternative approach to welfare economics. Sen's core focus (what individuals are able to do, i.e. as 'agents' who act and bring about change) also emphasises the expansion of capability for development.

These enduring human capabilities are becoming much more important than skills themselves, but they cannot be developed in a vacuum by individuals. *Capabilities are built within skills ecosystems, through coordinated and life-course education and training investments, firm practices, labour market institutions, and social dialogue*[57]. In the context of an evolving AI landscape, inclusive governance, ethical considerations, and workplace safeguards (transparency, explainability, consent, and worker voice) are essential to improve human capabilities alongside digital, data and AI literacies to augment work and support decent outcomes.

Ongoing AI progress brings significant implications for learning and resonates with the discussions regarding the direction of future education systems and new pedagogical approaches such as experimental learning, reflection, collaboration and social interaction over content acquisition. For example, scientific literacy becomes critical in an AI-driven future due to the complementarity between AI literacy and STEM topics. According to OECD (2025e), the future science curricula must prepare students to become flexible, adaptive, creative and socially aware problem solvers and curious about the world around them[58]. This requires linking science learning to real-world phenomena to make the relevance of scientific knowledge visible to learners but also placing greater emphasis on ethics and civic responsibility in science education.

Although it is not the focus of this report, a highly capable AI system raises even more fundamental questions about the priorities and assumptions that currently underpin education. For example, using generative AI in writing urges education systems to consider which abilities are uniquely human and the corresponding knowledge that remains valuable (OECD, 2025g). While offering many opportunities, AI systems introduce risks that might challenge the basics of education in the long term. Even in the current context, information is widely and instantly available thanks to AI technologies, so *'knowledge' in itself is less important than the higher-order skills needed for its selection, application or implementation* (e.g., communication, innovation, decision-making, judgement) (see Box 5).

Box 5: 'Knowledge is cheap, but wisdom is scarce'

In the words of an educationalist, Ulf-Daniel Ehlers, knowledge is no longer the scarce resource in the age of AI. Generative AI, language models, machine tutors and recommendation engines have redefined access to information. If the act of *knowing* is being dislocated from the human mind, externalised into systems that simulate understanding, then the question is 'what remains the unique domain of the human'. Education should go beyond knowledge and instil wisdom – moving from information delivery to cultivating judgement, reflection, ethical decision-making, imagination and co-creative capability. The latter is becoming the true marker of human competence in the AI age. Education can be a tool to shape the kind of futures people can imagine and pursue. Students must be prepared to be ready, with the capacity to take responsibility and co-create solutions for the future of society (Ehlers, 2025).

These core competences or future-ready skills are not the mere accumulation of skills; it is the capability to act responsibly and effectively in complex, uncertain, and evolving contexts. The future of human competence does not lie in outperforming machines, but in doing what they cannot: exercising judgement in ambiguous situations; taking moral responsibility for collective futures; engaging in meaning-making and identity development; collaborating across diversity, systems, and disciplines; imagining alternative realities and bringing them into being. These are not just soft skills, they are the foundation of the ability to shape society ethically, sustainably and creatively; agility, reflection and uncertainty navigation are the new excellence. Focusing on employability as the primary goal of education is no longer enough, because the crises of our time—ecological, democratic, humanitarian—demand something more (Ehlers, 2025).

In conclusion, AI adoption in workplaces is reshaping the variety and depth of skills used across jobs (cognitive, socio-emotional, and manual skills). It often increases demand for cognitive and meta-

[57] This ecosystem perspective is discussed in the ILO's Global Employment Policy Review 2025, Chapter 7 "Building skills ecosystems for sustainable productivity improvements".

[58] This is an OECD report based on an expert workshop held in 2024 with leading science education scholars in the US on scientific literacy in the AI age. Accordingly, science curricula must enable students to understand and analyse how scientific and non-scientific knowledge intersect and how technical and social issues are linked to technological development (e.g. social impact of AI) (OECD, 2025e).

cognitive skills, particularly higher-order analytical and critical thinking. Moreover, the value of socio-emotional skills is amplified as human cognition, emotion, judgement, and creativity are key for effective human-AI collaboration and the fair and human-centric adoption of AI. While manual skills are less affected so far, the rise in demand for intermediate and advanced digital skills and data literacy is growing in order to integrate and use AI tools. As a result, the need for individuals to comprehend and safely use AI tools in an ethical manner has emerged as a new foundational skill.

Overall, most human skills will still be needed – but how people use them will change as they work alongside intelligent machines. AI increases demand for new skillsets that blend technical, cognitive and interpersonal abilities. This points to the need for a different approach to skills policy, centred on building 'hybrid intelligence': combining technical AI literacy with domain expertise and uniquely human capabilities and originality. This requires qualification systems to move from certifying tasks and occupations towards recognising capabilities, agency and learning capacity, while skills anticipation must shift from predicting job losses to understanding how AI reshapes skills, entry pathways and job quality.

Besides the need for incorporating AI literacy into educational curricula, this report argues for widespread AI upskilling of adults and workers, revising occupational standards, qualifications and curricula, and adapting assessment, certification and quality assurance systems in education and training. It also advocates shifting from teaching narrow skillsets to instilling broader capabilities, as the AI-powered future calls for a human-centred approach and resourceful and adaptable citizens in the face of growing uncertainties. Such capabilities underpin human agency and the ability to learn, apply, and adapt knowledge and skills for future needs.

Finally, skills policy alone cannot ensure inclusive and fair AI outcomes. The benefits of AI technologies are being unequally distributed, while persistent gender, racial and socio-economic imbalances in the AI workforce risk embedding existing biases into AI systems and limiting the inclusiveness of future labour market opportunities. Evidently, skills policies need to address access, progression pathways and retention for underrepresented groups, not only aggregate supply, in order to support vulnerable groups. However, investments in skills and AI literacy must be complemented by labour market institutions, social protection, and governance arrangements that shape how AI is introduced, how work is organised, and how the gains from technological change are shared.

ACRONYMS

AI	Artificial Intelligence
AI CFS	AI Competency Framework for Students
AI CFT	AI Competency Framework for Teachers
AI4E	AI for Everyone (Singapore)
AIM-WORK	Analysis on Impacts of AI and AM in the Workplace
AM	Algorithmic Management of Work
ARISA	Artificial Intelligence Skills Alliance
EC	European Commission
ESJS2	Second European Skills and Jobs Survey
ETF	European Training Foundation
EU	European Union
GenAI	Generative AI
ICT	Information and Communication Technologies
IQ	Intelligence Quotient
JRC	Joint Research Centre
ML	Machine Learning
MOOCs	Massive Open Online Courses
NLP	Natural Language Processing
OJAs	Online Job Advertisements
OJVs	Online Job Vacancies
RPA	Robotic Process Automation

SEL	Socio-Emotional Learning
SMEs	Small and Medium-sized Enterprises
STEM	Science, Technology, Engineering, Mathematics
TVET	Technical and Vocational Education and Training
UAE	United Arab Emirates
UK	The United Kingdom
US	The United States of America
WEF	World Economic Forum

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