

5 Skill needs and policies in the age of artificial intelligence

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The development and adoption of artificial intelligence (AI) will likely have a profound impact on labour markets, not only in terms of employment levels and job quality, but also on how work is organised, the type of tasks workers perform, and therefore on the skills that will be needed. This chapter discusses changes in skill requirements due to AI development and adoption and how adult learning systems should be adapted in response. The chapter reviews the available evidence on firm-provided training for AI. It makes the case for public intervention and presents examples of policies to promote training for AI. It also shows how AI technologies could be used to improve adult learning systems and concludes by discussing avenues for future research.

In Brief

Key findings

The development and adoption of artificial intelligence (AI) will have an important impact on skill needs, as they will modify the task and skill composition of jobs and the distribution of occupations in the economy. Adult learning systems will need to quickly adapt to these rapid transformations.

This chapter addresses two related questions: What is the specific impact of AI on skill needs? And how can adult learning systems be better designed and implemented to meet these needs? The main findings of the chapter are:

- As a result of AI development and adoption, some skills can be increasingly replicated by technologies. This is the case for manual and fine psychomotor abilities, as well as cognitive skills such as expression and comprehension, planning, and advising. ChatGPT, an AI model that made headlines recently for its performance in language tasks, is a striking example of how AI development and adoption are accelerating, which suggests that the impact of AI, including on skill needs, might be larger in the near future.
- At the same time, skills needed to develop and maintain AI systems, and to adopt, use and interact with AI applications, will become more important. In some cases, specialised AI skills will be required, but the shift in skill needs is much broader, and there will be growing demand for basic digital and data science skills, as well as for complementary cognitive and transversal skills. As AI becomes widespread, it will be increasingly important for workers in various occupations to possess a broad range of skills to effectively develop and interact with AI systems.
- Training for specialised AI skills requires a combination of formal higher education and on-the-job learning. Basic AI knowledge or “AI literacy” should be taught at different levels of formal education, including in schools.
- Training for AI should be provided not only to vulnerable groups (low-skilled and older workers in particular) to help them adapt to the changes AI will bring to the workplace, but also to higher-skilled workers and managers, to foster AI development and adoption.
- Following adoption, companies tend to provide training for AI. Yet, the lack of appropriate skills remains a major barrier to AI adoption. Firms may under-invest in training for AI for several reasons including the existence of an important informational gap around AI and the fact that the benefits of training for AI may be wider than the firm.
- Public policies have an important role to play to promote greater training provision by employers, to ensure an integrated approach to skills development for AI at all stages of the lifecycle, from initial education to lifelong learning, and to encourage diversity in the AI workforce.
- Although most policies and strategies for AI recognise the importance of skills, few propose sufficient measures to develop them.
- Greater use of AI could be made to improve the design, targeting and delivery of training. Several examples of its use already exist, but they are currently limited. Yet, using AI in training also poses non-negligible risks. These risks need to be considered carefully and properly addressed before the use of AI in training becomes more widespread.

Introduction

Even if the available evidence does not point to large employment effects so far (Chapter 3), artificial intelligence (AI) is likely to have a more sizeable impact on labour markets going forward, and in particular on skill needs. Emerging and growing occupations will require different skillsets to those needed in shrinking occupations. Further, much of the impact of AI on jobs is likely to be experienced through the reorganisation of tasks within occupations (Chapter 4), and changes in tasks carried out by workers will modify the skills required at work. This chapter examines how AI will impact skill needs, assessing both skills that may become redundant and those that will become more important.

The potential for firms and workers to adapt to the introduction of AI will depend largely on ensuring workers are equipped with the necessary skills. This chapter highlights the main challenges involved in designing adult learning systems for an AI-ready workforce and points to policy priorities. It provides details on the type of training that will be needed, and the groups of workers that should be targeted. It presents evidence suggesting that while some enterprises already offer AI training to their employees, in general most firms may not be doing enough. Public intervention is warranted but existing policies promoting training for AI are not sufficient.

AI poses challenges for adult learning systems but may also represent an opportunity to improve training design, targeting and provision. AI technologies could be used to better plan and deliver training, and to increase training participation and inclusiveness, and the chapter looks at some examples of where this is already happening. Yet, the use of AI in training also poses some risks and challenges: the costs related to AI adoption may exacerbate inequalities between small and large actors; the fact that interacting with AI requires a basic level of digital skills may limit participation by low skilled individuals; and the tendency of some algorithms to scale up human biases may decrease inclusiveness. An additional challenge is that the use of AI in training will likely bring about important changes in skill needs among teachers and trainers. These issues need to be considered carefully.

The chapter starts by reviewing existing evidence on changes in skill needs brought about by AI development and adoption (Section 5.1). Section 5.2 then discusses how training should be delivered in order to respond to these changes, focusing on the type of training and on groups of workers that should receive particular attention. Section 5.3 reviews available evidence on firm-provided training for AI. Section 5.4 makes the case for government intervention and reviews existing policies to promote training for AI. The chapter then shows how AI can be used to improve adult learning systems (Section 5.5) and concludes by discussing avenues for future research (Section 5.6).

5.1. The development and adoption of AI will have an impact on skill needs

There are two reasons why AI will modify skill needs. On the one hand, AI can replicate more and more skills, in particular cognitive and manual skills. On the other hand, AI raises the demand for skills needed to develop AI and for skills necessary to use AI. This section describes in details changes in skill needs due to AI, and is based mainly on several recent OECD studies (Green and Lamby, 2023^[1]; Lane, Williams and Broecke, 2023^[2]; Lassébie and Quintini, 2022^[3]; Milanez, 2023^[4]).¹

5.1.1. AI has made important progress replicating cognitive and manual skills

Recent technological advances in AI and automation technologies mean that several skills and abilities previously considered hard to replicate by technologies are now more susceptible to automation. This is the case of fine arts, several psychomotor abilities, and cognitive skills such as expression and comprehension, scheduling, and advising, as detailed below (Lassébie and Quintini, 2022^[3]).

AI can, in some cases, compose, produce, and perform works of music and visual arts, according to experts interviewed for the study by Lassébie and Quintini (2022^[3]). Zhang et al. (2022^[5]) make a similar point in the AI Index 2022 report, as they claim that for some constrained applications, text, audio, and images generated by AI systems are as good as if they had been composed by humans. However, one challenge developers face when developing the systems further is that there is no consensus on what can be labelled true or false, or good or bad. Hence, it is not straightforward to find or construct reliable training sets with which algorithms can be trained.

Important progress has also been made in the past few years in replicating psychomotor abilities, and in particular manual and finger dexterity, and the ability to work in cramped workspace, albeit to different degrees. Robots that have manual dexterity have existed for several decades and are present in many manufacturing plants. This can be considered a mature technology. Finger dexterity is more challenging for robots, but significant progress has been made. Thanks to deep learning-based vision systems, robots can manipulate objects, pick them up and place them at speeds that are practical for real-world applications (Littman et al., 2021^[6]). However, the gesture of pushing while applying the right force and all gestures that rely on feeling the texture of an object are much more challenging. Dealing with very small objects is also complex; one important difficulty is that tolerance for error must be very low because any mistake might lead the robot to harm persons, damage objects or disrupt systems (Nolan, 2021^[7]). Similarly, working in cramped workspaces that requires getting into awkward positions is difficult but not impossible for robots. Specialised robots can be built for specific applications: for instance, there are robots that can manoeuvre inside airplane wings to verify their condition, and there exist drones to inspect industrial buildings. In these environments, one difficulty for robots lies in the darkness and absence of vision. While humans can rely on other senses to form a mental image of the space, robots cannot, as it would be computationally too demanding. Hence, many of the solutions that now exist are remotely controlled and still rely on human intervention.

AI technologies are increasingly capable of oral and written expression and comprehension, thanks to important progress made in recent years. In 2017, an OECD report investigating computer capabilities with respect to certain human skills (Elliott, 2017^[8]) showed that computers were not performing as well as humans on answering literacy questions, even for those that were the easiest for adults, although the difference between computers and humans for these questions was small. However, a new study by the OECD (2023^[9]) finds that today, experts believe AI can answer around 80% of literacy questions asked to adults in the Survey of Adult Skills (PIAAC). These questions involve, at basic levels, locating information in short texts and identifying basic vocabulary, and, at higher levels, navigating across larger chunks of text to formulate responses. Experts suggest that AI technologies can answer most questions at basic levels and some more complicated ones and predict that AI will be able to successfully answer the entire literacy test by 2026. The difference between human and AI performance on the most complex linguistic tasks has been narrowing, due to the development of network architectures with enhanced capability to learn from complex and context-sensitive data and relying on increasing data resources and computing power (Littman et al., 2021^[6]).

One class of Natural Language Processing models that has drawn much attention recently are Large Language Models, in particular ChatGPT.² ChatGPT is a striking example of an AI model that can perform as well as humans on several language and more generally cognitive tasks, and much faster. Emerging experience with the use of ChatGPT shows that it can write jokes, computer code and essays, formulate medical diagnoses, create games, and explain complex scientific concepts to a wider audience. Its output is, in many cases, very convincing. When evaluated against answers given by experts on different questions, its performance has been assessed as good as a team of experts (Guo et al., 2023^[10]). It exhibits human-level performance on various professional and academic benchmarks, including passing a simulated bar exam with a score around the top 10% of test takers (OpenAI, 2023^[11]). Its adoption appears to happen at fast pace, for instance it has been added to Microsoft's industrial grade search engine Bing a few months after its release. However, ChatGPT produces in some cases superficial content, and

can even generate false information. In all cases, it needs to be prompted correctly and its output must be reviewed. Human intervention thus remains crucial.

Systems that provide recommendations to humans are also becoming more and more widespread. There exist AI-powered task planning and dynamic scheduling tools that perform better than humans in many cases. They also necessitate human intervention: time constraints have to be recorded in the system, and humans can accept or reject recommendations made by AI. For instance, in online marketing, “recommender systems”, that automatically prioritise products seen online by users, have become essential and have an important influence on individuals’ consumption of products, services, and content (news, music, videos...). In the case of preventive maintenance, AI systems can provide advice on what to replace or check on a machine. In the field of education, tasks that are complementary to pure instruction (targeting learning activities to students, determining which modules they should follow, or what instruction method to use) can also be performed by AI systems (these applications are discussed in more details in Section 5.5).

Looking at firms that have adopted AI reveals that there is already evidence of some skills becoming redundant. In the OECD AI surveys of workers and employers on the impact of AI on the labour market in the sectors of finance and manufacturing in seven OECD countries (Lane, Williams and Broecke, 2023^[2]), approximately half of AI users declare that AI has made some of their skills less valuable (51% of AI users in the finance sector and 45% in manufacturing), and these proportions were even higher among workers who reported that some of their tasks had been automated (56% in finance and 51% in manufacturing). In case studies of employers having implemented AI carried out by the OECD, Milanez (2023^[4]) finds that skills that are made redundant by AI adoption are mainly manual skills, and examples of skill redundancies were concentrated in the manufacturing sector. For instance, in a Canadian manufacturing firm, an AI-powered robot is used to measure and cut glass for tiles, a task previously performed manually by workers. After the introduction of the AI tool, workers only have to interact with the machine, loading input materials and monitoring the machine’s output.

5.1.2. AI increases the demand for both skills required to develop AI systems and skills to use AI applications

Higher skills demand will come, on the one hand, from the need to develop and maintain AI systems and, on the other hand, from using and interacting with AI applications. Jobs to develop and maintain AI systems are usually technical in nature and some of these jobs are new, in the sense that workers will perform tasks specific to AI that are not present in today’s occupations. In firms adopting AI, workers in several occupations will have to use and interact with AI. Most of these occupations are not new but, in some cases, the tasks involved, and the skills required to perform them, will change. This subsection discusses the skills required in these two types of jobs, and analyses commonalities and divergences.

Skills to develop and maintain AI systems

AI development requires specialised AI knowledge and skills, at the intersection between computer programming, database management and statistics. Skills mentioned together with the keyword “artificial intelligence” in online job postings include, for instance, programming languages such as Python, the ability to work with and manage big data, and skills for data analysis and visualisation. More specific 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) is also required (Alekseeva et al., 2021^[12]; Manca, 2023^[13]; OECD.AI, 2023^[14]; Squicciarini and Nachtigall, 2021^[15]). Findings from the OECD surveys of firms having adopted AI in Austria, Canada, France, Germany, Ireland, the United Kingdom and the United States, confirm that a majority of workers who develop and maintain AI possess such specialised AI skills (79% of workers in finance and 75% in manufacturing) (Lane, Williams and Broecke, 2023^[2]). Yet, these findings also show that not all workers that develop and maintain AI

possess such skills: 10% of them explicitly state that they do not have specialised AI skills. This suggests that some of these jobs, for instance to provide input to Machine Learning models or to correct outputs of AI systems, do not require specialised AI knowledge (see below for a discussion of different types of jobs that might be created as a result of AI and the skills they involve).

The demand for specialised AI skills in online job postings has been rising over the past few years. It grew fourfold between 2010 and 2019 in the United States, accelerating in the last three years, across a wide range of occupations. In comparison, over the same period, the share of job postings mentioning computer skills was stable and demand for software skills seems to have declined slightly (Alekseeva et al., 2021^[12]; Acemoglu et al., 2022^[16]). Similar trends have been observed in job postings in Canada, Singapore and the United Kingdom (Squicciarini and Nachtigall, 2021^[15]).

Job postings that require specialised AI skills also necessitate high-level cognitive skills, including creative problem solving, and transversal skills such as social skills (communication, teamwork, collaboration, negotiation, presentation) and management skills (project management, staff supervision and management, mentoring, leadership), suggesting that these skills are complementary (Alekseeva et al., 2021^[12]; Manca, 2023^[13]).

AI development thus requires a specific bundle of skills that few individuals may possess, although it is not straightforward to determine whether supply is keeping up with demand. Analysis of wage data by the OECD provides indirect evidence: while the wages of workers with specialised AI skills are high (see Box 5.1 that presents some socio-demographic and wage characteristics of the AI workforce), their wage growth does not exceed that of other occupations on average across OECD countries, suggesting that, so far, supply may be sufficient to satisfy the level of demand. However the OECD average masks important differences across countries. In particular, Austria, Belgium, Denmark and Finland, saw the largest gaps between hourly wage growth for those with AI skills and the economy overall. Furthermore, employers may use non-wage adjustments to adapt to imbalances. For example, they may use other types of financial compensation, such as lump-sum bonuses or shares of the company for which they work. This explanation is particularly relevant for the AI workforce. This may lead earnings growth to be understated (Green and Lamby, 2023^[11]). Other non-wage benefits may include pension schemes and retirement benefits, health insurance, student loan support, and workplace amenities. The issue of a potential shortage of workers with the right bundle of skills to develop and maintain AI systems thus deserves more research.

In terms of the new types of jobs to build, train, update, and maintain AI technologies, Wilson, Daugherty and Morini-Bianzino (2017^[17]) foresaw already in 2017 that three new types of jobs might be created. The first category would be composed of “trainers” of Machine Learning models to teach AI systems how they should perform. These roles usually involve technical and data science skills, but not only, and not all. For instance, chatbots need to be trained to communicate with humans using compassionate and sympathetic language and to understand humour and language subtleties. This requires behavioural training of the algorithm, and hence interpersonal skills for the “trainer”. The second category of new jobs could include “explainers” of AI systems that will clarify the functioning of algorithms and the different types of outcomes that are being generated, notably to managers and non-technical professionals in firms implementing or seeking to implement AI applications, but also to consumers and the general public. These jobs could become less necessary if or when AI systems become more transparent and self-explanatory, but remain crucial for the time being as governments start taking actions to ensure transparency (see Chapter 6). These jobs will necessitate a good knowledge of AI, but also communication skills and the ability to convey technical information to a non-technical audience, among others. Finally, “sustainers” will check that AI systems are working as intended, detecting biases, fakes and mistakes, and will ensure that unintended consequences are addressed as they should and in a timely manner. They will monitor algorithms’ outcomes, and ensure they continue to work as intended over time, as the technology, data and environment change.

Box 5.1. Characteristics of the AI workforce

According to OECD research, the AI workforce, i.e. workers with specialised AI skills, is concentrated in a few high-skilled occupations: mathematicians, actuaries and statisticians, software and application developers, ICT managers, database and network professionals, and electrotechnology engineers (Green and Lamby, 2023^[1]). The AI workforce is disproportionately highly-educated and male. Over 60% of the AI workforce has at least a tertiary degree, on average across OECD countries, and less than 40% of the AI workforce are women compared to more than 50% of the employed population with a tertiary degree across OECD countries. In contrast, the AI workforce is just as likely to be young or foreign-born compared to the employed population with a tertiary degree.

Regarding wages, Green and Lamby (2023^[1]) show that across European OECD countries in their sample, almost 50% of the AI workforce earns above the 80th percentile in the earnings distribution. Manca (2023^[13]) shows that job postings where skills related to AI are highly relevant offer higher wages than the average even after accounting for average years of schooling, skill complexity of the job and geographical factors related to the job offer. Similarly, Alekseeva et al. (2021^[12]) find a wage premium of 11% for job postings that require skills related to AI within the same firm, and 5% within the same firm and job title. This wage premium is the highest for management occupations, and higher than the premium associated to other skills (software, cognitive, or management skills).

Source: Alekseeva et al. (2021^[12]), “The demand for AI skills in the labor market”, <https://www.doi.org/10.1016/j.labeco.2021.102002>; Green and Lamby (2023^[1]), “The supply, demand and characteristics of the AI workforce across OECD countries”, <https://www.doi.org/10.1787/bb17314a-en>; Manca (2023^[13]), “Six questions about the demand for artificial intelligence skills in labour markets”, <https://www.doi.org/10.1787/ac1bebf0-en>.

These new roles are already emerging in firms implementing AI. Based on the OECD AI case studies, Milanez (2023^[4]) finds that a significant share of firms adopting AI experience job creation related to the further development and maintenance of AI. The new job profiles are not clearly defined yet, but usually involve providing suitable operating environments for machine learning models, developing, maintaining, and training the models, and tracking their efficiency and accuracy over time. For instance, a French banking and insurance firm mentions the role of employees that make sure that AI models remain accurate over time and that their predictive power is satisfactory as new data are used. They indicate when the AI model has to be modified, and how to prepare the data to this end.

Skills to use and interact with AI applications

In some cases, the implementation of AI technologies does not lead to changes in skills required in adopting firms. In the OECD study by Lane, Williams and Broecke (2023^[2]), 57% and 48% of employers that have adopted AI in finance and manufacturing report no change in skill needs to date. Similarly, in the OECD AI case studies of firms having implemented AI, 60% of firms say that AI adoption has not modified skill requirements (Milanez, 2023^[4]). To explain this, the study points to several possible explanations. First, in several instances, AI implementation has had, so far, a small impact on the tasks carried out by workers and hence a small impact on the skills required to carry out those tasks. In other cases, AI adoption affects the order and relative importance of pre-existing tasks rather than change or add new tasks, raising few additional skill needs. AI implementation sometimes necessitates digital skills that were not required previously, but at such a basic level that firms do not think it is worth mentioning as a change. Other reasons include the fact that, in manufacturing, the preservation of workers’ existing skills, at least for a small group, is sometimes seen as a safeguard if the AI system fails. In finance, several firms having adopted AI declare that it led to greater reliance on workers’ existing skills, as opposed to the need for different skills. This was the case when AI adoption leads to automation of simple versions of a task, while

complex versions were still performed by workers. Finally, it is important to note that AI adopters are a selected sample of employers that are able to implement AI precisely because their workforce possess the necessary skills. This could very well explain why many AI adopters report no change in skill needs.

But in a significant share of firms, AI implementation is associated with a need for higher and broader skills, and the demand for digital, analytical, and soft skills increases (Lane, Williams and Broecke, 2023^[2]; Milanez, 2023^[4]). General digital skills and elementary knowledge of AI are needed, most often at a basic level (ability to use a computer or smartphone), for workers to be able to use the AI application, even if some firms think such a marginal change is not worth mentioning. Analytical and soft skills are becoming more important for several reasons. First, the automation of simple versions of tasks often gives workers greater shares of complex tasks, requiring higher analytical skills such as specialised knowledge, comprehension and application of new ideas. Second, task automation often leads workers to take on greater shares of tasks requiring soft skills and interpersonal skills. New needs also arise for workers who are redeployed to other departments within the same firm (Milanez, 2023^[4]). Similar findings are reported in Lane, Williams and Broecke (2023^[2]): AI primarily increases the importance of skills such as creativity and communication within the company (42%/41% of employers that have adopted AI in finance/manufacturing), as well as the need for highly educated workers (55% of employers in both sectors).

Only in few cases does the use of AI applications require specialised AI knowledge or digital or data science skills. For instance, Bessen et al. (2018^[18]) found that only 10% of firms surveyed for their work require users to have expert coding or data skills, while 59% require general familiarity with computers, and the remainder require no special skills at all. In the OECD case studies of firms having adopted AI, Milanez (2023^[4]) reports that several developers explain that AI applications are designed to be user-friendly and intuitive and that their use requires the same level of digital skills than the utilisation of a smartphone. This low importance of specialised AI skills is also reported by Lane, Williams and Broecke (2023^[2]).

To sum up, Table 5.1 presents the different types of skills that are becoming more prevalent because of AI. Sophisticated AI and digital skills are necessary to develop and maintain AI systems, while elementary AI knowledge and basic data science skills are necessary, in some cases, to work and interact with AI applications. But beyond technical expertise, a broader range of skills are needed. Indeed, both sophisticated and general AI skills are increasingly required in conjunction with other cognitive skills such as analytical skills and problem-solving, and with transversal skills (social skills, management, communication, teamwork, multitasking). At the moment, these skills are harder to replicate by automation technologies (Lassébie and Quintini, 2022^[3]).

As AI becomes widespread, it will be increasingly important for workers in various occupations to possess this broad range of skills to effectively develop and interact with AI systems. The rest of this chapter discusses how adult learning systems can be adapted to respond to these new skill needs. In particular, Section 5.4.2 presents several country initiatives to foster the development of skills for AI.

Table 5.1. Skill needs in the age of AI

	Type of skill	Examples
Skills to develop and maintain AI systems	Specialised AI skills	General knowledge of AI (such as Machine Learning) Specific knowledge of AI models (“decision trees”, “deep learning”, “neural network”, “random forest”, etc), AI tools (“tensorflow”, “pytorch”, etc) and AI software (“java”, “gradle”, “galaxy cluster”, etc).
	Data science skills	Data analysis Software Programming languages, in particular Python Big data Data visualisation Cloud computing
	Other cognitive skills	Creative problem solving
	Transversal skills	Social skills Management skills
Skills to adopt, use and interact with AI applications	Elementary AI knowledge	Principles of machine learning
	Digital skills	Ability to use a computer or a smartphone
	Other cognitive skills	Analytical skills Problem-solving Critical thinking Judgement
	Transversal skills	Creativity Communication Teamwork Multitasking

Source: Authors’ elaborations on Alekseeva et al. (2021^[12]), “The demand for AI skills in the labor market”, <https://www.doi.org/10.1016/j.labeco.2021.102002>, Lane, Williams and Broecke (2023^[2]), “The impact of AI on the workplace: Main findings from the OECD AI surveys of employers and workers”, <https://www.doi.org/10.1787/ea0a0fe1-en>; Manca (2023^[13]), “Six questions about the demand for artificial intelligence skills in labour markets”, <https://www.doi.org/10.1787/ac1bebf0-en>, Milanez (2023^[4]), “The impact of AI on the workplace: Evidence from OECD case studies of AI implementation”, <https://www.doi.org/10.1787/2247ce58-en>; OECD.AI (2023^[14]), *Visualisations powered by JSI using data from www.adzuna.co.uk*, <https://oecd.ai/>; Squicciarini and Nachtigall (2021^[15]), “Demand for AI skills in jobs: Evidence from online job postings”, <https://www.doi.org/10.1787/3ed32d94-en>.

5.2. Changes in skill needs call for new training opportunities

5.2.1. AI development and adoption call for specialised education pathways as well as specific AI literacy courses

Training to develop and maintain AI systems

Skills to develop and maintain AI systems include specialised AI skills, data science, and cognitive and transversal skills (Table 5.1). The acquisition of specialised AI skills requires both advanced academic training and substantial hands-on experience. Initial education is key and a substantial part of the AI workforce possesses a tertiary degree (Green and Lamby, 2023^[11]). Learning-by-doing is also important (Daugherty, Wilson and Michelman, 2019^[19]), and may take the form of apprenticeships or informal learning (e.g. being part of a research team or the AI development process within their firms).³

Training to use and interact with AI applications

AI adoption and use in the workplace requires elementary AI knowledge, basic digital skills, as well as cognitive skills and transversal skills (Table 5.1). In firms adopting AI, although a minority of AI users said that they had AI skills, nearly three-quarters said that they were enthusiastic to learn more (73% of workers in finance and 72% in manufacturing) (Lane, Williams and Broecke, 2023^[2]). The question of how to promote elementary knowledge of AI is thus one that deserves particular attention.

Elementary knowledge of AI is often referred to as “AI literacy”, a concept that has recently gained attention in the literature focusing on adult learning. Long and Magerko (2020^[20]) define it as “a set of competences that 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”. Ng et al. (2021^[21]) insist that AI literacy does not necessarily refer to skills needed to develop AI models but rather to understand, use, monitor, and critically reflect on AI applications. Based on a review of existing literature, the authors distinguish four levels of AI literacy. At the most basic level, AI literacy entails the knowledge of basic functions of AI and how to use AI applications in everyday life. The second level of AI literacy involves the ability to apply AI knowledge, concepts and applications in different contexts. AI literacy at higher levels includes skills to implement and evaluate AI. It thus requires the ability to manage data needed for the development of AI algorithms and skills to critically reflect on their outputs. All levels necessitate basic analytical skills and knowledge of mathematics and statistics and include some elements of AI ethics. However, research in this area is still in its infancy and needs refinement in terms of how to define AI literacy in adult education and how to measure AI literacy of adults (Laupichler et al., 2022^[22]).

Another important but under-researched topic concerns the structure and content of AI literacy courses for non-experts. In a scoping literature review, Laupichler et al. (2022^[22]) show that most courses have one or several initial units aiming at providing a first understanding of what AI is, where it came from, and what it can and cannot do. Most courses review machine learning and deep learning, as they form the basis for most AI applications today. Finally, some courses also discuss ethical issues in AI, addressing algorithmic bias or the black box nature of AI. Another characteristic of AI courses designed for non-experts is that they are commonly presented in short modules that are easier to follow and integrate. They mostly rely on decentralised, digitally available instructional courses or learning materials.

5.2.2. Specific groups of workers deserve special attention

Training programmes should be developed for several groups of workers, for different reasons. On the one hand, equity arguments motivate the focus on vulnerable groups, in particular older workers and the low-skilled, so that they can adapt to changes brought about AI adoption in the workplace. The motivation for training the low-skilled stems from the disadvantage that they still have in general in terms of automation risk (see Chapter 3) and is not specific to AI only. This specific group is thus discussed in more details in Box 5.2.

The motivation for targeting older workers stems from the fact that they are particularly vulnerable to the implementation of AI in the workplace, because they are less likely to possess the new skills required (especially digital skills) and are also less likely to engage in training. The fact that older workers lag behind when it comes to digital skills has been extensively documented in the literature. For instance, results from the Survey of Adult Skills (PIAAC) show low levels of proficiency in problem solving in technology-rich environments among older adults (OECD, 2019^[23]). Furthermore, in every single country participating in the PIAAC survey, older adults are less likely to take part in adult learning. The average gap in participation rates between older (54+) and prime-age (25-53) individuals was about 22 percentage points in 2015 (OECD, 2019^[24]). While these issues are not new, they are likely aggravated by the introduction of digital and AI technologies in workplaces. Indeed, older workers are perceived by their colleagues as particularly sceptical and worried about AI technologies, and this may limit their desire and capability to adapt (Milanez, 2023^[4]). Yet, it is important to note that the study does not report examples of older workers themselves voicing their scepticism regarding AI or lack of willingness to work with it. The evidence is thus based on

other workers' beliefs and it is possible that these beliefs are contaminated by biases against older workers that do not reflect their actual abilities and attitudes. In any case, given their lower levels of digital literacy, training for AI for older workers should be carefully designed and adapted.

On the other hand, efficiency reasons may justify the targeting of higher-skilled workers, managers and business leaders. As shown in Chapter 3, workers in high-skilled occupations have been the most exposed to recent progress in AI, since these occupations are the most likely to involve non-routine cognitive tasks that AI is increasingly capable of performing. Examples of such occupations include business professionals, managers, chief executives and science and engineering professionals. At this early stage of AI adoption, higher exposure to AI for high-skilled workers appears to lead to the creation of new tasks and jobs rather than the destruction of jobs. Yet, for high-skilled workers to be able to adapt to changes in the task composition of their jobs and work with AI technologies, they need basic digital skills, elementary knowledge of AI, cognitive skills such as problem-solving and critical thinking, and transversal skills such as communication, teamwork, or multitasking (see Section 5.1.2). While it is likely, but not certain, that most high-skilled workers already possess many of these skills, it is important to make sure all high-skilled workers are equipped with the right skill bundle.

The skills and knowledge of managers and business leaders also matter for AI adoption. Indeed, in most cases, AI adoption would entail important changes in business processes and corporate culture and require managers and business leaders to reconfigure tasks and organisational structures accordingly. For this, managers need not only skills related to change management practices, but also some knowledge of AI and its potential risks and benefits. A German firm interviewed for the OECD case studies of AI implementation in firms reported that even managers planning AI projects are expected to have a minimum knowledge of how the technology works (Milanez, 2023^[41]). Understanding what AI systems can and cannot do is key to assess where and how the innovation could be used in a company, what the benefits and risks of AI are, and how to best integrate AI systems in existing processes (Lassébie and Quintini, 2022^[3]; Mc Kinsey, 2018^[25]). Managers would also have to decide which activities are to be performed by humans and which are to be carried out by the AI systems. To do so, they must understand the strengths and weaknesses of each actor. Furthermore, the relationship between AI systems and workers needs to be managed (Peifer, Jeske and Hille, 2022^[26]), and algorithms need to be managed too, as clear objectives have to be specified and compromises must be made (Luca, Kleinberg and Mullainathan, 2018^[27]). Robust systems and mechanisms need to be developed and maintained to ensure human oversight of algorithmic decision-making and management. However, managers and business leaders are likely to lack AI knowledge necessary to do so. Indeed misconceptions about AI seem widespread (Roffel and Evans, 2018^[28]) and there is no reason to believe that business leaders and managers differ in that respect.

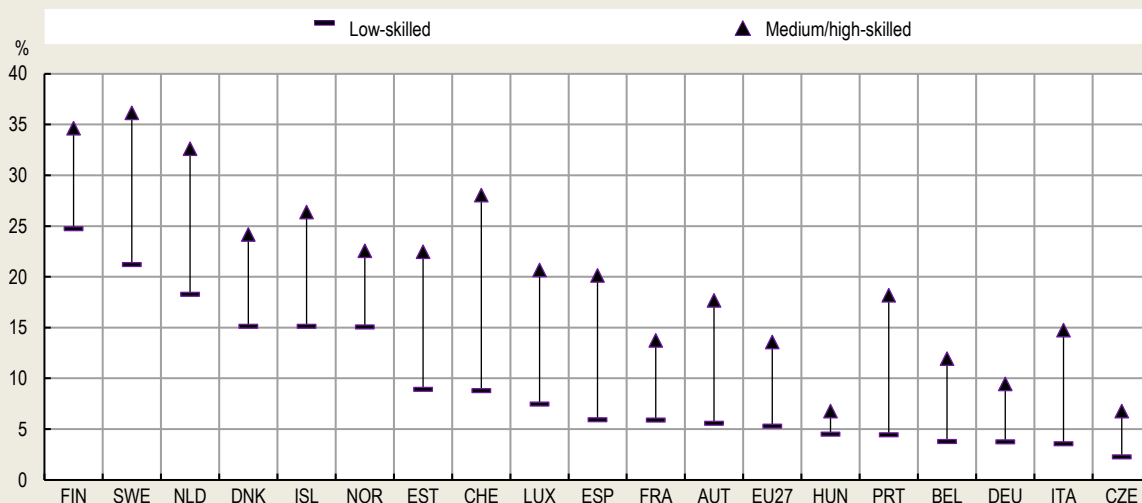
Finally, specific training actions should also be targeted at social partners to make sure they are equipped with the right tools to support workers facing and adapting to the challenges that AI development and adoption will bring about. Social partners report that changing skill demand is one of their main concerns related to AI (see Chapter 7). Yet, they could help identify changes in skill needs and promote and ensure fair access to training for AI to help workers face these changes. Trade unions and worker representatives also have a key role to play to give workers the trust to participate in training activities, especially low-skilled workers who are often reluctant to reveal their training needs to employers. Social dialogue is also particularly important to mitigate the impact of job restructuring resulting from technological change as social partners may agree on requalification schemes for existing staff that allow internal flexibility instead of mass lay-offs. More generally, they may negotiate collective bargaining agreements for the implementation of AI in the workplace. In practice, however, social partners are currently engaging mainly in outreach and information activities highlighting the need for new competences that will be required to work with digital tools, robotics and data, and the need to become "AI literate" (BusinessEurope, 2019^[31]; ETUC, 2020^[32]; ETUI, 2021^[33]; ILO/IOE, 2019^[34]; UNI Europa ICTS, 2019^[35]) but very few have engaged in negotiating agreements. This might be due to a lack of AI-related knowledge, as well as a lack of capacities and resources to attain it (see Chapter 7 for more details).

Box 5.2. Low-skilled workers should remain a policy priority for training

Even if AI enables the automation of some high-level skills, low-skilled workers continue to be disproportionately employed in occupations most at risk of automation, because older automation technologies remain and are in many cases improved by AI, and because these occupations usually do not require skills and abilities that cannot be replicated by automation technologies (see Chapter 3). However, and despite efforts made by governments over the past decade, in several countries the low-skilled still have participation rates in education and training activities that are lower than medium and high-skilled individuals (Figure 5.1). The participation gap ranges between 2 percentage points (Hungary) and 19 percentage points (Switzerland) and is equal to 8 percentage points on average in the European Union.


Figure 5.1. The low-skilled are still participating less in education and training activities

Percentage of individuals participating in education and training activities in 2021 over a four-week period, by education level



Note: The figure reports share of individuals that participated in formal and non-formal education or training activities during the four weeks preceding the survey, by education level. Sample is restricted to employed individuals aged 25-54. High-skilled individuals are those with tertiary education, medium-skilled individuals have achieved upper secondary or post-secondary non-tertiary education, and low-skilled have attained less than primary, primary, or lower secondary education. EU27 is the weighted average of countries in the European Union. Several countries are excluded from the graph because of low data reliability.

Source: EU-LFS.

StatLink  <https://stat.link/0knspv>

Broadening participation in training is necessary to help workers employed in occupations at high risk of automation to transition to jobs that are less at risk. OECD (2019^[29]) shows that low participation in training and education activities by the low-skilled is due to a myriad of factors, including lack of time, financial constraints, lack of prerequisites, lower willingness to train, and lower propensity of employers to train these workers. Addressing these challenges remains a priority. Policy options include raising awareness, notably through personalised guidance, creating relevant and flexible learning opportunities, including thanks to modular programs, and providing financial support to cover the different costs of training (OECD, 2019^[30]).

5.3. Firms implementing AI say they provide training to their employees, but more training may be necessary

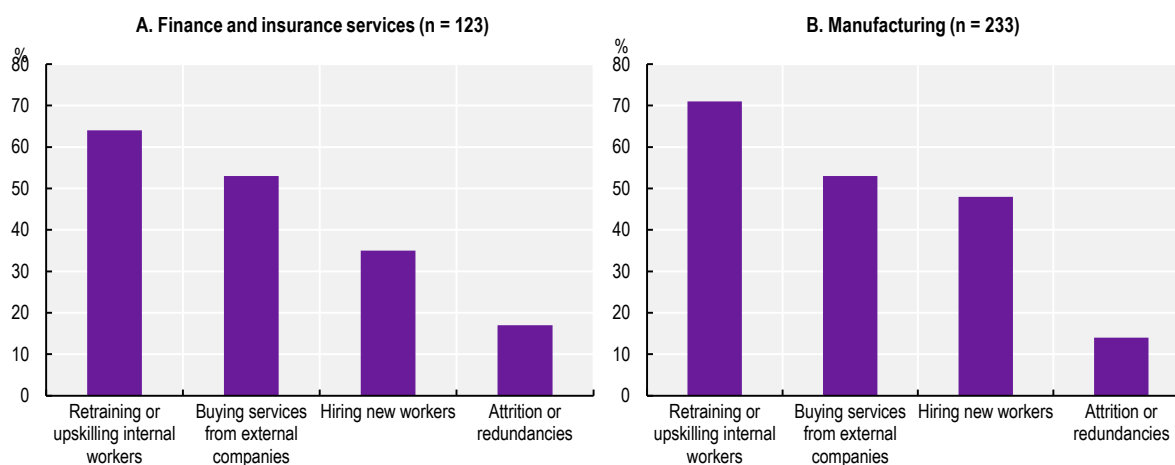
5.3.1. Firms provide training following AI adoption

A large share of firms adopting AI respond to changing skill needs brought about by AI adoption by retraining or upskilling workers. According to the OECD AI surveys, this is the case of 64% of firms in the finance sector and 71% in manufacturing that have adopted AI (Figure 5.2) (Lane, Williams and Broecke, 2023^[2]). Training is the most common response to changing skills needs due to AI by firms in the seven countries included in the survey (Austria, Canada, France, Germany, Ireland, the United Kingdom and the United States). An alternative strategy to deal with changes in skill needs is to buy services from external companies, which is chosen by 53% of firms interviewed.⁴

Workers also report firm-provided training following the adoption of AI. In the OECD AI surveys by Lane, Williams and Broecke (2023^[2]), more than half of workers who use AI said that their company had provided or funded training so that they could work with AI, even though the study does not investigate the type of training nor its content. Most workers trust their employers to make the right decisions regarding training for AI, at least to some degree: slightly more than a quarter of workers had complete trust in their companies to provide training for workers to work with AI and just under half trusted their companies somewhat in this area. Workers who participated in training were significantly more likely to report positive outcomes of AI on their working conditions and wages but were also more likely to report AI-related worries regarding job stability. It might be that workers participating in training learn about AI's potential to automate work and become concerned about the stability of their job, but it might also be the case that workers who worry about losing their jobs because of AI are more likely to take part in training. The study does not allow to distinguish between these two explanations.


Figure 5.2. Employers are most likely to address skill needs by retraining and upskilling existing workers

Percentage of employers that reported that AI has changed skill needs in their company



Note: Employers that reported that artificial intelligence had changed skill needs in their company were asked: “Has your company addressed these changing skill needs in any of the following ways? By retraining or upskilling internal workers?/By hiring new workers?/By buying services from external companies?/By attrition or redundancies?”.

Source: OECD employer survey on the impact of AI on the workplace (2022).

StatLink  <https://stat.link/8v95c3>

When the AI technology is simple to use, training is brief and takes the form of webinars, presentations, workshops, etc. to introduce employees to the AI technologies adopted and to provide an overview of their basic functionalities. Only in a limited number of cases do large firms report more ambitious training programmes to help employees transition to other occupations. Finally, some large companies also try to support AI talent in-house to have employees with specialised AI skills able to develop and maintain AI systems internally, as opposed to seeking those employees on the external labour market or outsourcing these activities. However, several firms call for more government funding for AI education and training and recognise that these specialised AI skills should also be developed in initial education (Milanez, 2023^[4]).

5.3.2. Yet, more training would help address existing barriers to AI adoption

A lack of skills is a major barrier to AI adoption

AI cost and a lack of skills are the two most common barriers to adoption of AI reported by firms in surveys. More specifically, in the recent OECD AI surveys of employers and workers, around 40% of employers in finance and manufacturing declare that the lack of relevant skills is a barrier. This is particularly the case in the United States, Germany and Austria, as almost half of employers in the manufacturing and finance sectors of these countries report the lack of relevant skills as an obstacle (Lane, Williams and Broecke, 2023^[2]). These two obstacles were also reported by firms of all sizes and sectors in a Europe-wide survey of enterprises on the use of technologies based on AI led by the European Commission. The skills barrier comes from a lack of relevant skills amongst existing staff, as well as from difficulties hiring new staff with the necessary skills (European Commission, 2020^[36]).

A recent review of the goals and practices of institutions supporting AI diffusion in firms⁵ by the OECD (Barreneche, forthcoming^[37]) confirms these results. Interviewed institutions say the lack of AI skills is an important constraint, not only among employees but also among managers. The authors note that implementing AI in a firm necessitates staff with extensive experience in several AI fields (see Section 5.2.2 for a discussion of the reasons why managers' and leaders' skills matter too), but that AI talent is highly concentrated in some localised hubs. Interviewed institutions also report that uncertainties about the return on investment and poor understanding by managers of how AI could be used to address workplace challenges constitute significant barriers to adoption. Managers also tend to underestimate the changes in business culture and practices needed to effectively implement AI solutions.

Data and cultural acceptance constitute other important adoption barriers that can be addressed through training

Obstacles to AI adoption related to data, such as a lack of internal data or data complexity, are also reported by firms, although less frequently than other barriers (European Commission, 2020^[36]; IBM, 2022^[38]). In most cases, the challenge to having good quality data is closely related to the skills issue. Businesses often possess rich data but that they lack the capacity to process, clean, analyse, and ensure the quality of the vast amount of information included therein. In particular, small and medium-sized firms appear to be lagging behind in that respect (OECD, 2021^[39]).

While acknowledged by only a relatively small share of firms in surveys, challenges related to data availability and management are reported by several institutions supporting AI diffusion. These institutions underscore that most businesses could in theory gather very rich datasets, but they generally lack well-functioning data collection mechanisms including data quality assurance processes, standardised and efficient data collection methods, privacy, data security and ethical considerations, and on-going monitoring and evaluation protocols. When good data collection mechanisms are there, businesses sometimes face data management challenges, as several sources of information of different type, periodicity and format need to be integrated. and challenges related to the need to ensure that AI respects

and promotes workers' right to privacy and complies with legislation and regulatory standards, including data protection requirements (Barreneche, forthcoming^[37]).

Training can help ensure firms possess necessary skills to build, consolidate, and manage high-quality datasets, and know how to deal with issues of data security and privacy. Training is important not only to foster AI adoption but also for an ethical use of AI (see Chapter 6 for a discussion of policies to ensure trustworthy AI in the workplace). Furthermore, issues related to cultural acceptance of the new technologies by existing employees are also often mentioned by companies (Lassébie and Quintini, 2022^[3]) and existing evidence shows that training can help improve employees' attitudes towards AI (Lane, Williams and Broecke, 2023^[2]). Yet, the challenges related to data quality and cultural acceptance are broader than just a skills issue and cannot be solved entirely thanks to training.

5.4. Existing public policies supporting training for AI are not sufficient

5.4.1. Public policies could encourage the provision of more training for AI

The role of governments for the development of skills related to AI is primarily justified by the fact that an important share of training activities for the development and adoption of AI should take place in initial education. Basic AI literacy should be taught and promoted in secondary education, while specialised AI skills necessitate vocational and higher education. Other cognitive skills needed to both develop and work with AI should also be developed during initial education.

Regarding continuous education, the justification of public intervention and public funding of training programmes is less clear. The case for public funding of training programmes targeting low-skilled workers who face a high risk of automation (Box 5.2) is justified on the grounds of equity reasons, but the need for policy intervention is, *prima facie*, less clear for high-skilled employees. However, as discussed in Section 5.2.2, the fact that skills remain a major barrier to AI adoption suggests that the amount of training that is provided in general is not sufficient.

Public intervention would be warranted if market failures or barriers to training provision and participation prevent firms from providing the optimal amount of training. Whether this is the case still needs to be proved. However, what is clear is that among the barriers to training that have been described in general (OECD, 2021^[40]), one type in particular, informational barriers, is likely to be particularly important in the case of training for AI. In the OECD AI surveys of employers and workers (Lane, Williams and Broecke, 2023^[2]), the vast majority of workers surveyed had heard of AI (95% in finance and 93% in manufacturing), but most said that it was difficult to explain what the term "artificial intelligence" means (52% in finance and 60% in manufacturing). Workers whose firms had adopted AI were more likely to be able to explain what it is. Information on relevant AI-related training programmes is also limited. Yet, individuals seem interested in learning more about AI (Lane, Williams and Broecke, 2023^[2]). This suggests that there may exist an important informational gap around training for AI. Addressing this type of barriers to training provision would not call for public funding of training programmes but would rather take the form of awareness campaigns.

Another reason why the amount of AI training provided by firms might not be sufficient, and hence public intervention may be justified, is that the benefits of training for AI may accrue not only to the firm but also to the society more generally. When firms do not reap all the benefits of the training that they may provide, there is a clear risk of under-provision. This could be the case for training programs designed for managers and business leaders so that they understand the implications of increased AI adoption in their industry and are able to ensure that AI technologies are implemented in a trustworthy way.

Finally, public policy could promote diversity in the AI workforce. In particular, career guidance for AI could encourage more individuals to develop skills for AI, including specialised AI skills, AI literacy, and other

skills needed to use AI. Actually, the aim would be twofold: addressing the lack of diversity in the AI workforce, and more particularly the under-representation of women (see Box 5.1 above for figures on the share of women in the AI workforce), and tackling the issue of skills shortages that prevent AI adoption.

5.4.2. Few policies propose sufficient actions to develop skills for AI

The vast majority of OECD countries have issued national AI strategies, even though they are at different stages of implementation (Galindo, Perset and Sheeka, 2021^[41]).⁶ Most national AI strategies recognise the importance of skills, but not all propose concrete actions to develop them. Yet, interesting examples exist and are discussed in this section.

First, the increased use of AI in professional environments requires the anticipation of future skill needs and several national strategies explicitly mention skills anticipation and assessment for AI. For instance, in the United Kingdom, the national AI strategy mentions research activities to understand skills that are needed to enable employees use AI in a business setting and to identify how national skills provision can meet those needs.

Many national strategies acknowledge that advances in AI will make several skills redundant and emphasise retraining for those likely displaced by AI. For example, in Lithuania, the national AI strategy (Lithuanian Artificial Intelligence Strategy: A Vision of the Future)⁷ mentions the creation of vocational training programs in AI and other emerging technologies, specifically targeted to workers in occupations at higher risk of automation. The aim of the programs will be to teach individuals how to work with AI in their current job, rather than re-training for a different occupation.

In several cases, national AI strategies discuss training policies to develop specific skills. This is often addressed within the wider framework of the digital agenda and thus focuses on digital skills, overlooking basic and specialised AI skills, and cognitive and transversal skills that are needed to develop AI systems or use AI applications (see Section 5.1). Spain is an interesting exception: within the framework of the third investment of Component 19 of the Recovery, Transformation and Resilience Plan of Spain, the State Public Employment Service finances, through a public call for grants, state-wide training for the acquisition and improvement of professional skills related to technological change and digital transformation. Basic, medium and advanced training programmes have been developed. Medium and advanced training courses include extensive modules on AI, such as “Introduction to artificial intelligence and algorithms”, “Artificial intelligence applied to the company”, and “Machine Learning and artificial intelligence”.

The issue of basic AI skills is gaining more and more attention and several initiatives aiming at developing them are emerging. For example, in Finland, the University of Helsinki together with MinnaLearn developed a programme called “Elements of AI”, offering free online courses to strengthen AI literacy for non-experts, to increase social acceptance of AI and individuals’ motivation to learn about it. The initial objective of training 1% of the Finnish population has been largely exceeded and the programme has subsequently expanded to other European countries. For instance, the national AI strategy in Germany (Artificial Intelligence Strategy of the German Federal Government – 2020 update)⁸ acknowledges that every individual should be well informed about the importance of AI and the opportunities and challenges it presents and explicitly refers to the course “Elements of AI”.

Employers are important stakeholders to foster the development of workplace-focused AI upskilling and reskilling strategies and for the development of relevant training programmes to foster AI adoption. Yet not all national strategies mention the role of employers in providing training for AI. Norway is an exception, as it relies on further education programmes in AI and data analysis launched by several large enterprises. One initiative discussed in the Norwegian strategy (Norway National Strategy for Artificial Intelligence)⁹ is a training course in data science proposed by a bank to its employees. The Norwegian Government also co-operates with employee and employer organisations to develop and provide industry-specific training programmes for the municipal care and industry and construction sectors. Another example of employers’

involvement is the Italian Tax Credit on Training 4.0. This programme implemented in 2021 and 2022 aimed to support employees' training for the consolidation or acquisition of skills in technologies relating to the technological and digital transformation of businesses.¹⁰ More specifically, eligible training topics included, for instance, big data and data analysis, virtual reality (VR) and augmented reality (AR), advanced and collaborative robotics, human-machine interfaces, and Internet of things and machines. The tax credit was available to all enterprises, regardless of their sector or size, although the amount of subsidy depended on company size.¹¹ The tax credit rate was higher for disadvantaged employees.¹² Eligible expenses comprised costs of employees participating in training (employees' salary), consulting costs relating to the training project, if any, training fee when provided by external training providers, and operating costs for the training programme (travel costs, materials, and equipment).

Institutions supporting AI diffusion in firms¹³ also develop on-the-job training programmes to facilitate AI adoption (Barreneche, forthcoming^[37]). For instance, the Vector Institute, one of the three national Artificial Intelligence Institutes based in Canada, offers training courses to raise management and technical staff skills and improve awareness of AI applications. Individuals are invited to analyse real-world AI use cases and identify opportunities and challenges underpinning successful adoption. It is part of the broader national strategy to support AI adoption in Canada.¹⁴ In the United States, the Digital Manufacturing and Cybersecurity Institute (MxD) offers another interesting example as it has developed an online platform where workers can access free and paid courses on frontier technologies developed by leading companies, and where companies can find information to support their AI skills management, including curricula and career pathways information.

An integrated approach to the development of skills for AI, including all levels of education, the various stakeholders and the different types of skills needed to develop and work with AI, is crucial. On-the-job training programmes and informal learning are necessary for employees to contextualise coursework with the specific challenges and requirements of work and for firms to address current skill shortages in a timely manner, but they are not a substitute for initial education. Several institutions interviewed in Barreneche (forthcoming^[37]) insisted on the fact that specialised AI education must be addressed in priority in tertiary education and that countries need to step up efforts in embedding AI across tertiary education programmes.

In general, while several existing programmes focus on digital or AI skills, few recognise the importance of complementary skills such as transversal competences, and a minority develop an integrated approach to AI skills development. The Irish national AI strategy (AI – Here for Good: A National Artificial Intelligence Strategy for Ireland)¹⁵ is one exception, as it mentions the provision of digital, technical, and complementary skills. The strategic actions listed in the strategy consider all relevant levels and types of education, including Higher Education Institutions and employers. Digital skills and technologies are developed in school, as outlined in the “Digital Strategy for Schools 2015-20 Enhancing Teaching, Learning and Assessment”. The “STEM Education Policy Statement 2017-26” also aims to improve STEM education for all learners at primary and post-primary levels. Key complementary skills such as communication, creativity and working with others are also embedded throughout primary and post primary curricula. The AI Strategic Vision for Luxembourg (Artificial Intelligence: a strategic vision for Luxembourg)¹⁶ also aims to address several dimensions of AI education and training. Key actions include the development of digital training modules for the general public to providing them with an introduction to AI, its opportunities and risks, the integration of AI courses into other disciplines, such as law, business, human sciences, environment and health, and into the curricula of secondary and postsecondary education, including vocational training.

Most national strategies also highlight the importance of AI skills in government, not only to exploit technological advances in AI to improve the quality and efficiency of public administrations, but also to be able to understand whether and what type of public intervention is needed (see also Chapter 6). In Canada, the School for Public Service's Digital Academy provides support to public servants to improve their digital skills, including in AI and Machine Learning. The Government of Singapore offers AI workshops to public

officers to increase their digital literacy and provide them foundational knowledge about the potential of AI for public organisations (Berryhill et al., 2019^[42]). More recently, in France, the Council of State issued an official statement advocating for the use of AI for better public services. The statement acknowledges the importance of human and technical resources to implement AI in the public sector and declares the training of public managers a priority, alongside the recruitment of data experts (Conseil d'État, 2022^[43]). In the United States, the AI Training Act¹⁷ is a legislation that aims to create an artificial intelligence training programme for the federal workforce to better understand the technology, know the potential benefits and risks of its use for the government, and be able to ensure that it is used in the federal administration in an ethical way.

Finally, training for AI for teachers and educators is another area in which governments should invest. An example of such initiative can be found in Spain, where the School of Computational Thinking and Artificial Intelligence (EPCIA) has been set up by the Spanish Ministry of Education and Vocational Training in collaboration with the regional educational administrations. The objective of the project is to explore the possibility to introduce artificial intelligence for learning in the classroom. The school offers open educational resources, teacher training programmes, and a monitoring tool tracking the creation of didactic proposals and their implementation in schools. The school, together with a university, also conducts research focused on student learning and teaching practice for AI.

5.5. AI has the potential to improve adult learning systems but risks exist

While AI is generating new training needs, it may also provide an opportunity to improve adult learning systems in general. It can be used to better plan and deliver training, and to increase training participation and inclusiveness. While not widespread, several examples exist, and some are presented below. However, for AI to improve adult learning systems more generally, several risks exist and a number of challenges need to be addressed.¹⁸

5.5.1. AI could be used to help plan training

AI can help assess skill needs, build individuals' skill profiles, identify appropriate training courses, find viable job transitions and select appropriate training to facilitate these transitions. Regarding skill needs assessments, AI and machine learning algorithms can be used to process and analyse the text of online job ads to understand skills demanded by employers. This information is more granular and more timely than traditional sources of information such as annual surveys or expert consultations, but might be less representative, less stable over time, and less accurate, notably regarding skills required to perform a job. These two types of data can thus complement each other. In particular, the higher level of detail and timeliness are necessary to develop a training offer that is well-aligned with labour market needs. For instance, the European Centre for the Development of Vocational Training (Cedefop) processes and analyses information gathered from more than 100 million online job advertisements collected in 28 European countries to build the Skills Online Vacancy Analysis Tool for Europe (Skills OVATE). The skill information is extracted from job advertisements using ESCO, the European classification of skills, competences, qualification and occupations, and machine learning techniques.

AI may also be used to build individual skill profiles – i.e. the characterisation of a person's skills based on his/her level and field of formal education, previous work experience and direct and indirect skill assessments – to be compared to the skills required in available jobs. AI can help automatically categorise vast amounts of textual data, such as the descriptions of education programmes and occupations, into pre-defined skill categories. This can facilitate the translation of an individual's information on education and professional background into a profile of knowledge, skills and abilities. It can also help categorise manually imputed text describing tasks carried out in everyday life or in one's job and feed the information into the individual's skills profile. An interesting example of the use of AI for individual skill profiling is

provided by VDAB, the Flemish public employment service, that has developed a tool called Competence-Seeker. The tool helps jobseekers enrich the CV they upload online with additional skills they are likely to possess given their professional experience but forgot to mention, by automatically screening jobseekers' CVs. It uses the VDAB taxonomy of occupations and skills (Competent) to find skills required in occupations in which the individual has worked but that are missing in their online CV (Broecke, 2023^[44]). However, building these profiles requires stocking and sharing information on individuals, in a way that might not always be compatible with existing data protection and privacy regulations (on these issues, see Chapter 6).

AI can help identify appropriate training courses for individuals willing to undertake training. To do so, one pre-requisite is to understand what skills are developed in each training programme. While formal education follows structured and standardised curricula, this is not the case of non-formal training. The start-up Boosters applies natural language processing algorithms to automatically transform the descriptions of education and training programmes into pre-defined skill categories, thereby creating a mapping between training and skills that can be used by individuals who want to acquire specific skills to identify relevant training.

Furthermore, AI can be used to identify viable job transitions as well as training needs to permit these transitions. Frank et al. (2019^[45]) discuss how non-traditional sources of data such as online resumes and job postings could be used to have a better sense of labour market dynamics and to improve the understanding of the relationship between individuals' education and skills and possible careers. They talk about "viable job transitions" when workers of one job can meet the skill requirements of another job. This supposes some sort of skill similarity between jobs. Since this publication in 2019, real-world examples have been developed and tested in the field. For instance, the public employment service in Flanders, the VDAB, uses the application Jobbereik to help jobseekers consider transitions to occupations that require similar skill profiles. VDAB is also developing a new functionality that will enable Jobbereik to suggest a list of possible education and training programmes for each proposed career move (Broecke, 2023^[44]).

More generally, AI can be used in career guidance activities. Using focus groups, scenario work and practical trials, Westman et al. (2021^[46]) discuss requirements and possibilities for using artificial intelligence in career guidance from the viewpoints of students, guidance staff and institutions. They show that students were quite positive about AI-powered career guidance services, especially about the possibility of receiving personalised advice and their online accessibility, while career guidance staff expressed several concerns, notably related to individuals' agency and autonomy, data privacy, as well as ethical issues. Staff mentioned in particular the tendency of AI to scale up human biases as concerning. This particular issue is discussed in more details in Section 5.5.3 and in Chapter 6.

5.5.2. AI could be used to deliver and personalise training

AI can also be used by teachers and trainers to develop materials for their classes. For example, tools such as ChatGPT can help to create courses outlines and curricula, develop lesson plans with a list of objectives, activities, and assessments, create exercises, quizzes, discussion questions, and multiple choice exams, and write detailed answers to problems. It can also be used as a virtual tutor, especially for language training, as the chatbot can engage in conversations with learners, allow them to practice, provide feedback and offer suggestions for improvement. It is a useful tool for adapting teaching style (i.e. transforming a traditional course into a problem-based class or a flipped classroom) or to simplify topics for learners of any level. However, it is important to note that models such as ChatGPT are only probabilistic models with no explicit educational goals, have not been optimised for student learning, and do not provide the social experience necessary for efficient learning.

Several AI-powered technologies such as Augmented Reality (AR), Virtual Reality (VR), and technologies for speech recognition, could play a role in the provision of vocational training online or virtually. Augmented and Virtual Reality technologies expand the availability of practice-oriented training, allowing students to

complete exercises at distance, more often or more safely. For instance, virtual reality surgery training allows students and healthcare professionals to gain exposure to a surgical environment and procedures through life-like simulations. Users gain unlimited access to simulations anywhere, anytime, all while diminishing risks for patients. Yet, potential downsides and risks related to the use of AR, VR and other AI-powered technologies in the delivery of training exist, including the loss of the social aspect of learning, which is important from an information retention perspective.

AI can also be used to personalise training content to individuals' needs, selecting relevant modules and hence shortening training actions when possible. Traditional training usually requires all students to go through the same learning materials, irrespective of their abilities, preferences or learning styles. When training content is driven by AI, it can be adapted to the individual starting level and progress achieved during the course. By linking content to assessments or reading time, for instance, AI can suggest skipping certain content, and may provide additional learning materials when the student appears to be struggling.¹⁹ Training personalisation is done, for instance, by Duolingo, a language-learning platform.

The use of AI in training will lead teachers and trainers use and interact with AI technologies on a regular basis, and hence will bring about changes in the skills that are needed in teaching professions. In particular, as detailed in Section 5.1.2, using and interacting with AI will require that employees possess digital skills, at least at a basic level. Some elementary knowledge of AI would also be necessary to enable teachers and trainers to understand well the benefits and risks of using AI in training. Furthermore, and as discussed in Chapter 4, the use of AI in training could also decrease teachers' autonomy and agency and increase work intensity, ultimately affecting overall job quality. These represent non-negligible risks.

Another risk is that the use of AI-powered educational tools may modify the skills that learners acquire. In his essay on the potential harms of AI, Acemoglu (2021^[47]) argues that if students stopped learning arithmetic because calculators are better at it, their ability to engage in other type of mathematical and abstract reasoning may suffer. A similar argument may be made for Large Language models such as ChatGPT: if students use it to write essays and complete exams, this may lead to a decrease in their written expression skills and knowledge. Actually, this appears to be a concern for several schools and universities, and they are taking actions to make sure that students do not use this tool in exams. Some institutions are reconsidering the exam process, moving back to in-person written exams that allow a close monitoring of the use of technologies. Others are introducing tools to assess whether written tests have been answered by an algorithm. Other institutions, on the contrary, think about how to integrate the tool in the learning system, including in exams, in the view that students need to learn how to work with the technology.

5.5.3. AI may impact training participation and inclusiveness

AI technologies may increase training participation by: (i) decreasing the length of training (thanks to training modularity); (ii) alleviating time constraints (thanks to distance training and shorter courses); and (iii) increasing motivation (thanks to a better matching between individuals and training courses and with the use of interactive tools, such as Augmented or Virtual Reality). AI's potential to reduce training time may be particularly powerful as time constraints have been shown to constitute a major obstacle to training participation (OECD, 2021^[40]). AI could also assist policy makers or companies in identifying individuals most in need of training or those who would benefit most. For instance, an AI-based application is used by the VDAB, the Flemish public employment service, to target the most vulnerable jobseekers, i.e. those who are less likely to find a new job (Broecke, 2023^[44]). The use of AI in training may also facilitate training participation of disabled individuals. Text-to-speech and speech-to-text technologies may help hearing or visually impaired individuals access training. Technologies already exist to support the educational needs of blind and visually impaired students in initial education, for instance to facilitate notetaking (OECD, 2021^[48]), and there are no reasons to think that those technologies could not be implemented in training courses for adults. Non-native speakers could also benefit from AI-assisted translation technologies.

However, there are also several reasons why the use of AI in training may decrease, rather than increase, training participation and inclusiveness. First, using AI in training is costly, in particular to develop the necessary data and infrastructure and may increase overall training costs. The fixed costs related to AI adoption may exacerbate inequalities between small and large actors, e.g. between small and large firms for training provision, or between individuals who can afford training and those who cannot. Furthermore, the participation in training that is powered by AI technologies requires some degree of digital skills, which may limit participation by low skilled individuals. If used to inform participants' selection, AI may decrease the inclusiveness of learning systems rather than increase it as it may scale up human biases when appropriate safeguards are not put into place (a similar issue regarding labour market inclusiveness and how biased AI systems may decrease it is discussed in Chapter 4, Section 4.4, and Chapter 6 discusses legislation to address bias of AI systems). In this context, close monitoring of how widespread the use of AI for training is, and of its impact on inclusiveness, is necessary and will be key in deciding whether and what type of public intervention is warranted.

5.6. Despite a growing body of research on AI and its impact on skills and learning systems, important knowledge gaps persist

This chapter shows that the impact of AI on skill needs is not trivial. AI can now replicate more and more skills that have long been unique to humans, in particular cognitive skills. It is also increasing demand for other skills such as AI knowledge and digital skills (at a basic level to simply use AI applications and at a more sophisticated level to develop AI systems), as well as complementary skills such as social and management skills. The chapter discusses the new training opportunities that should be developed to address these changes in skill needs. It argues that training actions should be targeted at vulnerable groups (the low skilled and older workers) who risk being left behind if they do not have the necessary skills to adapt to changes in the workplace brought about by AI implementation, but also at higher-skilled workers, managers and leaders to facilitate the development and adoption of trustworthy AI and to allow them to work effectively with the technologies. While the evidence base on these issues is solid, other questions discussed in this chapter deserve more research.

First, more data on AI and training are needed. Cross-country data on the extent of training for AI is lacking. Firms implementing AI say they provide training to their employees, yet a shortage of appropriate skills remains a major barrier to AI adoption. This suggests that the current amount of training for AI is not sufficient, but there are not enough data to assess the veracity of this claim. There are still unanswered questions about the type of training for AI that exists, the amount of training that is provided (both in terms of the number of individuals participating and the length of the training), the groups of individuals that are covered, and the content, form and level of training that is offered. Further data and research on available training programs will be key to provide actionable policy recommendations.

There is also very little evidence on the effectiveness of policies for AI skills development. This chapter argues that governments have an important role to play in encouraging employers to provide more training for AI, embedding AI courses in all levels of education, and addressing the lack of diversity in the AI workforce. However, AI policies and strategies do not always include comprehensive and concrete actions to develop skills for AI. This is an area where more should be done, but information on successful policies does not yet exist, as the impact of most AI strategies has not been properly evaluated. Monitoring and evaluating initiatives will be key to better understand the benefits and costs of different policy interventions and permit an optimal allocation of public resources.

It is also important to collect data on the use of AI for training. This chapter presents examples of how AI can be used to improve training systems, but these technologies are still in their infancy and their use in training appears to be low, although there is a lack of robust quantitative evidence on this. Going forward, it would be interesting to monitor more consistently the use of AI in training, as it will be key in understanding the risks and benefits.

Finally, several related issues deserve more attention. The role of social partners in assessing and addressing changes in skill needs due to AI is touched upon in Section 5.2.2 but this topic is covered more extensively in Chapter 7 that presents examples of initiatives aimed at upskilling and reskilling workers so that they can benefit from AI adoption at their workplace. Another topic of interest is the adaptation of active labour market policies to make sure job-seekers possess the right skills to develop AI and work with it. Ultimately, the aim is to ensure that all workers are equipped with the necessary skills to thrive in an AI-powered economy.

References

- Acemoglu, D. (2021), *Harms of AI*, National Bureau of Economic Research, Cambridge, MA, [47]
<https://doi.org/10.3386/w29247>.
- Acemoglu, D. et al. (2022), “Artificial Intelligence and Jobs: Evidence from Online Vacancies”, [16]
Journal of Labor Economics, Vol. 40/S1, pp. S293-S340, <https://doi.org/10.1086/718327>.
- Alekseeva, L. et al. (2021), “The demand for AI skills in the labor market”, *Labour Economics*, [12]
 Vol. 71, p. 102002, <https://doi.org/10.1016/j.labeco.2021.102002>.
- Barreneche, A. (forthcoming), “The goals and practices of institutions supporting AI diffusion in [37]
 firms”, OECD Publishing, Paris.
- Berryhill, J. et al. (2019), “Hello, World: Artificial intelligence and its use in the public sector”, [42]
OECD Working Papers on Public Governance, No. 36, OECD Publishing, Paris,
<https://doi.org/10.1787/726fd39d-en>.
- Bessen, J. et al. (2018), “The Business of AI Startups”, *Law and Economics Research Paper*, [18]
 Boston University School of Law, https://scholarship.law.bu.edu/faculty_scholarship/537.
- Broecke, S. (2023), “Artificial intelligence and labour market matching”, *OECD Social*, [44]
Employment and Migration Working Papers, No. 284, OECD Publishing, Paris,
<https://doi.org/10.1787/2b440821-en>.
- BusinessEurope (2019), *Artificial Intelligence recommendations*, BusinessEurope strategy paper, [31]
<https://www.bu-business.eu/publications/artificial-intelligence-recommendations>.
- Conseil d'État (2022), *S'engager dans l'intelligence artificielle pour un meilleur service public*, [43]
<https://www.conseil-etat.fr/actualites/s-engager-dans-l-intelligence-artificielle-pour-un-meilleur-service-public>.
- Daugherty, P., J. Wilson and P. Michelman (2019), *Revisiting the Jobs That Artificial Intelligence [19]
 Will Create*, MIT Sloan Management Review (MIT SMR),
<https://sloanreview.mit.edu/article/revisiting-the-jobs-artificial-intelligence-will-create/>.
- Elliott, S. (2017), *Computers and the Future of Skill Demand*, Educational Research and [8]
 Innovation, OECD Publishing, Paris, <https://doi.org/10.1787/9789264284395-en>.
- ETUC (2020), *Resolution on the European strategies on artificial intelligence and data*, European [32]
 Trade Union Council Executive Committee, <https://www.etuc.org/en/document/resolution-european-strategies-artificial-intelligence-and-data>.
- ETUI (2021), *Algorithmic management and collective bargaining*, European Trade Union Institute [33]
 (ETUI), <https://www.etui.org/publications/algorithmic-management-and-collective-bargaining>.

- European Commission (2020), *European enterprise survey on the use of technologies based on artificial intelligence: Final report*, Publications Office, <https://data.europa.eu/doi/10.2759/759368>. [36]
- Fialho, P., G. Quintini and M. Vandeweyer (2019), "Returns to different forms of job related training: Factoring in informal learning", *OECD Social, Employment and Migration Working Papers*, No. 231, OECD Publishing, Paris, <https://doi.org/10.1787/b21807e9-en>. [49]
- Frank, M. et al. (2019), "Toward understanding the impact of artificial intelligence on labor", *PNAS*, Vol. 116/14, pp. 6531-6539, <https://doi.org/10.1073/pnas.1900949116>. [45]
- Galindo, L., K. Perset and F. Sheeka (2021), "An overview of national AI strategies and policies", *OECD Going Digital Toolkit Notes*, No. 14, OECD Publishing, Paris, <https://doi.org/10.1787/c05140d9-en>. [41]
- Green, A. and L. Lamby (2023), "The supply, demand and characteristics of the AI workforce across OECD countries", *OECD Social, Employment and Migration Working Papers*, No. 287, OECD Publishing, Paris, <https://doi.org/10.1787/bb17314a-en>. [1]
- Guo, B. et al. (2023), "How Close is ChatGPT to Human Experts? Comparison Corpus, Evaluation, and Detection", <https://doi.org/10.48550/arXiv.2301.07597>. [10]
- IBM (2022), "IBM Global AI Adoption Index 2022", <https://www.ibm.com/downloads/cas/GVAGA3JP>. [38]
- ILO/IOE (2019), *Changing Business and Opportunities for Employer and Business Organizations*, International Labour Organization and International Organisation of Employers, https://www.ilo.org/actemp/areas-of-work/WCMS_679582/lang--en/index.htm. [34]
- Lane, M., M. Williams and S. Broecke (2023), "The impact of AI on the workplace: Main findings from the OECD AI surveys of employers and workers", *OECD Social, Employment and Migration Working Papers*, No. 288, OECD Publishing, Paris, <https://doi.org/10.1787/ea0a0fe1-en>. [2]
- Lassébie, J. and G. Quintini (2022), "What skills and abilities can automation technologies replicate and what does it mean for workers?: New evidence", *OECD Social, Employment and Migration Working Papers*, No. 282, OECD Publishing, Paris, <https://doi.org/10.1787/646aad77-en>. [3]
- Laupichler, M. et al. (2022), "Artificial intelligence literacy in higher and adult education: A scoping literature review", *Computers and Education: Artificial Intelligence*, Vol. 3, p. 100101, <https://doi.org/10.1016/j.caeai.2022.100101>. [22]
- Littman, M. et al. (2021), *Gathering Strength, Gathering Storms: The One Hundred Year Study on Artificial Intelligence (AI100) 2021 Study Panel Report*, <https://ai100.stanford.edu/gathering-strength-gathering-storms-one-hundred-year-study-artificial-intelligence-ai100-2021-study>. [6]
- Long, D. and B. Magerko (2020), "What is AI Literacy? Competencies and Design Considerations", *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, <https://doi.org/10.1145/3313831.3376727>. [20]
- Luca, M., J. Kleinberg and S. Mullainathan (2018), "Algorithms Need Managers, Too", *Harvard Business Review*, <https://hbr.org/2016/01/algorithms-need-managers-too>. [27]

- Manca, F. (2023), “Six questions about the demand for artificial intelligence skills in labour markets”, *OECD Social, Employment and Migration Working Papers*, No. 286, OECD Publishing, Paris, <https://doi.org/10.1787/ac1bebf0-en>. [13]
- Mc Kinsey (2018), “Notes from the AI frontier: Insights from hundreds of use cases”. [25]
- Milanez, A. (2023), “The impact of AI on the workplace: Evidence from OECD case studies of AI implementation”, *OECD Social, Employment and Migration Working Papers*, No. 289, OECD Publishing, Paris, <https://doi.org/10.1787/2247ce58-en>. [4]
- Ng, D. et al. (2021), “AI Literacy: Definition, Teaching, Evaluation and Ethical Issues”, *Proceedings of the Association for Information Science and Technology*, Vol. 58/1, pp. 504-509, <https://doi.org/10.1002/pra2.487>. [21]
- Nolan, A. (2021), “Making life richer, easier and healthier: Robots, their future and the roles for public policy”, *OECD Science, Technology and Industry Policy Papers*, No. 117, OECD Publishing, Paris, <https://doi.org/10.1787/5ea15d01-en>. [7]
- OECD (2023), *Is Education Losing the Race with Technology?: AI’s Progress in Maths and Reading*, Educational Research and Innovation, OECD Publishing, Paris, <https://doi.org/10.1787/73105f99-en>. [9]
- OECD (2021), *OECD Digital Education Outlook 2021: Pushing the Frontiers with Artificial Intelligence, Blockchain and Robots*, OECD Publishing, Paris, <https://doi.org/10.1787/589b283f-en>. [48]
- OECD (2021), *The Digital Transformation of SMEs*, OECD Studies on SMEs and Entrepreneurship, OECD Publishing, Paris, <https://doi.org/10.1787/bdb9256a-en>. [39]
- OECD (2021), *Training in Enterprises: New Evidence from 100 Case Studies*, Getting Skills Right, OECD Publishing, Paris, <https://doi.org/10.1787/7d63d210-en>. [40]
- OECD (2019), *Getting Skills Right: Engaging low-skilled adults in learning*, OECD, Paris, <http://www.oecd.org/employment/emp/engaging-low-skilled-adults-2019.pdf>. [30]
- OECD (2019), *Getting Skills Right: Future-Ready Adult Learning Systems*, Getting Skills Right, OECD Publishing, Paris, <https://doi.org/10.1787/9789264311756-en>. [24]
- OECD (2019), *OECD Employment Outlook 2019: The Future of Work*, OECD Publishing, Paris, <https://doi.org/10.1787/9ee00155-en>. [29]
- OECD (2019), *Skills Matter: Additional Results from the Survey of Adult Skills*, OECD Skills Studies, OECD Publishing, Paris, <https://doi.org/10.1787/1f029d8f-en>. [23]
- OECD (2017), “The next production revolution and institutions for technology diffusion”, in *The Next Production Revolution: Implications for Governments and Business*, OECD Publishing, Paris, <https://doi.org/10.1787/9789264271036-11-en>. [50]
- OECD.AI (2023), *Visualisations powered by JSI using data from www.adzuna.co.uk*, <http://www.oecd.ai> (accessed on 24th April 2023). [14]
- OpenAI (2023), *GPT-4 Technical Report*, <https://cdn.openai.com/papers/gpt-4.pdf>. [11]

- Peifer, Y., T. Jeske and S. Hille (2022), “Artificial Intelligence and its Impact on Leaders and Leadership”, *Procedia Computer Science*, Vol. 200, pp. 1024-1030, <https://doi.org/10.1016/j.procs.2022.01.301>. [26]
- Roffel, S. and I. Evans (2018), *The biggest misconceptions about AI: The experts’ view*, <https://www.elsevier.com/connect/the-biggest-misconceptions-about-ai-the-experts-view>. [28]
- Squicciarini, M. and H. Nachtigall (2021), “Demand for AI skills in jobs: Evidence from online job postings”, *OECD Science, Technology and Industry Working Papers*, No. 2021/03, OECD Publishing, Paris, <https://doi.org/10.1787/3ed32d94-en>. [15]
- UNI Europa ICTS (2019), *Position on Artificial Intelligence*, UNI Europa. [35]
- Verhagen, A. (2021), “Opportunities and drawbacks of using artificial intelligence for training”, *OECD Social, Employment and Migration Working Papers*, No. 266, OECD Publishing, Paris, <https://doi.org/10.1787/22729bd6-en>. [51]
- Westman, S. et al. (2021), “Artificial Intelligence for Career Guidance – Current Requirements and Prospects for the Future”, *IAFOR Journal of Education*, Vol. 9/4, pp. 43-62, <https://doi.org/10.22492/ije.9.4.03>. [46]
- Wilson, H., P. Daugherty and N. Morini-Bianzino (2017), *The Jobs That Artificial Intelligence Will Create*, <https://sloanreview.mit.edu/article/will-ai-create-as-many-jobs-as-it-eliminates/>. [17]
- Zhang, D. et al. (2022), *The AI Index 2022 Annual Report*, Stanford University, <https://hai.stanford.edu/ai-index-2022>. [5]

Notes

¹ Box 4.1 in Chapter 4 presents the methodology used in the OECD AI surveys (Lane, Williams and Broecke, 2023^[2]) and in the OECD AI case studies (Milanez, 2023^[4]) and discusses their representativeness.

² ChatGPT is a chatbot developed by OpenAI and launched in November 2022.

³ However, it is important to note that even if informal learning represents a significant share of learning activities (Fialho, Quintini and Vandeweyer, 2019^[49]), ensuring that all workers have access to informal learning opportunities is difficult. Indeed, the provision of informal learning opportunities in enterprises seems to be particularly dependent on work practices and the work environment. As fostering a learning culture at work is difficult, encouraging informal learning is more difficult than developing formal and non-formal training activities (OECD, 2021^[40]).

⁴ Attrition or redundancies are used by a minority of enterprises to deal with changes in skill needs brought about by AI (17% of firms in finance and 14% in manufacturing).

⁵ Institutions for technology diffusion are public or quasi-public bodies that facilitate the spread and use of knowledge and methods that assist firms in adopting particular technologies (OECD, 2017^[50]).

⁶ Some countries, such as Canada, Finland, Japan, France, Germany and the United Kingdom developed their national AI strategies in 2017-18. Other countries, such as Brazil, Poland and Spain, launched a national AI strategy more recently – see also Chapter 6.

⁷ Available at https://wp.oecd.ai/app/uploads/2021/12/Lithuania_Artificial_Intelligence_Strategy_2019.pdf.

⁸ Available at https://www.ki-strategie-deutschland.de/files/downloads/Fortschreibung_KI-Strategie_engl.pdf.

⁹ Available at https://wp.oecd.ai/app/uploads/2021/12/Norway_National_Strategy_for_Artificial_Intelligence_2020.pdf.

¹⁰ This programme has been terminated in 2022.

¹¹ More specifically, the tax credit was available to: small enterprises, for an amount equal to 50% of eligible expenses, up to a maximum of EUR 300 000; and medium-sized enterprises and large enterprises, for an amount respectively equal to 40% and 30% of eligible expenses, up to a maximum of EUR 250 000.

¹² The tax credit rate increased to 60% for all businesses when training participants fell within the category of “disadvantaged employees”, as defined by the decree issued by the Italian Minister of Labour and Social Policies dated 17 October 2017.

¹³ These institutions are public or quasi-public bodies that assist companies in adopting new technologies. They use a bundle of mechanisms to support AI diffusion, such as technology extension services, grants for business R&D, business advisory services, industrial extension programmes, technology-oriented business services, grants for applied public research, networking and collaborative platforms, on-the-job-training, and information services and open-source code. Barreneche (forthcoming^[37]) reviewed practices of several institutions supporting AI diffusion in firms in Canada, France, Germany, Italy, Japan, Singapore, the United Kingdom, and the United States and identified the different mechanisms that they use to assist firms in overcoming adoption challenges. In addition to on-the-job training programmes discussed in this paragraph, three other mechanisms used by institutions supporting AI diffusion in firms can indirectly provide support for the development of skills. First, technology extension services, whose aim are to convey results stemming from scientific and technological research to the private sector, often involve employees from the beneficiary firm, who learn informally by working closely with diffusion institutions. The purpose of this mechanism is precisely to raise firm capabilities to implement and use AI, including workers’ skills. Second, business advisory services offer non-technical guidance and informal learning opportunities to managers and executives to support AI adoption. Third, information services may take the form of publication of case studies and open-source code for AI solutions, material that can be used for self-learning.

¹⁴ See the Pan-Canadian Artificial Intelligence Strategy available at <https://ised-isde.canada.ca/site/ai-strategy/en>.

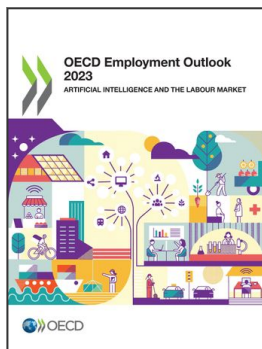
¹⁵ Available at <https://enterprise.gov.ie/en/publications/publication-files/national-ai-strategy.pdf>.

¹⁶ Available at https://wp.oecd.ai/app/uploads/2021/12/Luxembourg_Artificial_Intelligence_Strategic_Vision_for_Luxembourg.pdf.

¹⁷ Public Law No: 117-207 (17 October 2022) Artificial Intelligence Training for the Acquisition Workforce Act, also referred to as the AI Training Act.

¹⁸ This whole section is based on Verhagen (2021^[51]) and more examples can be found in the paper.

¹⁹ This is modular training as recommended by the European Commission (Council Recommendation on a European approach to micro-credentials for lifelong learning and employability) taken one step further.



From:
OECD Employment Outlook 2023
Artificial Intelligence and the Labour Market

Access the complete publication at:
<https://doi.org/10.1787/08785bba-en>

Please cite this chapter as:

Lassébie, Julie (2023), "Skill needs and policies in the age of artificial intelligence", in OECD, *OECD Employment Outlook 2023: Artificial Intelligence and the Labour Market*, OECD Publishing, Paris.

DOI: <https://doi.org/10.1787/638df49a-en>

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