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THE IMPACT OF AI ON LABOUR MARKETS

What we know so far

THE EU AGENCY SUPPORTING COUNTRIES TO DEVELOP THROUGH LEARNING

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EXECUTIVE SUMMARY

Artificial intelligence (AI) has emerged as a transformative force in the wake of rapid technological advances. Although still in the early stage of evolution with new advances every day, AI has already hit the headlines as one of the greatest disruptions in the labour markets, simultaneously automating, augmenting and redefining tasks and changing how work is performed and valued. Like every new technology, AI affects the task content and structure of jobs, as well as their demands and resources – with consequences on employment, working conditions and skills requirements. There is already an abundance of studies regarding AI's impact on the labour markets, covering various dimensions of employment by sector, occupation and skill. The results of these studies are often presented around three scenarios: **job displacement** (full automation), **job creation**, and **job transformation** or **augmentation** (changing task content). While early studies have focused a lot on job displacement with a gloomy picture, subsequent more refined studies recognise job transformation as the most common effect, by shifting the relative importance of tasks within each occupation.

This report provides **a comprehensive review of existing literature on the topic** and synthesises the main insights coming from academic research, policy analysis of international/EU organisations, and industry reports. After introducing AI technologies and AI-driven business restructuring, the report presents the main findings in three categories: **job quantity, job quality** and **inclusiveness**. A final chapter covers *AI's potential impact in developing countries,* given the ETF's focus on its Partner Countries. The report intentionally excludes 'changing skills demand as a result of AI', which will be the topic of another self-standing report. Despite the high-speed changes of AI that make it impossible to capture all the developments in one report, the report takes stock of the knowledge gained so far and presents the main findings in a more systematic manner for experts, practitioners and decision-makers dealing with employment and training policies, who seek to understand and navigate the profound changes that AI brings to the labour market.

AI's impact on labour markets is mixed for diverse reasons. Studies employ different methodologies, from measuring the theoretical exposure of occupations to AI (task-based framework) to empirical investigations of actual employment effects. The task-based framework is especially widely used in measuring the automation and augmentation impact of AI systems. However, empirical evidence is still scarce by virtue of AI being a newly developed field, limiting the grasp of its job-creating effects such as the emergence of new industries and occupations. Thus, the AI exposure studies often miss the system redesign perspective, since new technology can create new processes, handle coordination tasks and have decision-making capabilities with the potential for new management and operational models. Theoretical measurements often overestimate the extent of job displacement, as they often focus on the technical feasibility of automation rather than its economic viability or political acceptability.

AI's impact on labour markets is context dependent. Estimates of AI-related job losses and gains largely vary by type of economy, sector and occupation, but most experts agree with the job augmentation effect for high-wage/ high-skilled occupations and job displacement and/or precarity for routine-based occupations. The existing *institutional and regulatory environment* under which organisations adopt AI tools generally mediates the effects of technology. Depending on how governments and economies choose to govern AI deployment, labour market institutions often play a crucial role in moderating the negative impact. Similarly, workplace dynamics shaped by existing industrial relations, work culture and management style are key determinants for the outcome. Following the adoption of AI, organisations often develop several adjustment mechanisms through job (re)design, organisational changes or internal mobility, and the results of job (re)design may vary by top-down or bottom-up strategies (e.g. job crafting).

AI affects jobs substantially, but not necessarily in large numbers …

Employment trends in AI-exposed sectors and occupations reflect a mix of substitution and expansion effects. Occupations with higher automation risk (e.g. office and admin roles, translators) saw lower labour demand and slower employment growth compared to low-risk occupations, yet within occupations, task reallocation and firm-wide AI-driven growth help sustain overall employment levels. Rather than leading to broad job losses, AI appears to be reallocating labour across tasks and firms, although freelance platforms show early evidence of reduced writing jobs. Highly exposed occupations experience job transformation with large and heterogeneous effects due to the shift in the relative importance of tasks. However, the effects differ by tasks and skill levels: exposure to AI often means augmentation in highly skilled work, but automation in low/medium-skilled work. Augmentation can bring increased workers' productivity – particularly in professional writing, translation, financial and legal tasks, consultancy, customer services and software development – with higher quality and shorter turnarounds. AI seems to extend automation up the skill ladder in knowledge work, shifting routine analytical work down the value chain and threatening a broader set of mid-level skills.

Two opposing observations made on the automation patterns of knowledge work. *The first observation* suggests that *AI may destroy 'entry-level' jobs and break a career ladder of fresh graduates.* As AI is better at low-complexity tasks, entry-level tasks like research, data analysis, report writing and document review in white-collar jobs can now be handled by a few senior workers with an AI tool, instead of by many junior employees. Thus, AI can take over the initial stages of research and medical, legal and financial analysis, but their finalisation would still require specialist 'elite experts'. Demand for high-skilled expertise would rise, while a broader set of middle-skill jobs would be substituted by automation – this time in offices rather than factories. Fresh graduates – who rely more on codified knowledge gained through formal education – are more vulnerable to AI systems, whereas experienced workers benefit from tacit, context-specific knowledge that is harder to automate.

The second observation sees AI as *an opportunity to augment and broaden expertise (cognitive extension), which could lift vocational jobs and bring back medium-skilled employment*. This is because lower-skilled and inexperienced workers are observed to benefit more from AI's support in tasks like research, data analysis, report writing and document review. By improving the quality of outputs and reducing time spent on tasks, AI could support and supplement judgement, enabling a larger set of non-elite workers to engage in in high-skilled work. It would temper the monopoly that doctors hold over medical care, lawyers over document production, software engineers over computer code, and professors over education. This could improve the quality of jobs for workers without university degrees, reduce earning inequality and lower the cost of healthcare, education and legal services. Dubbed the '*democratisation of expertise*', this increased access to expertise could enable organisations to shift tasks down from high- to low-skilled occupations and potentially to creating more middle-class jobs.

AI's impact on total (aggregate) employment has been close to null. Empirical studies from workplaces that have adopted AI tools so far point to no visible effect, or only a small decline or a small increase in some of exposed jobs, as very few jobs are completely automatable. Despite no indication of net job destruction, occupations with a higher automation risk saw slower employment growth compared to low-risk occupations, while employment trends in exposed occupations differ across skill levels. Overall, it is difficult to find a clear and direct relationship between the AI exposure of occupations and their employment growth or decline. Nevertheless, *the jury is still out* on AI's ultimate impact on the number of jobs.

AI significantly affects working conditions, often in opposite directions …

There is evidence of AI having both positive and negative effects on job quality. AI can improve or reduce job quality through its effects on job intensity, autonomy, skill use and collaboration. Job quality improvements include more interesting tasks, improved physical safety, greater work engagement, increased complexity and responsibility, and higher job satisfaction, leading in some cases to job upgrading. On the contrary, examples of worsening working conditions include a higher pace of work, reduced autonomy, cognitive underload, higher control and monitoring, skills underutilisation and psychosocial effects, leading in some cases to job downgrading. AI tends to increase job demands and job resources, while algorithmic management (AM) practices alter how work is performed, monitored and evaluated. Workers tend to benefit most when AI acts as a support tool for workers, in contrast to when it is used to control work processes and monitor performance.

AI adoption often increases work intensity by leaving simple tasks to machines and shifting human effort towards more cognitively and emotionally demanding tasks – though some applications do reduce workload or strain. Increased work intensity seems to be a common result across the board in diverse sectors, occupations and skill levels. The use of AM practices in the workplace directly contributes to this impact, by increasing the degree of standardisation/routinisation, knowledge centralisation, and stronger monitoring and managerial control over work processes. AM practices also create conditions to reduce autonomy and opportunities for discretion and intrinsic skill use in the workplace, often with increased responsibility, but the outcome is shaped by the management decisions of organisations.

What is striking is the opposite effects in terms of skill levels. Despite its mixed outcomes regarding overall job quality, one can identify more positive effects of AI on highly skilled occupations, where it has become a new productivity tool, supporting and speeding up the execution of some tasks in these occupations. Highly skilled and digitally literate workers benefit from it in terms of employment growth, wage gains and transitions to higher value-added tasks. To the contrary, more negative effects are experienced in low-skilled occupations, where lower-wage workers face work intensification, loss of autonomy, stress, anxiety and burnout. This is particularly the case in location-based platform workers, logistics and warehouse workers or similar sectors where AM practices are common. In these cases, the digital control and monitoring systems leave workers little room for negotiation or recourse, resulting in them facing higher pressure and risk of displacement.

AI tools lead to increased workplace monitoring and surveillance. New forms of AI-supported tools are increasingly used to monitor all work processes in the workplace (*datafication of the workplace*). They collect and analyse large volumes of data about workers, which may be an invasion of their privacy. The same technologies that can assist workers and enhance safety carry a significant risk of privacy and data security breaches. By giving employers access to more and better data about workers, AI can lead to information and power asymmetries in favour of corporate business, especially when workers are unaware that they are interacting with AI. Depending on how it is deployed, AI has the potential to alter traditional work relations between workers and firms.

AI expands algorithmic management (AM) practices into traditional workplaces. The logic of AM and surveillance is now extending into traditional workplaces through the so-called '*platformisation of work*', a process enabled by the digitisation of economic activities, the wider use of digital tools and digital monitoring, and other AM features (short-term contracts and freelance work). With increased standardisation of tasks and remote work practices, the majority of workers are now using digital devices that are often connected to platforms for management and coordination, which become control and monitoring tools. Moreover, the AI value chain depends on many low-skilled gig workers – such as data labellers and content moderators – performing repetitive, low-wage tasks under heavy surveillance. Gig work is expected to grow as the demand for AI jobs grows, worsening access to decent work, fair remuneration and social protection for more workers.

AI's effect on job quality may not be a fixed one; it is constantly negotiated within the dynamics of the workplace. Depending on who is using it and how, AI can either empower or overwhelm workers. The negative outcomes for job quality often stem from organisational factors and management choices, rather than the technology itself. This, in turn, is affected by the moderating role (or lack thereof) of institutional and regulatory frameworks, as well as by the organisational structures of firms and work culture. As AI systems tend to replicate existing power dynamics in organisations, their impact on worker well-being depends on how it is implemented in the workplace and whether workers have any say on it. Consequently, disadvantaged groups may suffer more from the negative effects of AI, risking further labour market polarisation across socio-economic groups.

If left unchecked, AI has potential to deepen existing inequalities …

AI's impact is uneven by age, gender, education and occupation. In particular, workers' educational background, occupation and skill level seem to be key determinants of the impact. *Young white male workers with higher education gain the most from AI.* The level of impact escalates with income, creating several new opportunities for highly educated and high-income professionals who tend to be prime-age white male workers. Meanwhile, for low-educated, low-income workers, particularly in algorithmically managed environments, it creates risks of job displacement, deteriorating working conditions, and less access to decent work and productivity-enhancing AI tools in the workplace. These people tend to be women, older workers and marginalised workers due to their compounded challenges – from digital skills gaps to algorithmic screening tools that may filter them out due to non-conformity to standardised backgrounds. Overall, education seems to be the key moderator of AI's employment impact.

AI may compromise the access of disadvantaged groups to decent jobs. Like any technological tool, *AI is not a magic equaliser*. Technology development often replicates the prevailing power dynamics in society, so AI may amplify inequality by favouring privileged groups over disadvantaged ones. The power imbalance in AI development and implementation is pervasive across gender, race and socio-economic background, and it is often highly educated managers and technology developers who decide the features of AI systems from their own perspectives and interests. Some empirical studies identify older and low-educated individuals as the most vulnerable groups to AI. AI systems influence who gets seen, selected, promoted, supported or dismissed in the labour market by these systems' use in recruitment, performance monitoring and promotion. There are already examples of biased data due to incomplete, unrepresentative or historically discriminatory patterns used to develop AI systems, hence amplifying current inequalities. Overall, the findings so far resonate with the existing *digital divide* and provide evidence for an *emerging AI divide* among users.

The vicious cycle of digital and AI gender inequality continues. While women have been historically discriminated against and disadvantaged in many fields, there are numerous examples of how existing AI tools unintentionally amplify existing gender inequalities. This is a 'vicious cycle' because very few women study and enter STEM and ICT occupations, and even fewer are in the AI workforce. AI developers are facing a critical diversity crisis, with an overwhelmingly homogenous group of prime-age white male workers. As women are severely underrepresented among AI developers, existing AI tools reflect the social judgements of their developers. Very few women use AI, and women report less positive perceptions of AI than men. Moreover, women are overrepresented in clerical and admin roles that have a higher risk of automation. AI education and career guidance tools favour boys for STEM studies, while recruitment tools favour male candidates for ICT occupations. All these trends result in gender inequality being further exacerbated by algorithms.

For AI to serve for inclusive employment, conscious effort is needed with concrete policy actions. There are cases where AI tools are developed for, and contribute to, more ethical recruitment across marginalised groups, or to the inclusion of people with disabilities, by removing their barriers (e.g. speech-to-text applications, live captioning algorithms for deaf people; image recognition tools for blind people, etc.). However, these examples do not appear automatically; they are often the result of a deliberate action and effort. People with disabilities illustrate this well due to the frequency of the multiple disadvantages they have, such as low education and socio-economic status. Typically, AI developers have a low awareness of, and familiarity with, accessibility and disability needs, and AI tools are trained for 'average' users with limited and biased data on disabilities. Even when effort is made to develop AI tools especially for people with disabilities, their commercialisation and scaling beyond prototypes are not easy if left to market forces.

AI may widen inequalities between countries and regions …

Developing countries start the AI age with disadvantages, often exacerbated by the global digital divide. Access to AI development and governance is concentrated among a few countries with advanced AI capabilities, while developing countries have stark disparities – access to electricity, telecommunications infrastructure, the internet, cloud computing and quality STEM education. Limited digital infrastructure leads to limited use of digital devices at work and foundational digital skills, which are key preconditions for AI productivity gains. AI expertise is also highly concentrated in the North America and western Europe, with few exceptions like India, while emigration of AI talent severely undermines local AI capability building. This asymmetry may be further aggravated by the current geopolitical tensions and the AI innovation race.

A country's economic structure and income level are the main determinants for AI's impact. There is a strong correlation between the share of occupational groups in a country and their exposure to AI. Full automation risk is higher for developed countries, while it gradually decreases in middle-income countries and is lowest in low-income countries. Mature digitisation creates favourable conditions for higher AI adoption in advanced economies, where a larger share of jobs fall into the augmentation category with AI systems becoming productivity tools. The risk of job displacement is higher in middle-income countries in particular sectors, while it is much lower in low-income countries, which have the highest risk of falling behind due to the widening digital divide and income disparity.

Limited institutional and regulatory frameworks in developing countries create a higher risk of AI having a negative impact. There is evidence of the moderating role of institutional and regulatory frameworks in developed countries, but many developing countries lack effective implementation for their limited frameworks. AI technologies carry much higher risks in low- and middle-income countries, where weak policy frameworks bring higher risks of harmful applications such as mass surveillance and worsening societal divides due to higher socio-economic inequalities. One example is the 'AI production value chain' through platform work, where millions of gig workers perform repetitive and underpaid micro-tasks (e.g. content moderation and data annotation) under heavy surveillance. These tasks are often outsourced to developing countries such as Kenya, India, Venezuela and the Philippines to bypass workers' protection regulations. These conditions undermine the prospective benefits of AI in developing countries.

A final word …

Ultimately, the future of work in an AI-driven world is not predetermined. AI can drive innovation, increase productivity, and open new frontiers for economic growth. But it can also reinforce exclusion, inequality and insecurity if left unchecked. The challenge for policymakers is to actively shape the conditions of AI deployment so that it supports – not undermines – human dignity, equality and opportunity. This requires managing this transition to share the benefits of AI adoption equally in the workplace. The AI-related developments will depend on the regulations introduced at national and international level, as well as the mode of centralised versus decentralised development of AI systems. Leaving the development of AI to market forces with a short-term focus on increasing productivity is a choice that seems to be the current market-based approach. Regulating it to develop AI forms in ways that enhance human capacities and maximise human/AI benefits is another choice. Whatever is done or not done now will shape how AI makes its way into our lives.

The EU already has several policy initiatives on AI use in the workplace that focus on preventing potential misuse of AI systems and data protection via the General Data Protection Regulation (GDPR), Digital Services Act (DSA) and the EU AI Act, including the conditions for the use of AI in employment and education. Yet regulation alone is not enough. A robust policy agenda must also address foundational needs: universal access to digital education, inclusive skills development, targeted upskilling and reskilling for the workforce, ethical workplace governance, social dialogue, and active labour market policies that support mobility and adaptation. Strategic foresight, inclusive planning and agile public-private collaboration are necessary to shape AI's labour market trajectory.

INTRODUCTION

Artificial intelligence (AI) has been a transformative force, reshaping industries and redefining the nature of employment. From its early conceptualisation in expert systems to the sophisticated generative models of today, it has prompted heated debates and countless studies on how it alters the world of work and its wider socio-economic implications. Today, AI has moved from the fringes of automation to the centre of labour market transformation. This and other disruptions force us to be prepared by anticipating change and shaping it before it unfolds. Anticipating the future of work and shaping labour market transitions are no longer a luxury; they are essential for building more inclusive and resilient societies (ETF, 2021).

In this context, understanding the transformative impact of AI on jobs and workplaces has become crucial for seizing opportunities and reducing risks. There is already a significant body of literature to explore the effects of AI on labour markets, though primarily concentrated on the advanced economies of North America and western Europe. The research covering a wider range of countries, particularly in the Global South, is less available, and the ETF wants to contribute to this endeavour by focusing on the potential AI impacts in the economies and labour markets of developing countries. This starts with a systematic review of the existing literature on the global impact of AI in the labour markets, and presenting a synthesis of main findings for experts, practitioners and decision-makers in the ETF's partner countries.

With this report, the ETF aims to **provide a comprehensive review of existing literature** regarding the impact of AI on the labour markets and to synthesise the main insights from academic research, policy analyses of international/EU organisations, and industry reports. Based on the literature review, the report identifies key trends, challenges and opportunities arising from AI adoption in the workplace so far and provides a synthesis of key findings in a structured overview. Given the high-speed evolution of AI technologies, the trends identified in this report may change quickly in the future. Nonetheless, the ETF believes that the report would be still a good source of reading for experts, practitioners and decision-makers who deal with employment and training policies and programmes and seek to understand and navigate the profound changes that AI brings to the labour market.

The literature review has been conducted in a traditional way based on the following **research questions**: how AI adoption is restructuring business, and in what ways it affects the jobs, working conditions and inclusiveness (access to jobs and career progression by different groups). Although some keywords were used in the beginning to reach the most relevant sources, the rest was found from bibliographies via snowballing. Priority was given to sources from the field of labour economics, while open-source articles and reports were preferred for accessing relevant literature. The first selection of sources was based on the current period (sources prior to 2015 were excluded) and were in English (hardly any non-English-language sources were used). Sources from scientific literature and the reports of specialist international organisations and EU agencies were preferred. Once selected, the abstracts and bibliography of sources were checked, and often whole papers are skimmed. These sources included theoretical research papers, econometric analyses, empirical studies using scientific data, case studies, and literature reviews.

The report explores how AI-driven technologies are reshaping business operations, work structures, jobs and employment conditions, and it systematises both the opportunities and challenges associated with AI adoption. The analytical approach adopted in the report acknowledges the multifaceted nature of AI's impact, exploring both micro-level changes within specific occupations and broader macroeconomic and societal implications. It seeks to provide a thorough and balanced analysis of AI's role in the workplace, with an emphasis on the continuously evolving relationship between AI technologies and labour market dynamics. Overall, this is an attempt for a qualitative review of the findings from existing literature, synthesising them to provide answers to research questions, and inferring some conclusions.

The report is structured into six chapters, each addressing critical aspects of AI's influence on the different dimensions of employment and labour market functions:

- CHAPTER 1. UNDERSTANDING AI WITHIN THE LABOUR MARKET CONTEXT starts with an introduction of AI technologies such as key terminology, historical developments and widely used applications in the field, giving readers clarity for subsequent chapters on specific AI effects in the workplace. It also highlights some features of AI that are most relevant to labour market analysis and informs about the various difficulties of conducting such an impact analysis.
- CHAPTER 2. REVIEW OF AI-DRIVEN BUSINESS RESTRUCTURING continues with an overview of the AI-driven restructuring initiatives and practices in the business world before moving on to jobs and employment conditions. It discusses the trends related to AI adoption by sectors, and how it changes the organisational and managerial practices due to the digitisation of economic activities. As firms increasingly use algorithmic management (AM) practices, the chapter includes an introduction to AM and provides examples where algorithms are used in operational activities (e.g. work instructions, scheduling, task coordination, monitoring) and in human resources management (e.g. recruitment, evaluation, promotion, termination).
- CHAPTER 3: THE IMPACT OF AI ON JOBS presents the analytical frameworks used by researchers to document the potential effects of AI in an organisation and the different analytical approaches used to measure AI's employment effects. Following the three categories used by the OECD to analyse the results of AI in a workplace (job quantity, job quality, inclusiveness), the focus here is on the first two aspects, examining AI's role in automating tasks, transforming jobs, influencing employment dynamics, the quality of the working environment, earnings, and job security. Readers will find a summary of key findings and evidence at the end of each section.
- CHAPTER 4. THE IMPACT Of AI ON EQUALITY AND INCLUSIVENESS focuses on AI's effects on inclusiveness, particularly the risks of bias and discrimination for disadvantaged groups in equal access to decent jobs and career progression (e.g. in recruitment, promotion, worker monitoring and evaluation, dismissals). It includes a review of the most important determinants of inclusiveness from an AI perspective: age, gender, education, occupation, residence, income level and disability. While the vulnerability of older, low-educated and marginalised groups is highlighted, special emphasis is given to potential AI effects on existing gender inequality in the labour market.
- CHAPTER 5. THE IMPACT OF AI IN DEVELOPING COUNTRIES brings developing countries into the picture in terms of AI's impact, as access to AI development and governance is concentrated among a few countries with advanced AI capabilities. The starting position of AI in developing countries is presented to reveal some disadvantages, which are often exacerbated by global digital divide. The chapter shows the strong correlation between the share of occupational groups in a country and their exposure to AI, while drawing attention to limited institutional and regulatory frameworks in developing countries that create considerable risks of harmful applications and worsening societal divides.
- CHAPTER 6. CONCLUSIONS AND POLICY IMPLICATIONS concludes by synthesising key insights from the previous chapters based on the existing literature review and their policy implications for the employment and training fields. Though not aimed to provide any policy recommendations, it still emphasises the importance of proactive strategies such as workforce reskilling, inclusive employment policies, and ethical AI governance frameworks in the workplace.

CHAPTER 1. UNDERSTANDING AI WITHIN THE LABOUR MARKET CONTEXT

This chapter provides an introduction to AI technologies for general readers, starting with its definition and the main types used by different organisations. It is followed by a brief history of AI developments and its most widely used applications in the field, such as machine learning, neural networks, deep learning, cognitive computing, natural language processing, computer vision, large language models and agentic AI.

The second part of the chapter discusses the key features of AI that are most relevant to labour markets, such as AI as a general-purpose technology, the non-rivalry of algorithms, and AI's reasoning and perception capacity that enables it to perform non-routine cognitive tasks, which is particularly impacting highly educated professions. Finally, the chapter reminds us to be cautious about the findings of existing research so far, as the potential impact of AI could vary considerably due to the diversity of AI technologies, its context-dependent impact, and its continuous evolution every day with new applications.

1.1. Definition of AI

There is a rich body of research and policy discussions on the definition of AI. Across academic circles and institutions around the world, there has been a concerted effort to encapsulate what AI entails, reflecting its complexity and far-reaching impact. These definitions help shape our understanding of what AI means and contributes to influencing how policies and regulations are developed and managed to integrate AI into society. The rich diversity in defining AI highlights its multifaceted nature; however, at its core, there is a broad consensus on definitions of core AI characteristics.

John McCarthy from Stanford University, who first coined the term 'AI' in the 1950s, defines it as '*the science and engineering of making intelligent machines*' (McCarthy, 2012). In his pioneering research, McCarthy emphasises AI's foundational goal of creating machines that can perform tasks requiring human intelligence. It underscores the importance of the technological aspects of AI, focusing on the development of systems that can perceive, reason, learn and adapt autonomously, much like a human would. This research also includes definitions for a wide range of AI sub-fields – from machine learning to natural language processing – all aimed at enhancing machine capabilities.

AI is defined in several European Commission (EC) documents, starting with the definition of the high-level expert group on AI in 2018, and followed by another definition coined by the Joint Research Centre (JRC) of the EC in 2021 (see Box 1). The latter is officially used by AI Watch, the EC's knowledge service monitoring AI in Europe[1]. By reviewing many AI policy and institutional reports, research publications and market reports, it includes a taxonomy and definition of AI sub-fields. Later, the EU AI Act provided a similar definition in 2024. These are just a few of the many definitions of AI set out by researchers and international organisations in recent years.

Box 1: Definitions of AI in EU documents

Artificial intelligence refers to systems that show intelligent behaviour: by analysing their environment they can perform various tasks with some degree of autonomy to achieve specific goals (EC, 2018).

Software (and possibly also hardware) systems designed by humans that, given a complex goal, act in the physical or digital dimension by perceiving their environment through data acquisition, interpreting the collected structured or unstructured data, reasoning on the knowledge, or processing the information, derived from this data and deciding the best action(s) to take to achieve the given goal (JRC, 2021a).

[1] See AI Watch.

A machine-based system designed to operate with varying levels of autonomy and that may exhibit adaptiveness after deployment, and that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments (EU AI Act, 2024).

All the definitions emphasise the simulation of human intelligence in machines designed to perform tasks that typically require human cognition, such as learning, reasoning and problem-solving. The term '*intelligence*' is linked to the concept of rationality, the ability to choose the best action to take in order to achieve a certain goal, given certain criteria to be optimised and the available resources. Whether it is through autonomous decision-making, learning from data or performing complex tasks, the overarching goal is to enhance human capabilities and improve efficiency across various domains. Despite the nuances in each definition, they collectively underscore AI's role in transforming both technology and society by bridging the gap between human intelligence and machine execution.

AI can be broadly categorised into three main types: narrow AI, general AI and super AI. *Artificial narrow intelligence (ANI),* also known as weak AI, focuses on specific tasks such as facial recognition, internet search engines and self-driving cars. This is where we are for now. *Artificial general intelligence (AGI)* or strong AI aims to achieve human-level intelligence and perform various tasks. AGI is not yet a reality but is a major research goal in the field of AI. *Artificial superintelligence (ASI)* would potentially be smarter than humans and surpass human intelligence in all domains, but it is currently a theoretical concept and remains within the realm of science fiction. As a broad and multifaceted field, understanding key AI concepts and terminology is essential. For this reason, *an **AI Glossary** is provided in the Annex for a wide range of AI-related terminology.*

AI uses multiple technologies that equip machines to sense, comprehend, plan, act and learn with human-like levels of intelligence. AI systems perceive environments, recognise objects, contribute to decision-making, solve complex problems, learn from past experiences, and imitate patterns. These abilities are combined to accomplish tasks like driving a car or recognising a face to unlock a device screen. AI is increasingly used in many areas, sometimes without us realising it. Search engines, smart assistants, chatbots, language translation, navigation apps, online video games and many other applications use AI in our everyday lives. AI systems rely on lots of data, collected in different modalities (e.g. sound, images, text, posts, clicks), which altogether forms our digital trace.

AI is a broad and multifaceted field, encompassing diverse sub-fields that have evolved over time, each contributing to different functions. AI-based systems can be purely *software-based,* acting in the virtual world (e.g. voice assistants, image analysis software, search engines, speech and face recognition systems), or embedded in *hardware devices* (e.g. advanced robots, autonomous cars, drones, Internet of Things applications). Robotics can be defined as '*AI in action in the physical world*' (also called embodied AI). In addition to AI, however, other disciplines play a role in robot design and operation, such as mechanical engineering and control theory. Examples of robots include robotic manipulators, autonomous vehicles (e.g. cars, drones, flying taxis), humanoid robots and robotic vacuum cleaners (EC, 2018).

AI systems are encountered both in the form of algorithms or automated decision systems, and in embodied robots. As chatbots, voice assistance systems, service robots, collaborative robots, autonomous vehicles or toys, these machines communicate with humans, often in natural language, responding to human behaviour and adapting to different situations. They follow pre-programmed rules and expected behavioural norms and are perceived as social actors. Hence, 'AI systems' refers to a broad range of intelligent machines, embodied or not, which are already relevant in almost every aspect of life and will gain even more impact in the future.

As a scientific discipline, AI includes several strands, such as *machine learning techniques*, *machine reasoning* (i.e. planning, scheduling, knowledge representation and reasoning, search, and optimisation), and *robotics* (e.g. control, perception, sensors and actuators, integrating all other techniques into cyber-physical systems). Learning techniques include machine learning (e.g. supervised learning, unsupervised learning, reinforcement learning), neural networks, deep learning, decision trees and many other learning techniques. These techniques allow an AI system to learn how to solve problems that cannot be precisely specified, or whose solution method cannot be described by symbolic reasoning rules.

1.2. Brief AI history and main applications

AI has evolved significantly over the past 75 years, progressing from early rule-based systems to sophisticated models capable of advanced reasoning, perception, and content generation. Computer analytics (i.e. the use of data, statistical and quantitative analysis to drive decisions) had been used for years before the arrival of AI as we now know it, but it was largely coded and rigid, and dependent on structured data. From the early 2000s, there was a huge boom in the quantity of available data – largely aided by advancements in the technology associated with data recording and storage. These vast amounts of data are called 'big data', and it has become a key input in the development of AI tools – providing the fuel from which AI systems can learn and improve. AI systems are only as good as the data they are trained on or the expert input they are built on.

As depicted in Figure 1, the advances related to AI reflect continuous advancements in computational power, algorithmic innovation and the increasing availability of large-scale data, widely regarded as the foundational resource for contemporary AI systems. Overall, this AI evolution can be analysed in terms of five distinct periods, as categorised and summarised below (see Figure 1).

1950–1990: expert systems and symbolic AI. AI emerged as a formal discipline in the 1950s, spearheaded by researchers such as John McCarthy. Initial developments focused on symbolic AI, which employed logic and rule-based frameworks to replicate aspects of human intelligence. During this phase, small-scale expert systems were introduced, exemplified by applications like MYCIN, an early medical diagnostic tool. These systems, underpinned by deductive reasoning, applied predefined rules to derive conclusions from user-provided data. While promising, their dependence on manual rule encoding and narrow application domains led to a decline in expectations, contributing to the first '*AI winter*', a period marked by reduced funding and interest.

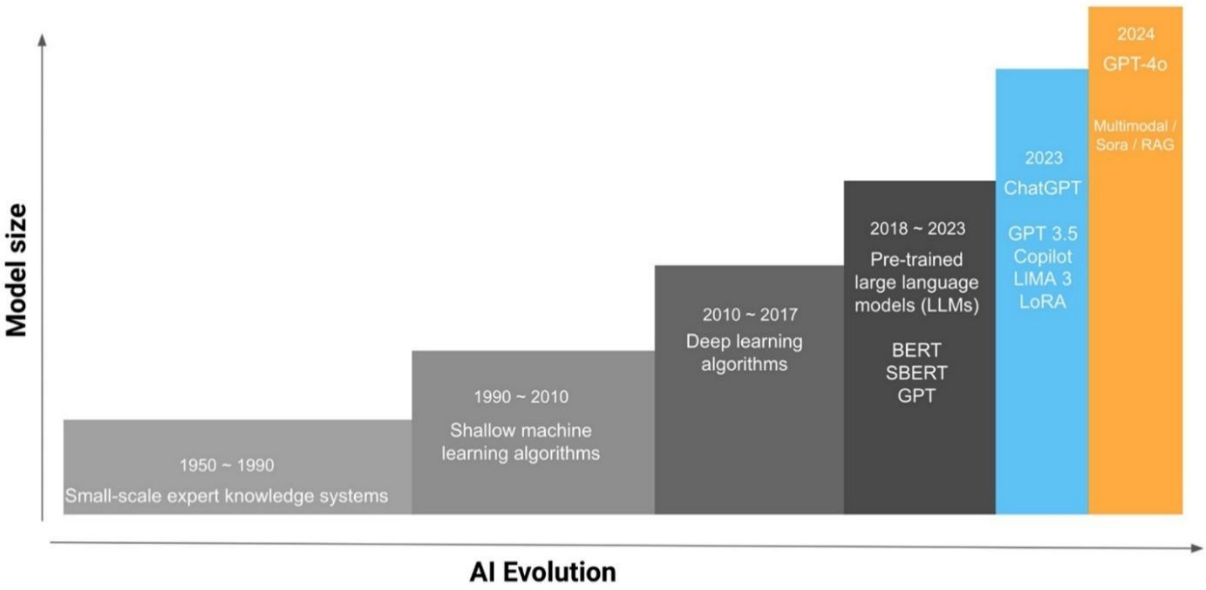
1990–2010: emergence of machine learning. A renewed interest in AI emerged in the 1990s with the introduction of shallow machine learning algorithms, marking a paradigm shift from rule-based to data-driven approaches. These models, based on inductive reasoning, inferred patterns from empirical data rather than relying on pre-established logic. Techniques such as decision trees and support vector machines enabled more flexible and adaptive systems. A key milestone in this period was IBM's *Deep Blue* defeating world chess champion Garry Kasparov in 1997, underscoring the potential of algorithmic learning.

2010–2017: deep learning and neural networks. The 2010s saw the rapid advancement of deep learning, a subset of machine learning based on multilayered artificial neural networks. These architectures significantly improved AI's ability to perform complex tasks such as image recognition, speech processing and natural language understanding. Enabled by greater computational capacity and access to large datasets, deep learning models demonstrated scalable performance in a range of domains.

2018–2023: the rise of large language models (LLMs). A significant development occurred with the introduction of pre-trained large language models (LLMs), including BERT, GPT and SBERT, which leveraged transformer architectures to process and generate human-like text. These models, trained on extensive textual datasets, enabled state-of-the-art performance in language-related tasks. The release of ChatGPT in 2023, along with models such as GPT-3.5, significantly expanded the applicability of AI in professional, educational and creative contexts.

2024 and beyond: multimodal and generative AI. The most recent advancements involve generative and multimodal AI, exemplified by models such as GPT-4o and Sora / RAG methodology / GRPO. These systems can process and produce content across multiple modalities, including text, image and audio, thus enabling more seamless and context-aware human-computer interaction. Their applications range from automated communication and content generation to real-time translation and personalised assistance.

Figure 1: A visual representation of the evolution of AI over the past 75 years



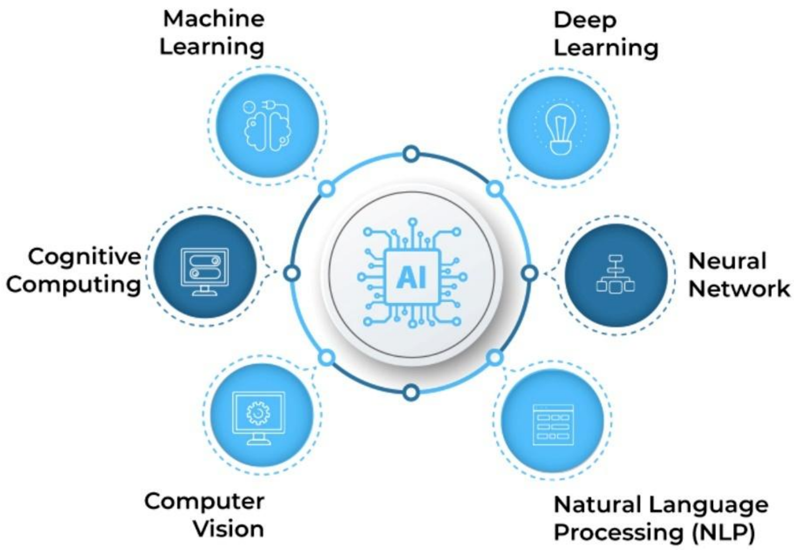
Source: Author's creation.

What makes these developments possible is data – lots of it. AI systems learn by analysing vast amounts of information that comes from big data. Today, almost every action we take online generates data, and this data is the essential fuel that powers AI systems. The more data AI can access, the better it can learn, adapt and perform. Within this context, it must be emphasised that the future of AI will depend on new developments regarding three key elements of AI:

- **Learning algorithms** and models developed by scientists to analyse data.
- The **big data** needed to train and validate AI models, which depends on IT for collection and storage and human's input to be provided.
- The **computational power** needed to process big data. Only relatively recently have computers become powerful enough to analyse large amounts of data fast enough.

AI's strength lies not only in its technical complexity, but also in its ability to turn raw data into meaningful insights. Yet, behind the scenes, everything depends on mathematical models, statistical analysis and powerful algorithms, combining computer science with mathematics and statistics to solve problems, recognise patterns, and make predictions based on data (Agrawal et al., 2016, 2022). These hidden layers allow machines to make sense of massive volumes of information in a short period, far more than any human could process alone. Over time, AI has grown into several specialist areas, each contributing to different types of applications. Figure 2 shows the six most important applications or branches in the AI field.

Figure 2: The main applications and/or branches of AI



Source: Author's creation based on the internet.

This report includes an **ANNEX:** AI GLOSSARY in the Annex, which provides definitions for many AI-related terms. Nonetheless, short definitions of six applications included in Figure 2 are provided here for easy reference. These are also foundational AI terms that are most relevant to the workplace and digital transformation.

Machine learning (ML) is at the core of AI to teach computers how to learn from data rather than being explicitly programmed. It underpins many modern AI applications, with over 70 algorithms and tools that support data analysis, pattern recognition, prediction and automation.

Neural networks (NNs) are a subset of ML programmes. They are models that are loosely modelled on neural connections in the human brain. They are a fundamental analysis technique in LLMs, and identify phenomena, assess different options and arrive at conclusions.

Deep learning (DL) is a specialist branch of ML that uses large neural networks with many layers to process the data. The more layers a neural network has, the more complex it becomes and is defined as deep learning.

Cognitive computing aims to recreate the human thought process in a computer model that can learn, reason, and interact with humans in a natural and meaningful way, similar to how humans think.

Natural language processing (NLP) combines machine learning, linguistics and computer science to enable machines to understand, interpret and generate human language and speech. It powers applications such as chatbots, voice assistants and automated text classification.

Computer vision employs deep learning and pattern identification to interpret image content (graphs, tables, PDF pictures and videos) so that machines can identify objects in photos, scan handwriting, or guide robots through space.

Large language models (LLMs) are the latest development in the AI space and are built using DL. Trained on massive text datasets to understand and generate human-like language, they analyse and learn the patterns and relationships between words and phrases.

Generative AI (GenAI) is a class of DL systems designed to recognise and utilise textual, visual or auditory patterns from extensive datasets to produce new content in response to prompts that cannot be distinguished from human content.

It must be emphasised that the AI evolution will continue at a high speed. This is because it attracts significant financial investment, with record initiatives of AI research and development projects and ever-increasing numbers of AI workforce. In particular in the US and China, AI investment is exploding. In the US, the so-called 'Magnificent Seven' alone (Apple, Amazon, Microsoft, Google, Meta, OpenAI and Oracle) are investing 7% of the US's GDP into AI and data centres. Those seven firms make up 34% of the S&P 500[2], the highest concentration in history[3]. This means that many new AI-related models and innovations are expected soon, changing the current parameters of today.

Future developments will depend on not only the pace of AI progress (either advancing rapidly towards autonomous, general-purpose AI, or plateauing at narrower applications) but also the distribution of AI development power (either centralised under a few players or decentralised among many). These high-speed developments in AI evolution have led several organisations to create monitoring structures and tools that track and analyse various aspects of AI. Five such structures are listed and linked below for readers who want to follow the latest AI-related developments.

AI Index. The AI Index, created by the Stanford Institute for Human-Centered AI serves as a resource for understanding the rapidly evolving field of AI, including its technological advancements, ethical considerations and societal implications[4]. AI Index is also the name of the Institute's annual report that is published to provide policymakers, researchers and the public with data-driven insights into the state of AI, its development and its impact.

AI Watch is the European Commission's Joint Research Centre (JRC) AI website, started as a European Commission knowledge service created to monitor the development, uptake and impact of AI in Europe[5]. The platform provides information on the JRC's activities regarding research and policy support on the development, uptake and regulation of trustworthy AI relevant for digital services and products in concrete sectors, such as public administration, health, transport and education.

AI World is another comprehensive observatory on AI, created by the Centre for European Policy Studies (CEPS) project with support from Google.org. It is designed to bridge the gap between the profound impact of AI on our world and the limited public understanding of its dynamics. Through the use of several datasets, AI World offers an overview of the status of AI in different countries, sectors, occupations and companies, with in-depth insights and tools to empower policymakers, business leaders, investors, students and citizens alike[6].

AI Policy Observatory. Developed and managed by the OECD, the AI Policy Observatory aims to design and implement a synthetic measurement framework for Trustworthy AI, leveraging the ten principles contained in the OECD Recommendation on AI[7]. This is because policymakers need a framework that they can trust to assess not just the innovativeness of AI policies and practices, but also their trustworthiness and benefit to people and the planet in developing those policies.

In addition, the OECD recently initiated the ***Global AI Initiatives Navigator (GAIIN),*** which is a living repository from more than 80 jurisdictions and organisations to track national and international policies and regulations about AI[8]. GAIIN gives a global overview of what is being done worldwide by providing a central resource of public AI policies and initiatives.

The **Observatory on AI and Work in the Digital Economy** is another international knowledge hub recently created by the ILO on the world-of-work dimensions of AI and the digital economy[9].

[2] Standard & Poor's 500 (S&P 500) is a stock market index that tracks the performance of 500 leading publicly traded companies in the US.
[3] See LSE Business Review Blog by Mairead Pratschke, published on 15 September 2025, Seven CEOs in Trump's AI dinner shape America's tech destiny - LSE Business Review.
[4] See AI Index | Stanford HAI.
[5] See AI Watch.
[6] See AI World (or https://aiworld.eu).
[7] See The OECD Artificial Intelligence Policy Observatory - OECD.AI and AI Index - OECD.AI.
[8] See the OECD's live repository of AI strategies & policies - OECD.AI
[9] See Observatory on AI and Work in the Digital Economy | International Labour Organization.

1.3. Key AI features most relevant to labour markets

Today AI is all around us: from voice assistants and chatbots to image recognition and autonomous vehicles, AI is reshaping the way we work, communicate and make decisions. It is not a single technology, but a collection of methods that allow machines to simulate aspects of human intelligence. Therefore, it is not surprising to see many ongoing discussions on the potential impact of AI on labour markets, often with competing opinions of its benefits and harms. One thing is clear: AI has distinct features that set it apart from past technologies, particularly regarding its impact on the labour market. Experts often mention three features of AI in creating such an impact:

AI as a general-purpose technology. Many experts think that GenAI has the potential to eventually become a general-purpose technology, an idea not shared by some others, who treat AI as the fifth and final wave of digitisation. If AI becomes a general-purpose technology, it could be comparable to computing, electrification and the steam engine, and have a similar historical impact (OECD, 2021a). Thus, AI is expected to substantially change entire economies and societies due to increasing and diversifying AI applications in many areas – though the full-scale transformation could take much longer time if it follows the previous examples[10]. If AI becomes a general-purpose technology, it is still too early to decide whether its uptake will follow a similar J-curve effect, with an initial negative impact due to heavy investments in reorganisation and retraining, following by rebounds in later years (Brynjolfsson et al., 2018; JRC, 2018; Nurski, 2024).

The non-rivalry of algorithms. AI may eventually lead to less competition in markets, as it would be sufficient for one scalable algorithm to have acquired the knowledge or skills for a specific task in order for it to be used in any production process anytime, anywhere. Contrary to robots, there is no need to replicate or embody that skill or knowledge in another object. Ever larger data inputs can lead to increasing quality and capability of algorithmic works, where a single firm or application could end up dominating a type of GenAI activity, by virtue of drawing on the largest possible dataset, which is prohibitively costly to replicate by other providers (KPMG, 2023). As a result, the use of knowledge becomes much more centralised in a world of non-rival AI algorithms, compared to a world where knowledge or skills are embodied in rival machines or human agents (JRC, 2018). A single algorithm can displace all workers who perform a particular task for which the algorithm is trained.

AI automating non-routine cognitive tasks. The automation of routine tasks has already been here since the early digitisation phase, but AI's reasoning and perception capacity enables the performance of non-routine cognitive tasks, particularly hitting the highly educated professions (OECD, 2023e). Contrary to previous technological changes, which have largely exposed middle- and low-skilled occupations, AI exposure is concentrated in white-collar jobs with the potential to automate tasks in virtually every occupation. It stands in contrast to other technologies such as computerisation and industrial robotics, which only allow a limited set of tasks automated by implementing manually specified rules. As a result, AI may substantially impact income distribution across occupations. Historically speaking, the benefits of past automation have tended to be highly unequally distributed across different skill groups, even contributing to a reduced labour share of national income, among other factors (Acemoglu et al., 2023).

There are, however, some factors that make AI's impact on labour markets quite challenging and reduce predictability. Several studies already remind us to be cautious about the findings of existing research so far, as the potential impact of AI could vary greatly due to several factors. As summarised below, these factors are already identified in the literature and must be kept in mind when reading this report:

Diversity of AI technologies. As already pointed out by many studies, AI is not a single, uniform technology that will steer the labour market in one known direction (OECD, 2023e). As emphasised by the OECD, AI comprises a range of different systems that can impact workers in different ways, from

[10] Since the 1750s, each wave of technological revolution has been followed by the rise of a new organisational paradigm and associated management models. The development of new paradigms takes a long time through cycles of problem-solving and adaptation, in which new models emerge to solve the dysfunctions of the previous ones, shaped by managerial theories and practical experimentation, and finally diffused across the economy (Eurofound, 2025c).

influencing the demand for their labour to changing the environment where they work and affecting the inclusiveness of the labour market overall. Fundamentally, the impact of AI on the workplace will depend on the type of AI, on how it is deployed, and on contextual factors, including policies and institutions (OECD, 2021a). Moreover, research on AI's impact employs various proxies for AI exposure, such as robotisation, digital evolution indices and vacancy-based measures. While these proxies are useful, they often lead to diverse and sometimes contradictory conclusions on AI's impact on employment and growth.

Context-dependent impact of AI. Whether AI is good or bad for employment is not inherent in the technology. Any new technology may be used for good or bad or both, to different degrees and in different ways. It is how humans decide to use and deploy them that underscores the importance of context, as are the choices made shaping the outcome. Moreover, the effectiveness of AI in job creation and productivity is complex and multifaceted, with significant variations observed across different regions indicating that the assigned patterns are not homogeneous. This regional variation suggests that AI's benefits and drawbacks are not uniformly distributed and are heavily influenced by local economic conditions, regulatory environments, political realities and industry characteristics.

It must be recalled that the technical feasibility of one automation does not mean that it is also economically viable or socially acceptable given the existence of different regulatory barriers or physical and ethical restrictions. Reviewing most of the existing research into how AI is transforming work (e.g. in terms of job displacement, job creation and job enhancement), the results remain mixed and very much context-dependent due to the political, economic and social decisions to be made by different people, firms and governments and the incentives shaped by newly created institutions.

AI in its infancy. With new advancements occurring every day, it is reasonable to say that we are still far from understanding the full potential of AI and predicting its full implications. GenAI is so new, evolving and improving so quickly that its applications will only grow, and no one can really know the future. Therefore, the results of the existing studies presented in this report may cease to be valid with new AI discoveries in the future. Moreover, the levels of AI adoption are still quite limited even in advanced economies, despite the promises of the technology, and the empirical evidence from actual AI use in the workplaces is still limited. With new advances every day in the AI field, the future can still bring us surprises that current studies cannot predict. Still, a broader understanding of the AI building blocks can help us better grasp the enormous potential of this technology, as well as the challenges it brings in terms of transparency, ethics and accountability.

Policy responses to AI. The distribution of AI development power and the potential responses to AI developments from political, economic and social stakeholders are other factors for unpredictability in the future. AI-related developments will depend on the regulations introduced at national and international level and on whether the development of AI systems is centralised or decentralised. As the 2025 Human Development Report put it, *'trying to predict what will happen is self-defeating, privileging technology in a make-believe vacuum over the frictional realities and messier promises of people's agency and their choices'* (UNDP, 2025). Eventually, what access societies have to AI and how they view and use it will largely affect the results. These are choices, to be made by the few or the many, whose consequences will resonate across generations. Focus could be on the overlaps and pitting AI against people for productivity gains, or on complementarities and collaboration to envision new development pathways. No path forward is about technology in isolation, but rather how it is deployed – by whom, with whom, for whom – and with what kind of accountability (UNDP, 2025).

One of the first pioneers in the field of AI-related regulations is the ***EU Artificial Intelligence Act***, which formally adopted on 1 August 2024[11]. It is a landmark effort to harmonise rules on AI across the EU. By introducing a risk-based framework from 'unacceptable risk' and 'high-risk' to 'limited risk' and 'minimal risk', the act increases obligations on providers (developers) with regard to risk levels. Practices that may violate fundamental rights are considered an 'unacceptable risk' and prohibited, such as emotion recognition in the workplace and educational institutions, or biometric categorisation systems. There are eight areas of 'high risk' for AI practices, two of which are related to the topic of

[11] See EU Artificial Intelligence Act | Up-to-date developments and analyses of the EU AI Act.

this report: *'employment, worker management and access to self-employment'* and '*education and vocational training'.* High-risk systems are subject to conformity assessment related to data and data governance, documentation and record-keeping, transparency and information provision to users. Finally, limited-risk AI systems are subject to lighter transparency obligations, while minimal risk is not regulated but mentions having a code of conduct.

Therefore, the *EU AI Act* considers AI systems used in *employment, worker management and access to self-employment* to be in the high-risk category, as those systems may impact the future career prospects and livelihoods of the people concerned. This includes AI systems intended to be used for the recruitment or selection of natural persons, notably for advertising vacancies, screening or filtering applications, evaluating candidates during interviews or tests, making decisions on promotion and on the termination of work-related contractual relationships, task allocation, and monitoring and evaluating the performance and behaviour of these people. Such AI systems will have to follow conformity assessment procedures before they can be placed on the EU market. This includes requirements regarding the quality of the datasets used, technical documentation and record-keeping, transparency and information provision to users, human oversight, and robustness and accuracy.

Similarly, AI systems used in *education and vocational training* are in the high-risk category, especially if the purpose is to determine access or to assign natural persons to educational and vocational training institutions, to assess students in educational and vocational training institutions, or to assess participants in tests commonly required for admission to educational institutions. The EU AI Act marks a turning point for labour markets: employers and developers must not only ensure compliance with technical standards, but also uphold workers' fundamental rights, including privacy, non-discrimination and autonomy.

This goes hand-in-hand with the *EU's Digital Services Act (DSA)* that governs online services (e.g. marketplaces, social media networks, app stores, and online travel and accommodation platforms) and *General Data Protection Regulation (GDPR)* that empowers people to control their personal data while holding businesses accountable for how they collect, process and store that data[12]. Alongside these Regulations, European social partners signed a *Framework Agreement on Digitalisation* in 2020, while a Code of Practice for General-Purpose AI is currently being drafted[13]. Negotiated during the COVID-19 pandemic in June 2020, the Framework Agreement on Digitalisation signed by the European social partners[14] guides employers, workers and their representatives in steering digital transformation in the workplace. It covers the public and private sectors in all economic activities across the EU, and promotes a process to encourage the consensual integration of digital technologies.

This aligns with recent calls from the European Parliament and social partners for a directive on psychosocial risks, as well as the need to modernise the Occupational Safety and Health Directive by including the prevention of occupational psychosocial risks[15]. The European Economic and Social Committee (EESC) also adopted an Opinion in January 2025 to advocate for '*Pro-worker AI: levers for harnessing the potential and mitigating the risks of AI in connection with employment and labour market policies*'[16].

[12] See The Digital Services Act | Shaping Europe's digital future, and The general data protection regulation - Consilium.
[13] See Final 22 06 20_Agreement on Digitalisation 2020.pdf and Drawing-up a General-Purpose AI Code of Practice | Shaping Europe's digital future.
[14] European Trade Union Confederation (ETUC), BusinessEurope, SMEunited, and Services of General Interest Europe (SGI Europe).
[15] See European Parliament calls for a directive on psychosocial risks - Eurocadres; and the Opinion of EESC SOC/745-EESC-2023-01-01 at Precarious work and mental health | EESC.
[16] See the EESC Opinion SOC/803-EESC-2024 at Pro-worker AI: levers for harnessing the potential and mitigating the risks of AI in connection with employment and labour market policies | EESC.

Other EU policy responses relevant to future of work concerns include the *EU Directive 2024/2831 on improving working conditions in platform work*, the *Directive 2022/2041 on adequate minimum wages in the EU,* and the *Directive 2019/1152 on transparent and predictable working conditions in the EU*[17]*.* The Platform Work Directive aims to ensure that digital labour platforms comply with employment laws – particularly concerning the classification and rights of gig workers – although enforcement remains a challenge in cross-border digital markets. Recently, due to the spread of the algorithmic management of work practices, there is currently a discussion at the European Parliament about a potential '*general directive on AI in the workplace*'.

Embedding these regulatory principles into AI-driven workplace innovation will be critical to ensuring that technology augments human capabilities rather than undermining dignity and fairness at work. However, this discussion is far from over due to the concerns over their impact on European competitiveness, as the European Commission's new 'simplification' package included both the EU AI Act, DSA and GDPR in its list of several laws targeted for possible amendment.

[17] See Directive - EU - 2024/2831 - EN - EUR-Lex; Minimum wages in the EU | EUR-Lex and Transparent and predictable working conditions in the EU | EUR-Lex.

CHAPTER 2. REVIEW OF AI-DRIVEN BUSINESS RESTRUCTURING

This chapter provides an overview of the AI-driven restructuring initiatives and practices observed in the business world, before moving to an analysis of the impact that AI has on employment. The first section focuses on the use of AI technologies deployed in selected economic sectors that are the most exposed so far – such as ICT, manufacturing, finance, retail, transport and healthcare – which signals a structural transformation of existing business models. It is important to grasp the wide-ranging applications of AI, from product development to process innovation and operational efficiency, so that its impact on workforce dynamics can be better understood.

One key concept coming out of this AI-driven restructuring is the algorithmic management of work. First born in digital platforms, several companies have already started to use algorithmic management (AM) logic and tools in traditional work settings. The second section introduces what the algorithmic management of work means, and which AM tools are deployed by firms, before discussing its impact on the workforce. The different effects of using AM in operational work (work instructions, scheduling, task coordination and monitoring) versus in human resources management (HRM) must be noted. Hence, the third and final section focuses on firms' AI use in HRM (recruitment and selection, evaluation, promotion, termination, learning and development).

2.1. How does AI shape business operations?

Today AI systems and tools are used by many firms, shaping how they operate and create value and produce, sell and organise their operations. Cedefop's 2024 AI skills survey shows that about 28% of European adult workers are already using AI at their workplace (Cedefop 2025)[18]. The more recent AIM-WORK survey conducted in 2024–2025 confirm a third of EU workers using AI for work-related purposes (JRC, 2025b)[19]. AI-driven automation and data-informed decision-making are redefining traditional business functions by driving efficiency, precision and innovation across sectors. From streamlined manufacturing systems to hyper-personalised customer engagement strategies, AI has become integral to the operational core of the digital economy. Moreover, its influence on organisational structures – particularly through intelligent systems for decision support and resource optimisation – is contributing to strategic reconfigurations within firms.

Increasingly embedded in daily business operations, this shift marks more than just a technological update; it signals a structural transformation in business models, workforce dynamics, and the way in which organisations interact with customers. AI is not only enhancing internal processes; it is enabling entirely new forms of service delivery. In sectors ranging from manufacturing and healthcare to finance and retail, AI-powered systems are improving productivity, reducing operational costs, and helping firms make faster, more informed decisions. Companies are increasingly relying on predictive analytics, computer vision and natural language processing to gain insights, automate workflows and offer tailored experiences.

According to the OECD (2021b), based on AI-related job vacancies as a proxy for AI adoption in different industries, AI adoption has grown primarily in the following sectors: information and communication technology (ICT); professional, scientific and technical services; finance and insurance; administrative and support services; agriculture; management; mining, quarrying, and oil and gas extraction; education; public administration; wholesale and retail trade; and manufacturing. Industries are experiencing and responding to AI in different ways; for example, AI adoption in

[18] Cedefop surveyed a total of 5342 adult employees in February-May 2024 in 11 EU member states: Belgium, Czechia, Germany, Ireland, Greece, Spain, France, Luxembourg, Poland, Portugal, and Slovakia.
[19] The AIM-WORK survey (Analysis on Impacts of Artificial Intelligence and Algorithmic Management in the Workplace) by JRC and European Commission collected responses from 70,316 individuals aged 16–65 across all 27 EU Member States.

healthcare and transportation is slower. Box 2 provides a brief review of AI technologies deployed in these sectors.

Box 2: The use of AI technologies in selected sectors

ICT: AI is used in IT for software development, data analysis, cybersecurity, and managing IT infrastructure. It has enabled the development of smart applications that can understand, learn, predict, and potentially function autonomously. AI is also used to optimise IT and ICT infrastructure by providing automated network monitoring and optimisation, and predictive maintenance.

Manufacturing: Industrial robots and AI algorithms enable predictive maintenance, optimising equipment uptime and minimising production downtime. AI enhances quality control through computer vision and automates supply chain operations. Virtual replicas of physical production systems (digital twins) allow to simulate, monitor and optimise workflows, while collaborative robots (cobots) and autonomous systems support workers.

Finance: AI algorithms analyse financial data and make predictions to support investment decisions. It enables real-time fraud detection and algorithmic trading. Automated trading systems execute trades with minimal human intervention, while AI-powered chatbots and virtual assistants provide personalised financial advice and customer support.

Retail: Customer-facing sectors such as retail and digital services are leveraging AI for personalised product recommendations, dynamic pricing, autonomous checkout systems, AI-powered inventory management systems to optimise stock levels and reduce wastage, and 24/7 virtual assistance.

Healthcare: Deep learning is powering diagnostic tools that rival or exceed human accuracy and analyse medical data, supporting everything from radiology to personalised treatment planning. Chatbots and virtual assistants enhance patient engagement, while robotic surgery systems enable precise and minimally invasive procedures.

Transportation: AI enables autonomous vehicles for ride-sharing services, delivery logistics and public transportation. Advanced traffic management systems use AI to optimise traffic flow, reduce congestion and enhance safety.

Source: Authors' creation based on the collection of information from the internet and the sources cited in this chapter.

Within the EU, the wider use of AI tools in the financial services, industry, transport, other services, commerce and hospitality sectors is confirmed by Eurofound (2025b), based on the results of the European Working Conditions Survey (EWCS) in 2024. Moreover, the ICT sector is often taken for granted in terms of the development and implementation of AI systems and models. However, the survey shows that only 12% of workers in the EU report using AI tools in their job despite the considerable hype surrounding generative AI, albeit with a significant variation in use among the countries, ranging from 20% in some to less than 5% in others (Eurofound, 2025b).

According to Kanagarla (2024), sector-specific analysis in the US reveals varying degrees of AI penetration and impact. Manufacturing leads adoption with a 43% implementation rate, driven primarily by robotics and predictive maintenance systems, resulting in a 26% average productivity increase. Financial services follow closely with a 39% adoption rate, where AI systems now process 35% of all trading volume and 28% of customer service interactions. Retail sector transformation shows a 32% automation rate in backend operations, while customer-facing AI solutions have increased by 47% year-on-year. Healthcare shows the fastest growth in AI adoption (41% annual increase), particularly in medical imaging analysis, where AI systems achieve accuracy rates comparable to specialist physicians in specific diagnostic categories (Kanagarla, 2024). Table 1 provides a summary of the AI impact on five sectors in the US.

Table 1: Comprehensive AI impact analysis across sectors in the US (2020-2024)

Sector	Primary AI applications	Impact level	Workforce changes	Required skills	Implementation challenges	Adaptation strategies
Manufacturing	Robotics, predictive maintenance, quality control	High	Role restructuring, technical integration	IoT, data analytics, system control	Legacy systems, worker resistance	Phased training, hybrid teams
Financial services	Risk analysis, trading, customer service	High	Process automation, advisory focus	Algorithm understanding, risk management	Regulatory compliance, data security	Certification programmes, mentoring
Retail	Inventory management, customer analytics	High	Role evolution, digital integration	Digital commerce, data analysis	System integration, cost	Modular learning, practice labs
Healthcare	Diagnostics, patient monitoring, admin	Medium	Skills enhancement, task augmentation	Medical AI, patient care, digital health	Privacy concerns, integration	Specialist training, continuous learning
Professional services	Decision support, research, analysis	Medium	Knowledge augmentation, tool adoption	Advanced analytics, AI collaboration	Client acceptance, method change	Custom programs, case studies

Source: Taken from the article of Kanagarla, 2024.

In the production field, AI is automating complex manufacturing processes, optimising resource allocation and improving quality assurance. Technologies such as AI-powered robotics, machine vision and adaptive algorithms are now standard in industrial environments, where they enable higher productivity and lower operating costs. According to an OECD study (2023c), more than 60% of manufacturing companies that have adopted AI report measurable improvements in production efficiency, with 40% highlighting benefits in predictive maintenance and quality control.

Predictive maintenance is one of the most impactful applications. Unlike traditional maintenance practices based on fixed schedules, AI systems monitor sensor data and machine performance in real time to anticipate equipment failures. Siemens, for instance, has implemented predictive maintenance in its manufacturing operations, achieving a 30% reduction in maintenance costs and a 20% increase in equipment lifespan (Annanth et al., 2021). Another innovation shaping the production landscape is the use of *digital twins* – virtual replicas of physical production systems. These allow firms to simulate, monitor and optimise workflows without interrupting real-world operations. BMW and Rolls-Royce have successfully deployed digital twins to enhance production efficiency, reduce errors, and experiment with operational improvements (Forbes, 2023).

AI also plays an important role in transforming sales processes: *predictive analytics tools* allow enterprises to anticipate demand, with analytics matching production output to real-time consumer demands; to optimise inventory; and to personalise offerings to customers. Major retailers including Walmart and Tesco use AI models to forecast purchasing patterns, schedule restocking and adjust pricing strategies. These AI-enabled systems have enabled companies to reduce overstocking by 30% and prevent inventory shortages by 20% (WEF, 2023).

Customer engagement has also been revolutionised through *AI-based chatbots and virtual assistants.* These tools provide instant, personalised support and product recommendations, significantly improving user experience. H&M's AI chatbot suggests outfits based on browsing history and local weather data, while financial institutions such as HSBC and JPMorganChase use AI systems to manage customer service, detect fraud and automate basic financial advisory tasks. According to

OECD (2023b), the introduction of such systems has reduced workload for human agents by up to 40% while maintaining high levels of customer satisfaction.

Similarly, PayPal and Mastercard use AI to detect fraudulent activity through real-time transaction analysis, reducing financial risks. *AI-driven compliance monitoring systems* are also being employed to ensure adherence to financial regulations and data protection standards (Financial Times, 2023), contributing to improved regulatory oversight and organisational accountability. AI further contributes to organisational transformation by supporting strategic decision-making and enhancing operational models. AI-based analytics platforms allow organisations to assess market risks, forecast trends and optimise internal workflows. Tools such as Microsoft Power BI with Copilot and Salesforce Einstein GPT are increasingly being used to translate complex datasets into actionable business insights.

Agentic AI is the latest addition, with autonomy, goal-directed behaviour and adaptive decision-making. Operating independently and interacting dynamically with workers, it can initiate actions, plan long-term strategies, and self-improve over time (Acharya et al., 2025). As such, it serves as an intelligent virtual assistant, providing real-time insights and data-driven advice to support complex decision-making processes, effectively reducing workers' cognitive load. AI agents are gradually becoming digital teammates, but companies need to develop an operational playbook for integrating them into hybrid teams and a workforce strategy (Stave et al., 2025). Deloitte, for example, is in the process of applying AI agents to every work process. This involves mapping work tasks and outcomes and clarifying roles, protocols and hand-off points when responsibilities shift in a workflow from one party to another (e.g. deciding which tasks are for people and which are for AI) (Stave et al., 2025).

The functions performed by AI tools in workplace settings include execution of several knowledge tasks (including both routine and non-routine cognitive), varying from data-driven business intelligence and content creation and improvement by generative AI to enhanced communication and collaboration, executing organisational and coordination tasks through algorithmic management of work (AM), and the use of agentic AI as virtual assistants. These developments point to broader shifts in organisational design and management, the implications of which will be discussed in detail in the coming chapters. Besides the automation of tasks as the most visible AI application, firms increasingly rely on AI-enhanced business intelligence and data analytics to extract insights from large datasets, support strategic planning, and improve forecasting in areas such as finance, marketing and operations.

AI is now embedded in the *communication and collaboration infrastructures* that support hybrid and remote work. Platforms like Microsoft Teams, Copilot, Zoom and Google Workspace employ AI for transcription, real-time translation, engagement analysis and intelligent scheduling. Similarly, project management systems such as monday.com and Asana incorporate AI to optimise task allocation, monitor productivity and streamline coordination. AI-supported recruitment and human resource management remain less widespread and more context-dependent (Gulia & Rastogi, 2024). AI-powered systems, ranging from robotic process automation (RPA) to virtual assistants, are increasingly used for schedule management, data entry and standardised customer interactions (Sinha et al., 2023).

These examples of AI applications lead to significant changes in all three core business areas: *product development, process innovation* and *operational efficiency*. An analysis of global job postings seems to confirm these changes (see Box 3). AI has become more than a tool; it is a foundation for rethinking how businesses function. Whether through smarter logistics, faster diagnostics or more adaptive customer service, AI is redefining the rules of competition. As AI systems continue to evolve, the challenge for businesses will not be whether to adopt AI, but how to do so responsibly, ensuring transparency, inclusiveness and long-term sustainability in the digital economy.

Box 3: AI-driven changes in business

AI in product development. AI plays a critical role in developing new products by facilitating innovation in data science, robotics and computational fields. Occupations such as data scientists (73% of job postings requiring AI skills), robotics engineers (23%) and biostatisticians (18%) are at the forefront of AI-driven product development (Lightcast, 2024). AI applications in this cluster include deep learning for predictive modelling, generative AI for design automation, and neural networks for complex problem-solving. The Lightcast study (2024) finds that AI-enabled computer vision and automated decision-making are central to the development of autonomous systems, particularly in industries like automotive engineering and pharmaceuticals.

AI in process innovation. AI is reshaping work processes by automating decision-making, optimising workflows and enhancing efficiency in managerial roles. This cluster includes positions like operations managers, HR managers and environmental engineers, where AI assists in workflow automation, AI-powered recruitment, and sustainability modelling. AI is particularly useful in financial forecasting, HR analytics and fraud detection, helping businesses optimise decision-making. Technologies such as natural language processing and machine learning-driven analytics are widely used to process large datasets and automate administrative functions.

AI in operational efficiency. AI improves existing processes by enhancing efficiency and reducing operational costs in logistics, administration and customer service. Occupations like CAD designers, office managers and budget analysts utilise AI for predictive maintenance, automated scheduling and intelligent customer support. Robotic process automation and AI-powered performance tracking tools are widely used to improve supply chain management and operational planning. AI's impact on workplace management is particularly evident in its application to employee monitoring systems and automated reporting tools, which streamline routine administrative tasks.

Source: Lightcast, 2024.

All these AI functions in the workplace are poised to significantly transform employee roles and responsibilities in the workplace, but significant concerns about AI's reliability and quality persist. Overall, the successful deployment of AI requires substantial investment in infrastructure, employee training, and organisational change. Small and medium-sized enterprises may not be able to afford these investments. Additionally, the lack of clear legal frameworks around AI governance and liability adds another layer of complexity to its integration into existing business models. In particular, concerns over data breaches and unauthorised access prevent the widespread use of AI on large volumes of personal and corporate data. Ensuring compliance with data protection regulations and having robust cybersecurity measures in place are essential to mitigate these risks.

For example, the digital transformation in the automotive industry has introduced significant challenges concerning data privacy and cybersecurity, particularly as vehicles generate and share vast amounts of personal and operational data (OECD, 2017). The integration of AI technologies in connected cars raises critical concerns about the secure collection, processing and transmission of sensitive information. Evidence from real-world applications, such as connected infotainment systems and on-board diagnostic tools, highlights vulnerabilities inherent in the pooling of personal data. While digitisation unlocks new revenue streams and efficiency gains, it simultaneously exposes sectors to an enhanced risk of unauthorised access and data breaches. These challenges underscore the imperative for data privacy, robust cybersecurity and comprehensive regulatory frameworks.

AI adoption also intersects with other structural changes in organisations: AI is used not only for redesigning operational processes, but also for administrative support functions, mainly thorough the increasing use of the *algorithmic management of work* in the workplace. Following Nurski's categories, the types of decisions and activities by algorithmic management in organisations can be divided between their *production function* and their *governance function* (Nurski, 2024). Algorithms can be used in operational activities for work instructions, scheduling, task coordination and monitoring – referred to as *algorithmic operational management* by Nurski. Examples include just-in-time scheduling based on historical patterns and real-time data or allocating rides to drivers on online platforms such as Uber (see Section 2.2). Meanwhile, using AI to support human resources management (HRM) processes is known as *algorithmic HR management* (Nurski, 2024), including recruitment and selection, evaluation, promotion, termination, learning and development (see 2.3. AI use in human resources management).

2.2. Algorithmic management of work

Algorithmic management (AM) can be defined as the use of software algorithms to automate organisational functions traditionally carried out by human managers; as a result, computer-programmed codes and procedures coordinate labour inputs and outputs in an organisation (OECD, 2025; ILO, 2022)[20]. While it is relatively new, its underlying mechanisms appear to be a continuation of long historical trends of the rationalisation and bureaucratisation of economic activity and the organisation of work. Indeed, bureaucracy and scientific management have been historical precedents of algorithmic management, well before the digital revolution. The key assumption in all these cases is that decisions are based on an 'impersonal rule-based system guided by data analysis' (ILO, 2022).

AM relies heavily on the use of digital technologies and data, leading to the further standardisation and rationalisation of tasks. As technological developments have increasingly extended the scope for collecting and processing input data through cameras, sensors, audio devices, biometrics and text, so too have the potential economic advantages of algorithmic decision-making. A diverse set of technological tools and techniques are used to remotely manage workforces, relying on data collection and surveillance of workers to enable automated or semi-automated decision-making. This algorithmic management has entailed human jobs being assigned, optimised and evaluated through algorithms.

The use of software algorithms to automate the organisational functions of human managers are identified in both platform work and conventional employment settings. Since its emergence in platform work, it has transformed work organisation, where AI systems now oversee, allocate and evaluate work. At present, it is mainly confined to the reshaping of organisational control through the *automation of direction* (what needs to be done, in what order and time period, and with different degrees of accuracy); *evaluation* (reviewing workers' activities to correct mistakes, assess performance and identify those who are not performing adequately); and *discipline* (sanctioning and rewarding workers in order to elicit cooperation and enforce compliance) (JRC, 2021b). According to the JRC, differentiating algorithmic management from algorithmic assistance is important especially in traditional sectors, as it may involve partial, conditional, high or full automation.

Given the definition of AI as a system that autonomously generates cognitive outputs and decisions, AM means applying AI to a particular set of decisions within organisations. The types of decisions and activities by algorithmic management in organisations can be related to the *production function* or *governance function* (Nurski, 2024). Three elements remain essential for AM to be widely used in any economic organisation: (i) the data about the workers and/or the work process to feed the algorithms; (ii) processing and drawing up this data through the algorithms; and (iii) the coordination and control exerted on workers through the management decisions made or supported by the previous two elements (ILO, 2022). This is why digital technologies are increasingly being introduced in workplaces through cameras and wearables that can continuously monitor workers, their interactions and movements to provide data for management decisions (so-called 'datafication of the workplace').

Unlike traditional managerial oversight, AM often replaces human judgement with an automated decision-making process. While these systems offer operational efficiency and real-time responsiveness, they also introduce new challenges related to transparency, fairness and worker autonomy. Questions remain about who bears responsibility for flawed credit decisions or incorrect medical diagnoses based on the AI systems trained on historically biased datasets. In traditional sectors, AM is used most significantly in logistics and warehouse operations, but also to a lesser degree in retail, manufacturing, marketing, consultancy, banking, hotels and call centres, and among journalists, lawyers and the police (JRC, 2021b). As AM monitors productivity, coordinates tasks and optimises workflows in logistics, handheld and wearable devices are used to produce metrics on

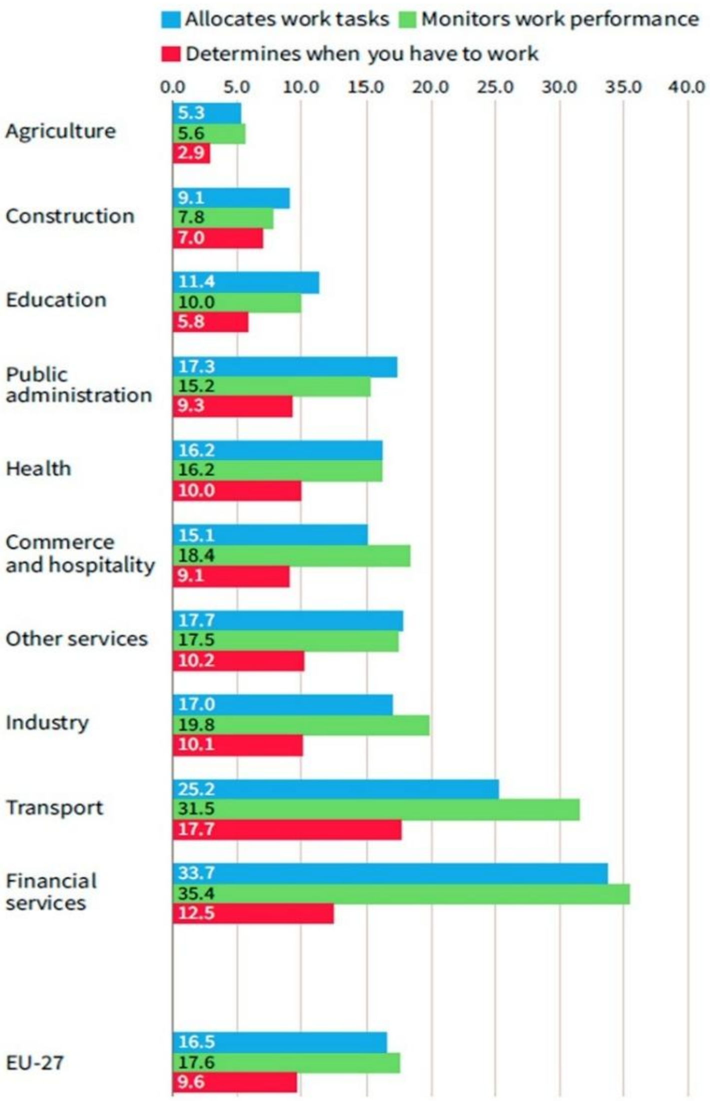
[20] There are two components in this definition: an 'algorithm', which is a set of predefined rules to be followed in sequence to solve a problem, and 'management', which is a set of tasks necessary for the administration of an organisation (planning, staffing, commanding, coordinating and controlling) (ILO, 2022).

productivity (i.e. the collection of products, or ‘pick rate’) and to create rankings of worker performance. Amazon’s fulfilment centres use machine learning models to monitor worker pace, flag inefficiencies, and suggest performance improvements (Delfanti & Frey, 2021).

Technologies such as ‘voice-picking’ systems guide workers through order retrieval based on real-time algorithmic calculations that optimise speed and route efficiency. Customer service operations also rely heavily on AI-driven monitoring systems. These tools assess call duration, speech patterns and sentiment to inform employee performance metrics and recommend automated responses. AI is used to detect frequently asked questions, track tone and engagement levels, and optimise workflow distribution. However, such practices can intensify surveillance and performance pressure, diminish autonomy and contribute to stress and burnout (Mateescu & Nguyen, 2019). In professional sectors such as finance and healthcare, AI-assisted decision-making is becoming increasingly prevalent. Banks apply AI algorithms for credit risk assessment, while hospitals use diagnostic tools to support clinicians in predicting patient outcomes and treatment options.

According to the findings of the EWCS in 2024, some 17% of workers in the EU report that a computer program monitors their work performance to a large or some extent, while 16% report that a computer program is used to allocate their work tasks (Eurofound, 2025b). As **Error! Not a valid bookmark self-reference.** shows, the use of a computer program to a large or some extent for work task allocation and performance monitoring is most prevalent in financial services, at 34% and 35% respectively, whereas the automated scheduling of work is most common in the transport sector (18%). This is also a sector with a higher-than-average proportion of workers reporting automated task allocation and performance monitoring to a large or some extent (Eurofound, 2025b). The more recent AIM-WORK survey conducted in 2024–2025 confirms that algorithms determine the workflow or task prioritisation at work for 24% of EU workers (JRC, 2025b).

Figure 3: Use of AM forms to a large or some extent, by sector, EU (%)



Source: Taken from Eurofound 2025b, p. 22.

In another recent survey of employers, the OECD (2025) found that AM is widely used in many traditional economic sectors in member countries[21]. Compared to the responses of workers in Eurofound's survey above, the employers here report a much higher use of these tools. 'AM tools are widespread in the USA (adoption rate of 90%) and in the European countries surveyed (average of 79%), but less prevalent in Japan (40%). The intensity with which AM tools are used varies across countries. Use tends to be intensive in the USA, with more than three-quarters of firms using ten or more of the 15 tool categories. In contrast, intensity of use is moderate in Europe (using three to five tools) and low in Japan (using only one tool). The USA firms commonly use tools of all types, including monitoring tools (e.g. software to monitor the speed of work) and evaluation tools (90%), while European firms often use instruction (adoption rate of 69%) and basic monitoring tools (33%) (e.g. software to track working time)'[22].

In the view of managers, AM improves the quality of their own decision-making (60% of managers), which is driven by increases in the information available to managers to make decisions, increases in

[21] This is a survey of 6 000 mid-level managers across six countries (France, Germany, Italy, Japan, Spain and the United States) in 2024 on managers' perceptions of algorithmic management tools used to manage workers, covering tools to instruct workers, tools to monitor workers, and tools to evaluate workers (OECD, 2025).
[22] According to this survey, In the US, 55% of firms monitor the content and tone of conversations, voice calls and emails. This compares to only 6% in Europe and 8% in Japan (OECD, 2025).

the speed of decision-making, and increases in the autonomy of managers to make decisions (OECD, 2025). Managers are also more likely to report that AM improves their job satisfaction than that it decreases it. Increases in managers' job satisfaction are driven by reductions in stress and repetitive work, which may also benefit workers through greater consistency and objectivity of decisions. However, managers are undecided on the decreased human bias from managerial decisions. While managers in the US believe that AM has brought about a decrease in decision bias, managers in Europe and Japan are more likely to believe that there is no effect or increased bias (OECD, 2025).

Moreover, nearly two thirds of managers have at least one concern regarding the trustworthiness of the AM tools they use. The most reported concern is unclear accountability for wrong decisions (28% of managers), followed by an inability to follow the logic of algorithmic decisions or recommendations (27%) and inadequate protection of workers' physical and mental health (27%) (OECD, 2025). It is important to emphasise that the adoption of AM tools requires some organisational choices that are shaped by socio-institutional factors. These new practices must often be implemented over pre-existing work organisation structures and processes. As such, the principles guiding the decisions (algorithms) are set by higher management and are *always political rather than technical* (ILO, 2022).

As algorithms are central to the functioning of digital labour platforms, it is not surprising to see AM first developed in this sector and that it is the most widely used sector in which new entities incorporate it for all key management functions: planning, staffing, commanding, coordinating and controlling. Other precedents of AM can be found in IT firms, business process outsourcing companies and call centres. Platforms such as Uber and Upwork govern nearly every aspect of the employment relationship, from assigning tasks, through determining compensation, to monitoring performance (see Box 4).

Box 4: Platform work and AI-driven matching algorithms

Platform work refers to labour mediated through digital platforms such as Upwork, Uber, Fiverr, Deliveroo and Amazon Mechanical Turk, where workers connect with clients or customers for short-term, project-based tasks or on-demand jobs. These platforms operate in various sectors, including ride-hailing, the delivery of goods, freelance services and micro-tasking. While these systems offer efficiency and scalability, they often introduce unpredictability and opacity into the employment relationship. Workers frequently report having little insight into how algorithms determine their task availability, wages or performance status, leaving them vulnerable to automated decisions without recourse.

AI algorithms play a central role in optimising worker-task connections by analysing vast datasets to predict the best match between jobseekers and tasks. These algorithms consider factors such as skill sets, experience, customer ratings, geolocation, availability, past activity, real-time demand and customer preferences. The key AI approaches in matching workers with tasks in platform work are the following:

- *Reinforcement learning:* AI adapts over time based on feedback loops from completed tasks, improving the accuracy of job recommendations.
- *Collaborative filtering:* used in platforms such as Upwork, this technique suggests jobs or freelancers based on similarities with past hiring patterns.
- *Dynamic pricing algorithms:* Uber employs surge pricing models that adjust fares based on real-time demand, optimising driver allocation.
- *Natural language processing:* AI interprets job descriptions and freelancer profiles to facilitate precise skill-based matching.
- *Geospatial analysis:* ride-hailing platforms such as Uber use AI to predict demand hotspots and direct drivers accordingly.

The JRC (2022) argues that AM considerably increases organisations' ability to control complex economic and work processes, as they benefit from AM's massive capacity to collect, store and process information from digital technologies. These technological developments are combined and used in AM for reorganising control and reshaping power balances in the workplace. Therefore, its use enables knowledge and control to be centralised, while also redefining workers' roles and tasks and blurring the organisational boundaries (JRC, 2022). While its use can bring some potential benefits to workers, such as increased consistency and more objective managerial decision-making, evidence also documents increasing work intensity, stress brought on by digital surveillance, and doubts regarding the quality of automated decisions (JRC, 2022). The effects of AM's use on working conditions and inclusiveness in the workplace will be discussed in more detail in CHAPTER 3: THE IMPACT OF AI ON JOBS and CHAPTER 4. THE IMPACT Of AI ON EQUALITY AND INCLUSIVENESS

2.3. AI use in human resources management

The functions of human resource management (HRM) have changed radically in the past 20 years due to market and technological forces, often becoming more cross-functional and data-driven. According to Fenwick et al. (2024), HRM practices can be grouped into three specific bundles: people management, culture, and compliance. People-related functions encompass talent acquisition, development and management, focusing on the workforce's growth and well-being. Compliance-related functions revolve around adhering to legal and ethical standards, ensuring that organisations operate within regulatory boundaries, and maintaining fairness and equity. Culture-related functions concentrate on shaping organisational culture, fostering collaboration, and promoting values and behaviours that align with the firm's mission.

AI further transforms these HRM functions. Currently, AI-based tools are used in HR planning, selection and recruitment, training and development, performance monitoring and evaluation, promotion and termination, and influencing employee attitudes (e.g. engagement, work satisfaction, employee retention) (Fenwick et al., 2024; Nurski, 2024). In addition, AI-powered job matching platforms are becoming quite visible and widely used. These platforms do not merely filter applicants by education or job title; instead, they use more nuanced parameters to assess skills, experience, and even inferred capabilities, offering a more dynamic match between jobseeker potential and employer demand (S4YE, 2023). A study estimated that the information currently used by e-recruitment recommender systems comes from CVs and job posts (43%), social networks (38%), behaviour or feedback (13%), and other types of online information (6%) (OECD, 2023a).

The increasing use of AI in HRM is facilitated by new applications. In 2020, 28% of US employers were using data science tools to 'replace line manager duties in assigning tasks and managing performance, and 39% were planning to start doing so the following year' (Cappelli & Rogovsky, 2023). Several private companies have partnered with technology start-ups to use cutting-edge technologies to improve their recruitment processes. Automated tools can now screen CVs, rank candidates and conduct interviews through chatbots. For example, companies such as Unilever and J.P. Morgan are using the games-based platform Pymetrics to hire entry-level employees using neuroscience-based games to measure inherent traits (S4YE, 2023)[23]. AI tools embedded in platforms such as *LinkedIn* and *Indeed* help employers articulate skills needs more precisely and suggest tailored opportunities to jobseekers.

This not only saves time for HR professionals but also improves scalability in large organisations. At the early stage, AI tools can enhance job description parsing and skills extraction, allowing for more accurate identification of core requirements and better alignment between job postings and candidate profiles. During the recruitment phase, algorithms are used for CV screening, candidate ranking and interview scheduling, increasing efficiency while aiming to reduce human bias – though concerns about fairness and transparency persist. AI-powered career guidance systems and personalised job recommendations support jobseekers by identifying suitable roles based on competencies, aspirations and experience, while employer-side tools help detect hidden skills and optimise job design.

[23] Pymetrics has developed a gamified assessment tool that collects cognitive and behavioural data to enable companies to assess the soft skills of job candidates. It consists of 25 minutes of behavioural exercises that assess candidates' decision-making, generosity, learning, quantitative reasoning, effort, fairness, attention, numerical agility, focus, risk tolerance and emotion (S4YE 2023; OECD 2023a).

According to Ferrazzi (2025), AI agents designed to streamline HRM processes are increasingly integrated in several big firms. For example, Workday's 'Recruiting Agent' and Mantrika's AI-driven platform proactively source passive candidates, automate outreach, and recommend top talent for open roles. Eightfold's talent intelligence platform analyses vast datasets to infer skills that may not be explicitly listed on a candidate's CV. LinkedIn's AI-powered recruitment tool helps companies identify high-potential candidates, reportedly reducing hiring time by 50%[24]. Once hired, AI also provides support to ensure seamless onboarding for new hires, such as pre-start immersive experiences, onboarding scheduling, new hire paperwork, virtual AI-generated mentors, new hire engagement, AI-driven people introductions, performance prediction and adaptive learning (Ferrazzi, 2025).

Social networks give easy access to an infinite amount of talent around the world and allow direct communication with them in an informal way. Allal-Cherif et al. (2021) call this growing phenomenon 'e-recruitment', which starts by identifying candidates on social networks, continues through gamifying recruitment and job interviews with chatbots, and ends by matching a candidate with a job using AI[25]. At the same time, a survey found that more than half of companies review candidates' social media activity in the recruitment process, mainly for the background check and discrepancies with CVs, but also to assess professionalism and connections (Henderson, 2019). This means that candidates need to avoid inappropriate behaviour on social media (e.g. unprofessional photos, discriminatory posts, sexual comments, drug/alcohol abuse) and ensure consistency between CVs and social media profiles.

AI-supported employee well-being and professional development are also growing (Cramarenco et al., 2023). Personalised learning platforms, adaptive training systems and well-being monitoring tools are being deployed in selected innovation-driven firms to promote workforce resilience and continuous skill development. Companies such as IBM and Accenture have invested in AI-based training platforms to support workforce reskilling through personalised learning paths[26]. In a rapidly evolving digital landscape, supporting employee growth and well-being is becoming a strategic necessity. However, adoption remains limited due to ethical concerns, particularly around the monitoring of employee behaviour and the potential misuse of sensitive personal data. Additionally, regulatory uncertainty around the use of AI in mental health and performance tracking continues to discourage widespread deployment. Nonetheless, this domain holds considerable promise, especially for large organisations aiming to integrate upskilling into internal mobility and retention strategies.

Recent Lightcast research found that the demand for AI skills in HRM has grown by 66% year-on-year, which is one of the fastest growth rates in any sector (Lightcast, 2025). While only 2% of HR job postings explicitly require AI skills, that demand is heavily concentrated in frontline roles such as talent acquisition and training specialists. In talent acquisition and recruitment roles, 3.9% of job postings now require AI skills due to the process-driven, repetitive and data-intensive nature of this job. Recruiters are using machine learning to rank candidates, AI chatbots to answer applicant questions, and GenAI to draft custom job postings in seconds. For HR departments managing hundreds of CVs, AI adoption significantly increases productivity while ensuring consistency and quality in execution.

Training and development roles also embrace AI (1.9% of job postings mention AI skills). They use generative AI to create course outlines, learning activities and assessments tailored to different roles and skill levels. They are beginning to leverage adaptive learning systems that use AI to adjust and personalise training in real time, ensuring that employees stay engaged and develop relevant skills. Traditional HR roles such as compensation and benefits analysts (1%) and HR assistants (0.9%) show much slower adoption, as these positions still rely heavily on human judgement, relationship-building and organisational context (Lightcast, 2025). HR professions require knowledge where AI adds value across the employee life cycle, and technical skills and ethics to use it in practice fairly,

[24] https://www.thetimes.com/business-money/companies/article/how-linkedins-ai-hiring-assistant-finds-candidates-for-jobs-xh0gb8wvl.
[25] Their study analysed the combination of several technologies dedicated to recruitment: (1) a social network with LinkedIn; (2) a massive open online course (MOOC) with Udacity; (3) a serious game called *Reveal* from L'Oréal; (4) a chatbot called *Ari* from TextRecruit; and (5) a massive data analysis matching system with Randstad.tech (Allal-Cherif et al., 2021).
[26] See https://skillsbuild.org/.

inclusively and transparently. This involves understanding data privacy, spotting potential bias in outputs, and consistently applying human oversight in sensitive decisions.

Despite AI's efficiency gains for firms, increased automation in HRM tends to cause more stress and anxiety in the workplace, among other psychosocial risks. Thus, HR departments face new pressures such as recruitment bias, fear of job loss, ineffective human trust in machines, managers' incomplete understanding of AI systems and their impact on employee outcomes, and a lack of human consideration in AI decision-making (Fenwick et al., 2024). Thus, the promise of enhanced efficiency and reduced hiring bias is tempered by the perceived risks of algorithmic discrimination, lack of transparency, and non-compliance with data protection regulations. Trust in AI systems within HR functions remains limited, and the ethical sensitivity surrounding employment decisions poses a significant barrier to full automation (Gulia & Rastogi, 2024).

CHAPTER 3: THE IMPACT OF AI ON JOBS AND WORKING CONDITIONS

AI is now embedded in everyday work – sometimes visible, often invisible – reshaping what jobs exist, who performs them and how they are valued. Due to AI's ability to perform non-routine cognitive tasks, the jobs most exposed to AI are *white-collar occupations* that require tertiary education (OECD, 2024a, 2024b). These occupations are generally more cognitive, less physical and less social. They face the most disruption so far, with both opportunities and risks. As AI systems become increasingly adept at replicating and augmenting human tasks, the impact of AI is going beyond simple automation, leading to the redefinition of the whole work process and employment relations.

The first section of this chapter starts with a brief introduction of an analytical framework for potential AI effects in organisations, as proposed by Nurski (2024), and reviews analytical approaches used in the literature to estimate automation trends and measure AI's employment effects. Though some studies use broader frameworks combining different vectors of change, such as automation, digitisation and platformisation (JRC, 2025a), this report focuses on the use of a *task-based framework* to analyse AI effects (including automation), a widely used method by researchers. This section also introduces concepts used in the literature to categorise AI's impact on jobs: job displacement, job creation and job transformation and/or augmentation.

To keep the discussion focused on the workplace setting, this report follows three categories used by the OECD in terms of AI's impact on labour markets: job quantity, job quality, and inclusiveness (OECD, 2023e). The second section provides a comprehensive literature review of AI's impact on job quantity. Job quantity points to the number of jobs displaced or created because of AI, covering the labour market situation in terms of unemployment, working time and labour force participation. The review presents the results of different studies on the number of jobs by sector, occupation and skill.

After this, the third section reviews the literature regarding AI's impact on the quality of jobs. Job quality refers to working conditions that have changed due to AI, including the quality of the working environment, earnings and job security (OECD, 2023e). The findings from existing studies on changing working conditions are presented by sector, occupation and skill. Finally, the chapter ends with a short summary of key findings regarding the quantity and quality of jobs, while inclusiveness is covered in CHAPTER 4. THE IMPACT Of AI ON EQUALITY AND INCLUSIVENESS.

3.1. How to measure and classify AI's effects on work

There are different methods and data sources to measure AI's employment effects, e.g. case studies, representative firm- or worker-level surveys, administrative data, web-based big data. Measurement often starts with analysing 'individual jobs' that are made up by a set of tasks and decisions – the result of a division of labour within an organisation (Nurski & Hoffmann, 2022). According to Nurski and Hoffmann (2022), in every organisation there are both production and governance activities. While production activities contribute directly to transforming an input to an output, governance includes preparation (planning, staffing), coordination (communication, monitoring, resolving disputes) and support activities (logistics, maintenance). 'The division of labour across these production and governance activities results in an organisational structure made up of a horizontal production structure and a vertical governance structure' (Nurski & Hoffmann, 2022).

The effects of AI can be felt in both production and governance processes (see Table 2). While *AI's use in the production process* often leads to changes in job tasks (e.g. automation and/or augmentation), affecting the quantity of work and division of labour, *AI's use in governance processes* has more implications on the quality of work and equality/inclusion, especially through the use of algorithmic management tools. In the governance process, algorithmic management could be used in operational work (e.g. work instructions, scheduling, coordination, monitoring) or in human resources management (e.g. recruitment and selection; evaluation, promotion and termination; learning and development) (Nurski, 2024). Each has different implications: while the former directly impacts the quality of work, the latter may determine accessibility and equality at work.

Table 2: Potential effects of AI in an organisation with production and governance activities

AI in the production process	→Task automation and/or augmentation	→Quantity of work
	→New division of labour	→Division of work
AI in the governance process	→Algorithmic (operational) management (work instructions, scheduling, coordination, monitoring)	→Quality of work
	→Algorithmic HR management (recruitment and selection; evaluation, promotion and termination; learning and development)	→Discrimination and inclusion

Source: Taken from Laura Nurski's presentation at the ETF IAG Workshop on 14 May 2025 in Turin (based on Nurski & Hoffmann, 2022; Nurski, 2024).

AI in the production process, particularly the impact of automation technology on jobs, has been the most widely discussed topic in the literature. The main question is *whether AI will substitute or complement humans in jobs*. Much of the modern labour market analysis relies on job tasks, which describe what people do at work and how they work. The task content of work acts as a determinant of labour market outcomes, often classified as routine versus non-routine, but also as cognitive versus manual dimensions in the literature. A large body of literature aims to measure the *theoretical exposure of occupations to AI,* estimating the *potential* employment impact by occupation, sector or country.[27] To identify the substitution or complementarity effect, researchers take as a unit of analysis a whole *occupation*, the *tasks* within an occupation, or the *abilities* necessary to pursue an occupation. This is referred to as the task-based or ability-based approach.

Based on Frey and Osborne's study (2017), the task-based approach is widely used to assess how occupations are exposed to technology and automation. It involves mapping current technologies' capabilities against occupational task profiles to generate exposure scores. Each task is scored according to its susceptibility to change, and these scores are then aggregated to estimate the overall exposure of an occupation or sector. Typically, scores do not account for variation within occupations across sectors, assuming fixed job profiles. In matching technologies with job tasks, it relies on both quantitative data and qualitative insights to assign accurate task scores. These insights often come from experts, workers or crowdsourcing, providing a crucial context for the nature of tasks – including how routine, social or context-dependent they are – and how organisational factors might influence their susceptibility to change. This combination of quantitative scoring and qualitative input provides a more nuanced understanding of how work is likely to evolve (Nurski & Monaco, 2025, p. 5).

Several studies have measured the impact of AI by focusing on tasks or abilities within occupations (Felten et al., 2021; Acemoglu et al., 2022; ILO ,2023; Eloundou et al., 2023; OECD, 2023b; IMF, 2024; EY-Parthenon, 2024).[28] As explained by Nurski and Ruer (2024), researchers may choose different sources for *occupational information* (e.g. job description databases such as O*NET or ISCO, worker surveys, or job vacancies like OJVs); and for *technological innovation* (e.g. patent texts, technological performance benchmarks or judgements by experts, crowds or algorithms) in their analyses.[29] The sources for technological advancement and occupational characteristics can be linked and compared in several ways too, e.g. using natural language processing for patent texts, or judgements by experts, or using algorithms in other cases (Nurski & Ruer, 2024). Some studies

[27] 'Exposure' is defined by most authors as the potential for time savings when using an AI tool, or the overlap between AI abilities and human abilities required in an occupation. Thus, exposure includes both automation (speed or quality increases) and augmentation (Eurofound, 2025c, p .47).
[28] For example, while the ILO (2023) used the ISCO classification in the task-based approach, Felten et al. (2023) used 52 work-based abilities from the O*NET database.
[29] O*NET is the most widely used data source (more than ISCO or ESCO) in the task analyses, because it includes the combination of generic and specific task statements from the surveys of experts and samples of workers in each occupation, which enables researchers to classify occupations in terms of broad task characteristics – the frequency and complexity of routine, cognitive and manual tasks (Eurofound, 2025c).

estimate general exposure, while others distinguish between automation and augmentation. Most studies compute scores at task level and aggregate them into occupation-level scores using weighted averages based on task importance (Eurofound, 2025c).

As a result, the findings of this automation estimate sometimes vary, although the main direction is often the same and the differences are not significant. While early studies emphasised that practically all occupations would be exposed to AI technology, later more refined studies showed a higher exposure in high-skilled occupations (Eurofound, 2025c). These called for more empirical studies as well, which have increasingly emerged. Examples are experimental studies with treatment and control groups (workers with AI support versus workers without AI support) or empirical surveys with actual companies sometime after their AI adoption. There was also more refinement in the task-based approaches. For example, the theoretical task framework developed and implemented by Eurofound and the JRC included not only tasks describing the content of work (manual, cognitive and social tasks), but also the methods of work (routine and autonomy) and the tools of work (machines or digital) in their analytical framework. As a result, they developed six task indices – manual, cognitive, social (communication), digital tools, autonomy and routine – for analysis (see Eurofound, 2025a; JRC, 2025a).

The task-based approach has some limitations. It often treats tasks as isolated units, overlooking how changes reshape broader work processes and organisational dynamics. 'It is insufficient to assess overall AI's impact on work' (Nurski, 2024). The conceptual distinction between automation and augmentation is not clear-cut at task level, since a task can often be split into smaller subtasks. Each occupation may include considerable differences in a job task bundle, and occupational dictionaries such as O*NET, with task descriptions, oversimplify the reality. Translating complex realities into numbers can create a false sense of precision and certainty, masking assumptions and inherent uncertainty, while they often imply that the future is fixed, rather than shaped by social and political choices. Moreover, the interdependence between the limits on how far a task can be automated until the point of coordination across tasks is reconsidered[30]. The existence of task differences within the same occupation proves that task bundling is not a fixed or deterministic feature of the labour market. Instead, it is the result of choices made by organisations, departments and teams.

A good example of these differences in task bundles can be found in the recent Eurofound research based on the *2022 EU labour force survey (LFS)* module on 'job skills' (Eurofound, 2025a)[31]. The findings confirm a wide variation of tasks and the way in which they are performed, even in the same occupation, across countries, sectors, firm sizes and gender. For example, in the case of office clerks (ISCO 411), cognitive tasks such as reading are performed by almost 61% of clerks in Austria, compared to 6% in Greece. The most notable difference concerns the use of digital devices and the degree of autonomy. Around 95% of office clerks in Spain, Austria and Sweden say that they use digital devices at least half of their working time, while only 61% of clerks say the same in Greece and Romania (Eurofound 2025a, p. 15). Autonomy levels of clerks are highest in Luxembourg, where around 40% have a high level of control over the content of their tasks, whereas fewer than 4% of their Greek and Cypriot counterparts say the same (Eurofound, 2025a, p. 15). This is striking evidence of large variations in task profiles and skill utilisation in the same job across different countries.

Another example is on digital tasks: Sweden has the second-highest digital task index and Romania the lowest in the EU. This is because Sweden has a proportionally larger share of digitally intensive occupations than Romania does. For example, ISCO 251 (software and applications developers and analysts) accounts for 5.1% of workers in Sweden and 1.2% in Romania. This means that even occupations that normally have fewer digital tasks, such as nurses, are more likely to use digital devices in Sweden than in Romania. In Sweden, 60% of nurses (ISCO 222) say they use digital devices at least half of their working time, while in Romania only 12% do (Eurofound, 2025a, p. 16).

[30] Accordingly, tasks are interdependent parts of larger processes, which requires coordinating the actions of the people executing them. Tasks can be interdependent across time, methods and resources. Therefore, organisations create coordination mechanisms for interdependent tasks handled by multiple workers and units –the so-called *governance process* as opposed to the *production process* (Nurski, 2024).

[31] This extra module on job skills includes responses from over 440 000 people from across the EU, which simultaneously measured task content, methods and tools on a large scale at EU level for the first time.

Whether clerks or nurses use digital devices does not necessarily depend on their skills, but rather on whether their firms integrate digital devices into their work. Likewise, national differences in institutions and culture can affect forms of work organisation, which results in workers experiencing different levels of autonomy or routine across Member States (Eurofound, 2025a, p. 18).

A proactive approach to task-based analysis is Singapore's *Guide to Job Redesign in the Age of AI,* a task-based method to support the reorganisation of jobs and career paths[32]. It goes beyond analysis and emphasises redesigning jobs not just to meet business needs, but also to enhance the value of employees' contributions and to maintain trust in the workplace. At the heart of the approach is a task-based analysis that helps identify how AI can be used effectively while preserving the human elements of work. The guide proposes a six-step approach: (i) breaking down jobs into tasks; (ii) assessing how AI might affect each task; (iii) deciding whether and to what extent AI should be used; (iv) gathering input from managers and staff on which tasks they value most; (v) setting timelines for implementation; and (vi) reassembling the tasks into redesigned job profiles (Nurski & Monaco, 2025, p. 7).

The results of AI's impact on jobs from the literature can be grouped into three broad categories: (i) *job displacement*, where AI fully performs tasks that were previously performed by humans in a given occupation (full automation); (ii) *job creation*, where AI creates completely new jobs that did not previously exist; and (iii) *job transformation*, where AI alters how work is performed and reorganises tasks if it has both automatable and non-automatable tasks (JRC, 2018; ECB, 2023). Under the category of job transformation, the term most often mentioned is *'job augmentation'*, which points to increased productivity and reduced cognitive load for workers, where AI partially performs tasks in such a way that it effectively enhances human capabilities through human-machine collaboration (WEF, 2024; OECD, 2022; Hampole et al., 2025). Less mentioned terms are *job upgrading*, which occurs when AI creates more complex tasks to be performed by workers with higher skills use, and *job downgrading*, when AI standardises or simplifies complex tasks to be performed by workers with lower skills use (Eurofound, 2024, 2025a).

The AI-induced *job displacement* is widely discussed as AI introduces powerful tools for a new wave of automation – including machine learning, natural language processing and robotics – that are capable of replicating cognitive and manual tasks previously thought to be uniquely human skills. The McKinsey Global Institute (2017) estimated that by 2030, automation, including AI technologies, could displace up to 800 million jobs worldwide. It suggests that the impact of AI on employment will vary across countries, sectors and occupations, with developed economies and labour-intensive industries being more vulnerable to job losses. While the discourse often focuses on job destruction, the full picture is far more nuanced, encompassing job creation, task transformation, and the slower-than-expected pace of AI adoption.

The *creation of new jobs* is also anticipated as a result of AI, often in technology sectors demanding advanced technical skills (e.g. data scientists, machine learning engineers, prompt engineers, fintech engineers, AI ethics specialists). The World Economic Forum (WEF) estimated in 2020 that the number of jobs generated by emerging technologies – including AI – would reach 97 million globally by 2025 (WEF, 2020). Later, in 2025, having surveyed over 1 000 leading global employers across 22 industry clusters and 55 economies, it projected that around 22% of total jobs would be affected by structural labour market transformation. This means 170 million new jobs (14% of all jobs) to be created and 92 million (8%) displaced by 2030, resulting in a net increase of 78 million jobs (7%) (WEF, 2025). In addition to technical roles, AI is giving rise to job creation in all sectors – ranging from AI-driven health diagnostics to autonomous vehicles – that will require new organisational structures and workforces.

The most widespread AI impact is *job transformation*, particularly with *task augmentation*. Some hope that augmentation may even go beyond technical productivity and also enhance job quality and worker well-being (WEF, 2024; Autor, 2024; Acemoglu et al., 2023). Instead of replacing entire roles, AI is

[32] The *Guide to Job Redesign in the Age of AI* was developed in 2020 by Singapore's Lee Kuan Yew Centre for Innovative Cities, and it offers organisations practical support for adopting AI in a responsible and inclusive way; see ai-guide-to-jobredesign.pdf.

increasingly embedded in how these jobs are performed. From writing, marketing and coding software to designing presentations and translating text, AI is stepping in as a tool for support. Tools like ChatGPT and Copilot have shown that a journalist, a teacher or a clerical worker can now automate parts of their job that were once considered uniquely human – creating lesson plans, drafting reports and emails, or scripting client routines. The work remains, but the way in which it is performed (with AI tools) changes fundamentally, as do the skills required to perform them.

Thus, AI is expected to change the task composition of jobs in several ways: by making workers more productive in certain tasks (a *complementary* effect), by automating certain tasks (a *displacement* effect), and by creating new tasks (a *reinstatement* effect) (Eurofound, 2025c, p. 32). Many jobs include all three categories of tasks at the same time. The automation category can be further split into *partial* and *full* automation, where partial automation means that only the simple versions of a task are automated, while the complex versions are still handled by humans.

3.2. AI and job numbers

This section reviews the existing literature regarding AI's impact on employment numbers, the most debated aspect of the digital transformation of labour markets. In a context of 'accelerated automation' by AI, several studies have reviewed tasks or abilities in occupations for their exposure. The key research question is *whether automation leads to substitution or complementarity of labour in jobs*. Complementarity between humans and machines generally brings higher wages and more employment, while substituting humans for machines generally leads to polarisation, de-skilling and possibly a jobless economy (OECD, 2023e; IMF, 2024). The social, ethical and physical context of each occupation, along with the required skill levels, determine whether AI may complement or replace these roles.

For example, the *AI Occupational Exposure Index* developed by Felten et al. (2021) classifies all occupations into three broad categories:

- high-exposure and high-complementarity occupations (e.g. judges, doctors)
- high-exposure and low-complementarity occupations (e.g. clerical workers)
- low-exposure occupations (e.g. agricultural workers, elementary occupations).

An occupation having a 'high exposure' does not necessarily mean a negative impact, but rather a disruption. According to historical patterns from the UK and US, occupations with high-exposure and high-complementarity roles offer wage premiums, whereas switching to low-exposure roles might decrease wages. The criticality of decisions and the gravity of the consequences of errors are two job aspects that may motivate societies to require humans to make final decisions or decide on the final actions to take. Judges and doctors, for example, are highly exposed to AI, but they are also highly shielded from displacement because society is currently unlikely to delegate judicial rulings or medical decisions to unsupervised AI. Consequently, AI will likely complement judges and doctors, increasing their productivity rather than replacing them (Felten et al., 2021; IMF, 2024; Eloundou et al., 2023).

A crucial feature for an occupation to be fully automated is the high exposure and low complementarity of tasks. Many studies point to 'office and administrative support roles' with the highest exposure to AI-driven task replacement (ILO, 2023; IMF, 2024). According to an ILO (2023) study, 24% of the tasks in clerical support workers fall into the category of having a high exposure to automation, and another 58% of tasks having medium exposure. Other occupational groups are less exposed, with only 1% to 4% of tasks considered to have high automation potential, and medium-exposed tasks not exceeding 25% (ILO, 2023). Estimates suggest that between 5% and 20% of jobs may be at high risk of automation in the coming years, depending on country, sector and skill level (ILO, 2023; IMF, 2024). Generally speaking, low-skilled occupations are most exposed to robots, whereas middle-skill occupations are most exposed to software (Webb, 2019).

Using Goldman Sachs' analysis as a basis[33], another study covering US and European occupations found the highest exposure rate (46%) for office and administrative roles (McNelly and Smith, 2023). This group is followed by legal professions at 44%, architecture and engineering at 37%, and life, physical and social sciences at 36%. Business and financial operations are exposed at a rate of 35%, while community and social services, management, and sales roles show exposure levels of 33%, 32% and 31% respectively. High-skilled fields such as computer and mathematical occupations (29%), healthcare practitioners and technical staff (28%), and educational instruction (27%) are significantly affected, while arts, entertainment and media roles have an exposure rate of 26% (McNelly and Smith, 2023). High-exposure occupations such as administrative support, legal research and software development are already seeing AI systems perform a large share of their tasks (Hering, 2023; EY-Parthenon, 2024; Goldman Sachs, 2023).

To illustrate how AI exposure differs across sectors and occupations, Table 3 presents examples of occupational roles categorised by their estimated level of exposure to AI technologies. It highlights how roles that involve routine, codifiable tasks, such as data entry, standardised content grading or telemarketing, are more susceptible to automation, whereas jobs requiring complex human interaction, creative judgement or hands-on expertise tend to be less exposed. Although not shown in the table, AI disruption also has a gender dimension, since the healthcare, clerical and education sectors – which are at a higher risk of substitution – typically have high female employment in many countries. Ultimately, the distribution of the AI impact is neither random nor neutral: it mirrors existing structural dynamics and inequalities within the labour market.

Table 3: AI exposure levels by occupational role in selected sectors

Sector	High-exposure occupations	Moderate-exposure occupations	Low-exposure occupations
Healthcare	Medical transcriptionists, radiology technicians	Pharmacists, medical coders	Surgeons, nurses
Clerical & admin services	Data entry clerks, call centre agents	Office assistants, payroll clerks	Executive assistants
Education	Standardised test graders, content developers	Lecturers using AI tools	Professors, researchers
Retail/customer service	Cashiers, telemarketers	Retail salespeople	Luxury brand consultants
Creative & media	Routine video editors, stock photographers	Journalists using AI summaries	Fine artists, scriptwriters
Manufacturing	Assembly line workers, quality inspectors	Equipment operators, supply chain managers	Skilled machinists
Construction & trades	Automated welding, bricklayers	Structural engineers, site planners	Plumbers, electricians

Source: Authors creation based on the studies cited in the section.

Sector-specific analyses reveal varying degrees of AI penetration and impact. According to Kanagarla (2024), AI automation has led to a 23.4% reduction in traditional middle-skill jobs across the manufacturing, logistics and administrative sectors in the US, while it has simultaneously generated a 31.7% increase in new employment categories, particularly in AI development, human-AI collaboration and digital transformation roles. The findings reveal significant sectoral variations in job displacement rates (ranging from 8.2% to 37.6%) and identify critical factors influencing successful workforce transition, including the timing of reskilling initiatives, the nature of institutional support, and the elasticity of labour market responses (Kanagarla, 2024).

[33] See Global Economics Analyst The Potentially Large Effects of Artificial Intelligence on Economic Growth (BriggsKodnani).

The European Central Bank (ECB, 2023), based on a study of 16 European countries, found that around 25% of all jobs in Europe are highly exposed to AI-enabled automation, while GenAI could potentially affect 20 million workers in Europe. It also confirms that the degree of exposure is not necessarily bad – except in low-complementarity occupations – as many high-skilled jobs more exposed to AI increased their employment share in Europe. The scale of the impact varies substantially across countries, due to differences in underlying economic factors (e.g. pace of technology diffusion and education, market regulation, employment protection laws) (ECB, 2023). Another study analysing GenAI's impact based on the occupational structure of the Australian LFS showed that 41% of tasks performed by the Australian workforce are directly exposed to LLMs, representing 39% of the time allocated to different tasks (Walkowiak & MacDonald, 2024). With GenAI, these figures rise to 53% of tasks and 51% of work time exposed to GenAI.

GenAI is a new type of breakthrough with the potential to accelerate automation (KPMG, 2023). It affects 2.5% of overall tasks in the UK economy, equivalent to the working time of 670 000 workers (KPMG, 2023). According to Hampole et al. (2025), the most badly impacted occupations fall under the business, financial and engineering categories. In terms of the share of overall employment, they estimated a decline of 2% to 2.5% of these jobs over a five-year period (Hampole et al., 2025). AI exposure is concentrated in higher-wage positions, with employment effects that depend on the dispersion of exposure across tasks. Higher average exposure reduces within-firm employment, while greater dispersion in exposure mitigates these declines by reallocating labour towards complementary tasks. However, firm-wide AI adoption generates positive employment effects, consistent with AI-driven productivity gains increasing aggregate labour demand (Hampole et al., 2025, Acemoglu et al., 2022).

Another case study on translators reveals that despite employment for translators having grown moderately over the past decade, it would have been significantly higher (around 28 000 jobs) if not for advances in machine translation (Frey & Llanos-Paredes, 2025). Between 2010 and 2023, overall employment in the US increased by about 13%, whereas employment for translators and interpreters grew by only 3% during the same period. Additionally, their findings highlight a broader trend: significant reductions in the demand for foreign language skills across various occupations, indicating that it is not only translation jobs being affected, but foreign language competencies more generally (Frey & Llanos-Paredes, 2025). Research focusing on freelance knowledge workers on platforms shows that generative AI reduces overall demand for knowledge workers of all types, who saw a decline of 2% in advertised jobs and a 5.2% drop in monthly earnings (Hui et al., 2023). In particular, freelancers in writing-related services have suffered from the introduction of GenAI, experiencing greater reductions in both employment and earnings than other professions (EPC, 2024).

In a similar analysis of job posts from a leading global online freelancing platform, an immediate decline of 21% is observed in the weekly number of automation-prone job posts for online gig workers following the introduction of ChatGPT (Demirci et al., 2024)[34]. Writing jobs were affected the most (30.37% decrease), followed by software, app and web development (20.62%), and engineering (10.42%). A similar magnitude of decline in demand was observed after the introduction of popular image-generating AI tools (including Midjourney, Stable Diffusion and DALL-E 2). There were no signs of demand rebounding over time, revealing a growing trend of job replacement. Instead, this short-term job replacement led to an increase in the complexity of automation-prone jobs, requiring a wider range of skills. The number of job posts seeking ChatGPT skills has grown steadily, with an average increase of 0.68 posts per week on the platform since its introduction. The results suggest that the ability to integrate AI tools into work has become valued, and workers are likely updating their skill sets to include GenAI capabilities (Demirci et al., 2024).

According to the ILO, the share of jobs worldwide at high risk of full automation due to generative AI is small (2.3%), but the outcome of AI on jobs varies across diverse geographies (ILO, 2023). The IMF estimates that around 40% of global jobs will be affected in some form, and in roughly half of those

[34] In Demirci et al.'s 2024 study, a total of 1 388 711 job posts from a leading global online freelancing platform from July 2021 to July 2023 were analysed, and classified into three categories: (i) manual-intensive jobs (e.g. data and office management, video services and audio services); (ii) automation-prone jobs (e.g. writing; software, app and web development; engineering); and (iii) image-generating jobs (e.g. graphic design and 3D modelling).

cases, AI could eventually take over a substantial share of tasks. In advanced economies, however, about 60% of jobs are exposed to AI due to the prevalence of cognitive-task-oriented jobs, while this share is 40% in emerging market economies and 26% in low-income countries (IMF, 2024). For example, almost 70% and 60% of UK and US employment respectively is in high-exposure occupations, while high-exposure employment in emerging market economies is much lower (IMF, 2024).

The ILO published an update of its 2023 estimates of potential occupational exposure to generative AI (GenAI) technology and the employment shares of affected occupations in 2025. Overall, it revised exposure of global employment to 3.3%, but the automation scores are slightly lower than in 2023; however, the variability of scores is considerably lower (ILO, 2025a). The growing abilities of GenAI models in such areas as voice, image and video generation have increased automation scores for a range of tasks in media- and web-related occupations. Therefore, several highly digitised occupations – such as web and media developers, statistical and database specialists, and financial and software-related roles – saw an increase in their mean scores compared to 2023 (ILO, 2025a).

Empirical surveys of employees using AI at work portray mixed results. An OECD survey of firms in the manufacturing and financial sectors in seven countries[35] found that task displacement was more prevalent than task creation: 66% of employers in finance and 72% in manufacturing reported that AI had automated tasks previously performed by workers, while only about half in each sector said that AI had created new tasks. Around one third of employers noted that AI had both automated and created tasks (OECD, 2023b). In another representative survey of workers in 11 EU Member States, Cedefop found that complementary task change was the most prevalent effect in 2024. Overall, 67% of workers using AI at work reported that AI had helped increase the speed at which they carry out their tasks. 41% reported handling new or different tasks due to AI, while only 30% reported that AI had displaced some of their tasks completely (Cedefop, 2025)[36].

The results from the EWCS in 2024 also portray a more positive impact of technology than is commonly perceived. Their data shows that technology creates more tasks than it removes in the EU: while 43% of workers report that technology has created new tasks in their job to a large extent or to some extent, another 31% say that technology has removed tasks in their job to a large extent or to some extent. Men are somewhat more likely than women to report the impact of technology as being to a large extent or to some extent, both in terms of removing tasks and creating new ones (Eurofound, 2025b).

[35] The OECD survey covered Austria, Canada, France, Germany, Ireland, the UK and the US, with a total of 5 000 workers and 2 000 companies from the manufacturing and financial sectors.
[36] The Cedefop AI Skills Survey had a representative sample of 5 342 employees from 11 EU Member States: Belgium, Czechia, France, Germany, Greece, Ireland, Luxembourg, Poland, Portugal, Slovakia and Spain.

Table 4 provides a comparative overview of key studies conducted over the past decade to visualise the range and diversity of findings regarding AI’s effects. It summarises how different research efforts – ranging from the task-based approach to firm-level vacancy data and online job postings analysis – assess AI’s impact on job creation and destruction. While early studies pointed to a higher risk of displacement, more recent research from the ILO, the IMF, the OECD, the JRC and Eurofound reveals a more nuanced picture, highlighting the interplay between augmentation, task transformation and new job emergence. Across these studies, a recurring theme is the highly sector-specific and context-dependent impact of AI, shaped not only by technological capabilities but also by choices in governance, investment, and workforce development. The insights from the studies emphasise that AI is not inherently a job-maker or a job-taker; instead, its influence is mediated by how institutions and economies adapt.

Table 4: AI's impact on job creation and destruction: comparative findings of key studies

Study/region	Approach/ methodology	Job creation	Job destruction
McKinsey Global Institute (2017) – global; McKinsey, 2023 – US	Executive surveys, scenario modelling. Midpoint automation adoption by 2030 as a share of time spent on work activities in the US	Up to 375 m jobs may need to switch occupational categories	Up to 800 m jobs displaced by 2030. Share of time spent on work activities without GenAI by 2030: 21.5% of hours
WEF (2020, 2023, 2025) – global	Employer surveys, market forecasts	97 m new jobs by 2025. By 2030, 170 m new jobs created (14%) 92 m displaced, with net increase of 78 m jobs (7%)	85 m jobs displaced by 2025 without upskilling. 92 m jobs (8% of total) displaced by 2030.
OECD (2021b, 2022, 2023f) – global or OECD	Online job postings analysis (Lightcast data) + automatability of 100 skills/abilities and linking them to occupations from O*NET + Company interviews in 7 OECD countries+	Rising demand for AI roles, esp. in high-tech (2021b). Self-reported numbers from employers and workers. AI will rather transform than eliminate jobs (2022b).	Sector-specific task displacement. Even in highly exposed jobs, only 18% to 27% of skills are easily automated (2022b). 20% of workers are very worried about job loss (2023g).
OECD (2023b) – 7 member countries	Interviews with 5 000 workers in 2 000 companies in finance and manufacturing in Austria, Canada, France, Germany, Ireland, the UK and the US	Self-reported numbers from employers and workers. About half in each sector said AI had created new tasks.	66% of employers in finance and 72% in manufacturing reported that AI had automated tasks previously performed by workers. Around one-third of employers noted that AI had both automated and created tasks.
ILO (2023) + ILO (2025a) update Across 160+ countries	ISCO-08 exposure modelling	13.4% of jobs in high-income countries may be AI-augmented. 34% exposure in high-income countries, 11% exposure in low-income ones. GenAI models increase automating tasks in media- and web-related occupations.	2.3% of jobs at risk of automation. For high-income countries it is 5.1% of jobs; 2.4% in upper-middle-income; 1.3% in lower-income and 0.4% in low-income countries. Later, 3.3% of global employment, but automation scores are slightly lower.
Eurofound (2025b) + Cedefop (2025)	European Working Conditions Survey in EU-27 + Cedefop's representative survey of workers in EU-11	43% of workers report that technology has created new tasks in their job. 41% reported handling new or different tasks due to AI.	31% of workers say that technology has removed tasks in their job. 30% reported that AI displaced some of their tasks completely.
Acemoglu et al. (2022) – US	Firm-level AI job vacancy data (2010–2018)	No significant net creation	AI substitutes for tasks, lowers non-AI hiring
Hering (2023) – Indeed AI Report	Analysis of 55 m job postings & 2 600 skills	Augmentation dominant in most roles	19.8% of jobs highly exposed, 46% moderate exposure, and 35% lowest. Admin roles most at risk.
IMF (2024) – 142 countries using ILO employment database	Cross-country labour exposure modelling, assessing the potential for complementarity and substitution with labour	Varies by income & skill level. Advanced economies: 60% of jobs are exposed (27% of jobs in high-exposure / complementarity, 33% in high-exposure, low-complementarity jobs).	40% of global jobs affected, with half of those tasks automatable. 40% in emerging market economies (with corresponding shares of 16% and 24%) and 26% in low-income countries (with

Study/region	Approach/ methodology	Job creation	Job destruction
			corresponding shares of 8% and 18% respectively).
ECB (2023) – 16 European countries	Used occupational indices to measure AI exposure in different occupations (task-based framework)	The scale of the impact varies substantially across countries, due to differences in underlying economic factors	Around 25% of all jobs are highly exposed to AI-enabled automation, potentially affecting 20 million workers in Europe.
Nurski and Ruer (2024) – EU Member States	Two sets of GenAI occupational exposure scores applied – one task-based, one ability-based – to European LFS	An organisational perspective is necessary in analysing task automation.	High-income countries (DE, NL) more exposed to AI; higher exposure among women, younger higher-educated workers, urban workers and teleworkers.
EY-Parthenon (2024) – global and US	O*NET + industry classification	New high-wage AI roles emerging. Globally, 59% of occupations have a high to moderate exposure, with 67% in advanced economies and 57% in emerging markets.	8 m US jobs highly exposed (5% of total).
Demirci et al. (2024) – global	Reviews of online job postings from a leading global online freelancing platform	Immediate decrease of 21% in the weekly number of automation-prone jobs for online gig workers after the introduction of ChatGPT and image-generating tools.	Writing jobs decreased the most (30.37%), followed by software, app and web development (20.62%), and engineering (10.42%).
Eloundou et al. (2023) – US	Exposure as a proxy for potential impact (without distinguishing augmenting/displacing effects)	Human annotators and GPT-4 are used as classifiers to apply this rubric to US occupational data (O*NET database)	Maximum: 80% exposure Minimum: 19% exposure
Georgieff & Hyee (2022) – 23 OECD countries	OJV data AI occupational impact measure developed by Felten et al.	In occupations where computer use is high, greater exposure to AI is linked to higher employment growth.	No clear relationship between AI exposure and employment growth.
McNelly & Smith (2023) – US and European occupations	Case studies in occupations in several sectors	New roles to be created by AI. About two thirds of jobs will be impacted by GenAI.	GenAI may potentially replace the equivalent of 300 million full-time jobs. A quarter of the work tasks could be automated by GenAI.
Hui et al. (2023) + EPC (2024) – global	Loss of jobs after launch of ChatGPT based on OJV analysis	Not addressed	The demand for freelance knowledge workers on online platforms saw 2% decline in job vacancies and 5.2% drop in monthly earnings – esp. writing, image creation, programming
KPMG (2023) – UK labour market	Identified three main applications of GenAI: classification/summary, technical content creation, and subjective works. Contrasted with the range of tasks that	60% of jobs facing no effect	10% of jobs facing impact on over 5% of tasks

Study/region	Approach/ methodology	Job creation	Job destruction
	make up the UK labour market.		
Hampole et al. (2025) – US	Task-based approach for workers' exposure to AI between 2010 and 2023 by using LLM and NLP techniques applied to CV and job posting data and through comparison with ONET data	AI exposure accounts for roughly 14% of the variation in occupational employment growth. AI appears to be reallocating labour across tasks and firms, with the magnitude depending on the structure of AI adoption at company level.	Jobs in business, financial and engineering declined by 2% to 2.5%.
Autor (2024) – US	Historical comparison of tech revolutions	Middle-tier roles may return with AI	Clerical and admin jobs in steep decline
Frey and Llanos-Paredes (2025) – US	Reviewing the number of translator jobs in the US between 2010 and 2023	Without advances in machine translation, employment growth for translators would have been significantly higher (around 28k jobs)	Translator jobs grew by 3% versus the total employment increase of 13% – reduced demand for foreign language skills across various occupations
Kanagarla (2024) – US		AI has generated a 31.7% increase in new employment categories, particularly in AI development, human-AI collaboration and digital transformation roles.	AI automation has led to a 23.4% reduction in traditional middle-skill jobs across the manufacturing, logistics and administrative sectors. Sectoral variations for job displacement range from 8.2% to 37.6%.

Source: Author's creation.

Based on a wide range of empirical research, the JRC (2025a) concludes that automation has had a modest and often positive impact on employment in Europe. While specific tasks are automated, this has primarily boosted productivity and led to a reallocation of labour rather than a net destruction of jobs. In manufacturing, robots have boosted productivity and have even induced job creation in related sectors. A similar picture is visible in the services sector without any labour displacement, while *job upgrading* is taking place across the EU. For the JRC, the most profound transformation stems from digitisation[37]. This process, while enhancing efficiency, has fundamentally altered work organisation by enabling unprecedented levels of standardisation, monitoring and managerial control. They simultaneously introduce the standardisation and centralisation of information. Employment in routine occupations continues to decrease with AI-induced automation, while work processes within many non-routine professional roles are becoming increasingly routinised and subject to digital control, which impacts worker autonomy and job quality (JRC, 2025a, p. 79). This is referred to as the *'platformisation of work',* the next step of digitisation in traditional workplaces.

On the positive side, augmentation and productivity gains can be seen through the *transformation of tasks within jobs.* According to the ILO (2023), in global terms, the potential for augmentation is almost six times greater than it is for automation (13% vs 2.3% of total employment). AI simultaneously automates some tasks, augments others, and redefines jobs. In most cases, the jobs remain, but their nature is being steadily reshaped by AI. The examples of two professions provided by the World Economic Forum confirm these simultaneous effects of GenAI: 28.7% of software developer tasks are exposed to automation, 43.2% to augmentation, and 28% report no change. Conversely, 16.1% of HR manager tasks are exposed to automation, 22.2% to augmentation, and 61.7% report no change (WEF, 2024). This *task-based transformation* in existing jobs is already visible in online job postings,

[37] Digitisation is defined as the use of sensors and rendering devices to translate information from physical to digital and vice versa (JRC 2025a, p. 14). Digitisation both facilitates and necessitates standardisation and proceduralisation, and as such routinises work and paves the way for new rounds of data-driven automation.

which show a consistent rise in demand for AI skills across both technical and non-technical occupations (Lightcast, 2024).

The main result of task augmentation has been increased worker productivity, especially with the use of GenAI. As summarised in some meta-analyses (Kusters & Poli, 2024; Eurofound, 2025d), several empirical studies reported increased productivity among workers by raising the quality of outputs and reducing task deadlines. Tasks such as writing, coding, customer support and consulting can be performed much faster due to being supported by generative AI, though not all tasks benefit equally from this support (Nurski, 2024). Using GenAI-based conversational assistants to suggest responses to customer service agents in customer relations has led to a 15% average increase in productivity, particularly benefiting novice and low-skilled workers by disseminating the tacit knowledge of more experienced workers (Brynjolfsson et al., 2025). AI tools helped them gain experience in three months, while quit rates among new agents fell substantially. Based on another study, GenAI enabled consultants to complete 12.2% more tasks related to creative product innovation and development, 25.1% faster, and with a 40% increase in quality (Kusters & Poli, 2024).

Another example is GitHub Copilot a GenAI-based programming aid that has increased software developers' productivity – the treatment group that was given access to this tool completed the required programming task about 56% faster than the control group (Autor, 2024). The impact of using ChatGPT on mid-level professional writing also shows enhanced overall productivity by reducing the time taken and improving the quality of writing tasks. On writing tasks, one group of marketers, grant writers, consultants, managers and other diverse professionals were randomly given access to ChatGPT for writing tasks. The other group used conventional non-AI tools such as word processors and search engines. Similar improvements were observed in the speed and quality of writing output among those assigned to the ChatGPT group, with a 40% decrease in time spent on the task (Autor, 2024). ChatGPT did not eliminate the role of expertise: it enabled the most capable to write faster and the less capable to write both faster and better, so the productivity gap between adequate and excellent writers shrank. AI here replicates existing human capabilities at a greater speed and a lower cost.

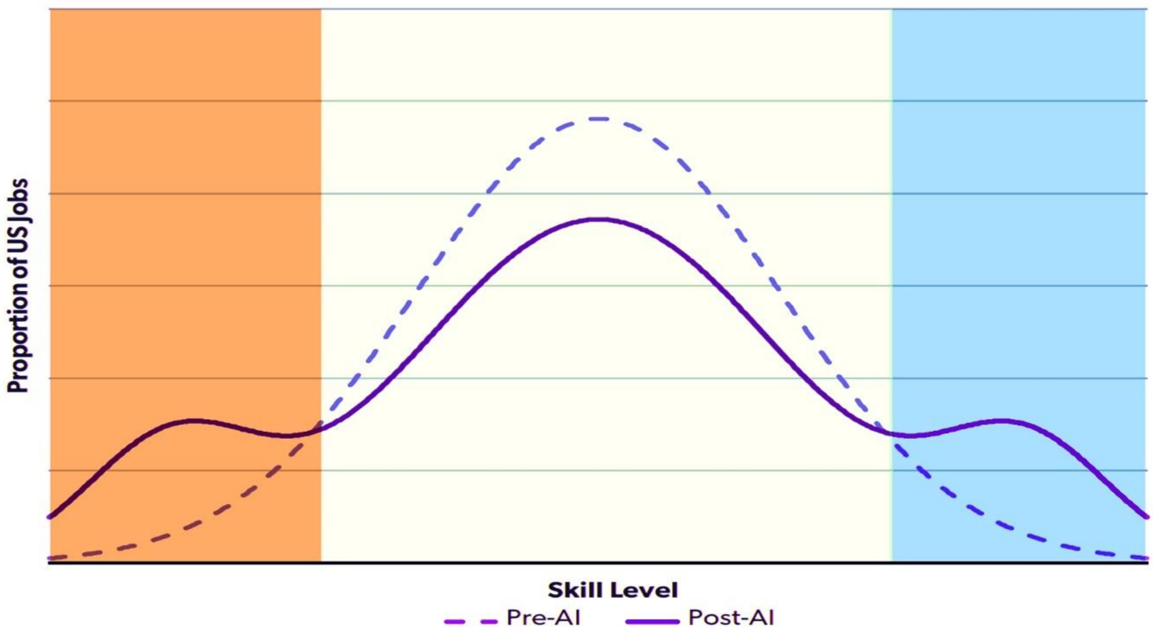
GenAI's ability to rapidly analyse data, synthesise information and generate content enables it to carry out simple cognitive tasks. For instance, in software development, tens of thousands of JPMorganChase software engineers have experienced productivity increases of up to 20% by using a coding-assistant tool developed by the bank. In financial services, firms report average daily time savings of 57 minutes per employee from AI applications, which streamline tasks such as fraud detection and risk management. In customer-support roles, ride-hailing company Lyft reports an 87% reduction in the average resolution time for customer requests after deploying Claude.ai through its partnership with Anthropic (cited in Tay et al, 2025). Similarly in experiments with multiple firms, access to Microsoft Copilot reduced the time spent on emails by nearly three hours per week for active users, equivalent to a 25% decrease. Changes were most pronounced in areas where tasks were relatively simple (Kusters & Poli, 2024; Autor, 2024). However, productivity gains depend on the adaptability of firms by introducing complementary changes in work organisation, workflows, hierarchies and skills (Eurofound, 2025c, p. 30).

Based on the reviews above, *two opposing observations* are made regarding the automation patterns of knowledge work. The first suggests that *AI may destroy 'entry-level' jobs and break the career ladder of fresh graduates.* AI is better at low-complexity tasks, which are exactly what entry-level workers used to do. GenAI tools are extremely quick at reading, synthesising, looking things up and producing reports – precisely the sort of things that fresh graduates do right out of university in white-collar firms (Thompson, 2025). Tasks such as research, data analysis, report writing and document review – which once required larger numbers of junior employees – can now be handled by a few senior workers armed with an AI tool (Spanz, 2025). Consulting firms realised that five 22-year-olds with GenAI could do the work of 20 recent graduates; thus, tech firms hire fewer junior developers and assign software programming to a handful of talented employees working with AI co-pilots, while law firms are cutting paralegal positions (Bloomberg, 2024). This decreases traditional paths offering gradual skill-building via junior roles, making it more difficult for fresh graduates to enter professional careers[38].

Orrell (2025) argues that much like the ITC and robotics revolution that reshaped manufacturing, AI is now reshaping knowledge-based services. Knowledge-worker tasks are well suited to AI-driven automation, as they are repetitive or can be ‘coded’ and replicated by AI platforms or involve analysing vast datasets that are cumbersome and inefficient for human workers to manage and use (e.g. biomedical research or investment data). With the changing demand for skills in clerical, administrative and research-oriented jobs in knowledge-intensive business and services, the next round of automation will shift routine analytical work down the value chain and put pressure on middle-skill jobs – this time in offices rather than factories. Orrell refers to this the ‘de-skilling of knowledge economy’ in high-skilled services (e.g. finance, insurance, business services, government, health and social services), where ‘information-intensive knowledge activities’ are delivered by workers with college degrees (Orrell, 2025).

Figure 4 shows how AI may change talent distribution in the US workforce, using data from McKinsey, the World Economic Forum and O*NET skill categories. The dotted line is the pre-AI bell curve, with most workers concentrated in middle-skill jobs. After AI, the solid line flattens in the middle as routine cognitive clerical and analytical tasks are automated. Meanwhile, the lower and upper ends of the distribution see modest growth, as some workers from the middle of the distribution have either upskilled into more complex and higher-level tasks or redistributed into less complex and probably lower-paying jobs. The overall result is a smaller middle group and slight growth at both ends of the skill range (Orrell, 2025). For example, in office and administrative roles, workers specialising in information-processing tasks leave and incur wage losses. By contrast, those specialising in customer-facing and coordination tasks stay and experience wage gains as work rebalances towards their strengths.

Figure 4: Shift in workforce talent distribution in the US: before and after AI



Source: Taken from Orrell, 2025.

A fresh study from Switzerland regarding GenAI’s impact found that unemployment increased most for application programmers, software developers, systems analysts, journalists, and advertising and

[38] According to Bloomberg (2024), entry-level jobs are on the way out and becoming obsolete because AI could replace more than 50% of the tasks performed by market researchers, analysts (53%) and sales representatives (67%), compared to just 9% and 21% for their managerial counterparts. Anthropic CEO Dario Amodei predicted that AI could wipe out half of entry-level white-collar jobs within the next five years.

marketing specialists (Klaeui & Siegenthaler, 2025). In some of the most exposed IT roles, registered unemployment has more than doubled since 2022, while younger employees are more affected than older ones – but the difference is smaller than in the US. Interestingly, these effects are taking place in the context of growing total employment. Although the results do not measure the effect of AI on total employment, they provide strong evidence of the relative shifts between occupational groups that are affected by AI to varying degrees. Overall, the results strongly suggest that GenAI is behind the recent increase in unemployment in some occupations that are highly exposed to AI (ibid).

The second observation sees AI as an *opportunity to augment and broaden expertise with cognitive tools (cognitive extension), which could lift vocational jobs and bring back medium-skilled employment*. This is because lower-skilled and inexperienced workers are observed to benefit more from AI's support, this may permit some high-skilled jobs more accessible to them (Acemoglu et al, 2023; Autor, 2024; Nurski, 2024). It helps newer hires and lower performers speed up, and less experienced workers end up becoming more productive compared to experienced workers, as AI mimics the actions of the best performers. For workers with foundational training and experience, by offering vast tools for augmenting workers and enhancing work, AI holds the promise of boosting their skills and expertise so that they can do higher-value work (Tay at el., 2025). In the experiments of GenAI use in professional writing, the biggest quality improvements were at the bottom, as the least effective writers in the GenAI group were to become median writers without GenAI – a huge quality jump (Autor, 2024). However, achieving these hoped-for productivity and opportunity outcomes will not be automatic and will require a determined, cross-society effort (Autor, 2024; Orrell, 2025).

Nevertheless, no visible AI's impact is seen on total (aggregate) employment so far (Humlum and Vestergaard, 2025). Nurski reports that the effects of partial automation and changing task content on human productivity vary depending on the specific type of task (e.g. decision-making tasks, creation-related tasks, idea generation and innovation) (Eurofound, 2025c, p. 30). Moreover, the results are shaped by whether the automated tasks belong to an 'expert' or 'inexpert' category (Autor and Thompson, 2025). When 'expert tasks' are automated (or inexpert ones added), the threshold for entry into an occupation drops, increasing employment but depressing wages. Conversely, when 'inexpert tasks' are automated (or expert ones added), the occupation becomes more expertise-intensive, raising wages but reducing employment (ibid, 2025). While AI-human collaboration is more productive in some cases, only AI or only humans are more productive in other cases.

3.3. The impact of AI on job quality

Several international frameworks exist on *job quality*, most of which share similarities. According to Eurofound, job quality has seven dimensions: the physical environment; work intensity; working time quality; the social environment; skills use and development; prospects (i.e. employment status, career progress, job security); and earnings (Eurofound & ILO, 2019). The OECD refers to the physical and social environment, workers' autonomy, work intensity and stress, privacy, work monitoring and management, wages and learning opportunities for job quality (OECD, 2023e). While there are significant similarities across countries on these job quality dimensions, there are also striking differences even before AI – e.g. stark differences in working time quality, job intensity, and consistent differences between different groups of workers (between men and women, and between workers with different education levels and occupations). At the same time, in every country, women earn significantly less than men, and the least educated get less access to opportunities to grow and develop their skills (Eurofound & ILO, 2019).

Every new technology affects job demands and job resources, with consequences for employee well-being, safety and performance. While AM has more direct impact on specific aspects of job quality, AI-driven automation and augmentation can also affect job quality by reshaping design – i.e. the content and structure – of jobs. When AI changes the bundle of tasks that make up an occupation, the impact depends on the (re)composition of those tasks. *Changing job demands* – physical, psychological, social or organisational – may come at a certain physiological and psychological cost for workers. *Automating management tasks* may change workers' control over their work, affecting their autonomy, skill use and workload (Nurski & Hoffmann, 2022). *Changing job autonomy* can lead to multiple outcomes for motivation, stress, learning, performance, etc. S*kill variety and use* at work may change the degree of interest and intrinsic motivation. *Task characteristics and feedback* (e.g. role clarity, opportunities for practice) can change learning and effective job performance.

Numerous studies agree that AI has a stronger influence on job quality than on quantity (ILO, 2023; EPC, 2024; OECD, 2023f; Nurski & Hoffmann, 2022). AI changes the content and design of existing jobs, the way in which workers interact with each other and with machines, and how work effort and efficiency are monitored (OECD, 2021a). As it spreads across sectors, its influence on working conditions is increasingly visible in how tasks are allocated, how performance is monitored, and how opportunities for growth are distributed. *The overall assessment is one of both promise and pressure:* AI can improve working conditions and automate routine tasks, leaving time for more engaging work, but it can also be implemented in a way that limits workers' agency, and it can erode autonomy, accelerate work intensity and polarise access to quality employment (ILO, 2023). The same technologies that monitor work can also assist workers. The challenge lies in how organisations choose to implement these systems: as *tools for control and lower costs* or *as human partners in productivity*.

The AI Risk Repository (2024) provides a structured overview of the broader risks associated with AI development and deployment, enabling a clearer mapping of vulnerabilities within labour markets and public services. The risks are organised across two main axes: causal taxonomies (e.g. diffusion of responsibility, flawed objectives, overconfidence in automation) and domain-specific risks (governance failure, systemic bias, discrimination, privacy and security, decline in employment quality). For instance, societal harms can stem from unintentional decisions made by humans who design opaque or overly autonomous systems, a concern especially relevant in employment contexts where accountability and transparency are critical. Under domain-specific risks, the repository also highlights skill erosion, inaccurate profiling and algorithmic HR management failures, which increase in digital hiring and performance systems[39]. Another study from Australia on the use of GenAI in the workplace identified several risks that could change working conditions substantially (Walkowiak & MacDonald, 2024). Box 5 summarises the degrees of the main risks identified in the Australian labour market.

Box 5: Degree of main risks from the use of GenAI in the workplace

The study of the GenAI impact on the Australian workforce measured eight risk categories: privacy; cybersecurity; professional standards; ethics and bias; misinformation and manipulation; safety and harm; liability; and accountability (Walkowiak & MacDonald, 2024). Their findings indicate that not all risks have the same degree of likelihood. According to Walkowiak and MacDonald (2024), these are the degrees of main risks, from highest to lowest, identified in the Australian labour market:

- Safety and physical and psychological harm worker well-being: 26.4%
- Decreased liability and accountability (who is responsible if something goes wrong): 26%
- Unethical or harmful bias (AI to replicate human bias against less advantaged groups): 14.1%
- Cybersecurity with high human dependence on machines: 13.7%
- Breaches of professional standards and ethical rules: 13.6%
- Privacy breaches and data security (increased worker monitoring and surveillance data): 12.4%
- Misinformation and manipulation risks: 10.6%
- Intellectual property risks (to whom ChatGPT-produced text belongs): 9.8%

On the other hand, the OECD (2024d) considers the potential risks of using AI in the workplace to be rising inequality; risks to occupational health and safety (OHS); privacy breaches; bias and discrimination; a lack of autonomy, agency and dignity; a lack of transparency; insufficient explainability; a lack of accountability; and challenges to social dialogue. For example, greater collection and analysis of data on workers through AI tools may be an invasion of their privacy and

[39] See also the AI Risk Repository, The MIT AI Risk Repository.

increase information asymmetry by giving employers access to more and better data about workers (OECD, 2024d). In another report of case studies, the OECD (2023f) notes an increase in work intensity brought on by higher performance targets and greater task complexity, where workers also reported increased stress linked to the need to learn new systems, as well as worries about greater monitoring.

Ultimately, the impact seems to depend on how AI is used: AI systems can be used to improve workers' health and safety at work by automating dangerous tasks, detecting hazards or monitoring worker fatigue, but AI-powered monitoring systems may also increase time and performance pressure, causing stress or ignoring safety standards (OECD, 2024d). The OECD case studies also reveal evidence on job quality improvements associated with AI: reduced dullness, greater worker engagement and improved physical safety may be its strongest endorsement from a worker perspective (OECD, 2023f)[40]. Job content often improved through the automation of tedious tasks, such as email routing and quality assurance inspection, which in turn improved worker engagement by freeing time for more interesting tasks. Safety and work environments improved through the automation of tasks characterised by one worker as 'the three Ds: dirty, dangerous and dull', while reductions in workloads improved mental well-being.

Recent studies from Eurofound (2024, 2025a, 2025b) confirm AI-induced job transformation, but the outcomes for job quality are mixed. In automated warehouses and manufacturing sites, tasks are often simplified for operators, leading to cognitive underload and skills underutilisation, even as physical demands remain unchanged. Conversely, some shop-floor workers report increased cognitive load and complexity, revealing the dual nature of AI's impact. In the case of advanced robots with embedded AI capabilities, shared goals and more synchronised tasks enable closer human-robot interaction and collaboration. While physical safety is often ensured, the psychosocial implications of human-robot interactions are overlooked. A recent OSHA survey on human-robot interaction found increased work intensity, increased surveillance, deterioration of the social environment and reduced autonomy (Eurofound, 2024), while the 2021 EWCS shows that work intensification and digital micromanagement are more common in platform-based and low-skill environments (Piasna, 2024).

In another study in Denmark, AI-based decision support was associated with enhanced autonomy in high-skilled roles, such as increased learning opportunities, reduced monotony and greater responsibility for quality (Eurofound, 2025c, p. 35). However, these positive effects weakened in medium-skilled jobs and were absent in low-skilled ones. For high-skilled occupations, AI was also linked to more teamwork and job rotation, but it came with a higher pace of work. When AI fully takes over cognitive tasks such as diagnostics or monitoring, it can lead to deskilling, particularly when human roles are reduced to passive oversight. For instance, in robotic surgery, AI-assisted systems have in some cases limited junior doctors' opportunities to perform complex procedures, and restricted professional development (Eurofound, 2025c, p. 36). AI that automated administrative burdens sometimes freed up time for cross-departmental support and meaningful collaboration. Yet in other cases, automation reduced informal learning and intellectual engagement, for instance, by bypassing interaction with specialists or replacing face-to-face training with remote solutions.

The results of the EWCS in 2024 covering 34 European countries also confirm increasing work intensity, but more for women than men (Eurofound, 2025b)[41]. Due to their concentration in certain sectors, women are more likely than men to face high-speed work, frequent interruptions and higher emotional demands. The main determinants of work pace seem to be the speed of automatic systems and machines. The transport sector has the most workers facing tight deadlines and high-speed work. Workers in education are most likely to feel that they do not have enough time, while healthcare workers experience the most disruptive interruptions. The industrial sector has the highest number of workers with three or more factors determining their work pace, often driven by automatic systems.

[40] The OECD collected a large amount of new qualitative data that resulted in nearly 100 case studies of AI technologies implemented in workplaces in the finance and manufacturing sectors in Austria, Canada, France, Germany, Ireland, Japan, the United Kingdom and the United States. A total of 90 firms from the manufacturing and finance sectors participated in the research, with 325 interviews held (OECD, 2023f).

[41] The countries are the EU Member States, Norway, Switzerland, Albania, Bosnia and Herzegovina, Kosovo, Montenegro, North Macedonia and Serbia.

Meanwhile, the digitisation of work processes and increased computer use led to many workers sitting at their desks and workstations for prolonged periods of time (Eurofound, 2025b).

Nurski also reports cases where AI adoption tends to increase the cognitive intensity of work by automating routine cognitive tasks and redirecting human attention to more complex responsibilities (Eurofound, 2025c, p. 37). Even when AI reduced workloads, such as by eliminating repetitive tasks, workers were typically expected to accomplish more in the same amount of time. However, there are other cases where AI adoption reduces cognitive demands and helps alleviate workload. AI-enabled virtual/remote forms of flexible work can also allow workers a greater choice over when and where to work, but expectations for constant connectivity could negatively impact these choices. A study of physicians in healthcare found that AI-supported systems for remotely monitoring patients improved work-life balance by increasing flexibility, while another study points to more work alienation and loneliness leading to emotional fatigue due to AI collaboration (ibid). Finally, the 2024 EWCS shows that technology facilitates increased interaction among workers, with 48% of respondents reporting this to a large and some extent (Eurofound, 2025b).

Other side-effects of AI adoption are the emergence of psychosocial risks and fear of job loss, which negatively affect workers' mental well-being. Stress associated with new technologies, referred to as 'technostress', increases emotional exhaustion. For example, the efficiencies gained through automation in logistics and warehouses were used to increase output or speed, which led intensified work demands rather than to improved job satisfaction or reduced strain. In manufacturing, the machine-paced environment and constant digital prompts regarding productivity can lead to mental fatigue, despite the intellectually stimulating nature of the tasks (Eurofound, 2025c, p. 41). Fear of job loss is another frequently reported concern in surveys on AI. In the 2024 Eurobarometer survey, 66% of the general population respondents in the EU believe that more jobs will disappear than will be created because of AI and robotics, although this proportion has decreased since 2017 (EC, 2025). Workers exposed to AI have become more concerned about job security compared to non-exposed workers (Eurofound, 2025c, p. 42; Cedefop 2025).

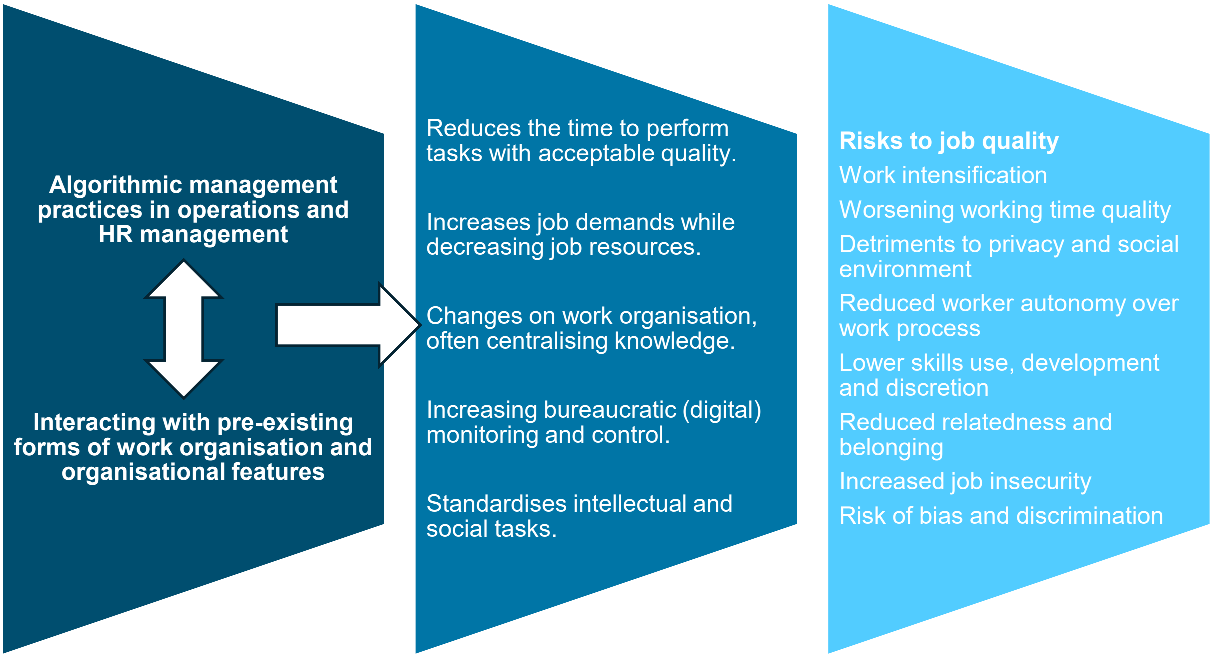
A new term has recently emerged for the AI-generated low-value content that appears professionally productive on the surface but shifts cognitive burden to colleagues: '*workslop*'. In this new phenomenon, which has been experienced in workplaces that have adopted AI tools, some employees are using tools to polish good work, while others use them to create content that is actually unhelpful, incomplete or missing crucial context about the project at hand (Niederhoffer et al., 2025). When employees use AI tools to generate useless content that appears professionally formatted, it shifts the burden of the work downstream, requiring the receiver of the content to interpret, correct or redo the work. In other words, workslop transfers the needed effort from creator to receiver, creating frustration in the workplace. When other employees receive low-quality AI-generated content from colleagues, 54% consider the sender less creative, 42% less trustworthy, and 37% less intelligent. These are signals of eroding workplace relationships[42].

Another risk is the differentiated effect of AI on wages. Several studies refer to the risk of rising (income) inequality within sectors and occupations because of AI (ILO, 2023; OECD, 2024a; to be discussed further in Chapter 4). While highly skilled workers in data science, engineering and digital services see rising demand and better earnings, AI also appears to contribute to wage stagnation for middle-tier roles. In the finance and manufacturing sectors, twice as many workers expect AI to slow wage growth than to accelerate it (OECD, 2023b). Clerical and administrative roles, which are most exposed to automation, face the highest risks of wage decline. In contrast, occupations that blend technical skill with human judgement (such as UX design, data analytics and applied AI development) are commanding a wage premium. GenAI has widened income differentials, rewarding those who can use it creatively while making routine writing or reporting skills less valuable (ILO, 2023). Nevertheless, in most case studies, AI-induced task changes were insufficient to trigger reclassification or affect pay (Eurofound, 2025c, p. 43).

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

The use of algorithmic management (AM) in both digital and traditional work settings is another factor affecting job quality (ILO, 2022; JRC, 2022). As explained in 2.2. Algorithmic management of work, different AM systems are used now in warehouses, call centres and delivery services, monitoring every movement and keystroke. These systems promise efficiency but often come at the cost of autonomy, reducing the degree of power and control that individual workers have over the work process. When software tracks your speech tone or flags you for working too slowly, the job becomes less about decision-making and more about compliance. Research has shown how this kind of surveillance – common in fulfilment centres and customer service – can generate anxiety, reduce motivation and lead to burnout (Mateescu & Nguyen, 2019). Delfanti and Frey's (2021) study of Amazon demonstrates a link between high work intensity and algorithmic direction, highlighting that workers are required to work at frantic pace and must often run to keep up with the speed instructed by their handled devices. Figure 5 below illustrates the steps and risks of AM practices from a worker's perspective.

Figure 5: Implications of the use of AM practices in regular work settings



Source: Based on JRC 2022, ILO 2022, and JRC 2025a and 2025b.

Even in an 'AI production chain' where highly skilled professionals (data scientists, machine learning engineers) develop and fine-tune in-house AI models or provide tailored AI products and services, there are many low-skilled data workers who label training data, evaluate AI outputs or moderate harmful content[43]. The latter task is less visible but equally essential in the production of AI systems, often performed by 'micro-workers' whose contributions are often mediated through specialist outsourcing platforms[44]. This is an industry fuelled by millions of gig workers performing repetitive, low-wage tasks under heavy surveillance, often avoiding labour regulations with job insecurity and below-minimum-wage jobs (Tan & Cabato, 2023). Some authors argue that this heavily reliance by the AI industry on micro-work through digital labour platforms is not a temporary phase but a structural feature of AI production. The poor working conditions and precarious jobs of these data workers with micro-tasks have led some to call them a 'new digital underclass in AI factories' (Eurofound, 2025c,

[43] The 'AI production chain' includes all types of activities required to build, train, test and maintain AI systems.
[44] To train AI on labelled datasets and teach it to produce similar outputs, humans must first label those texts and images by identifying their content. Additionally, reinforcement learning requires human evaluators to assess the quality of AI-generated content, and human oversight is also vital for filtering out harmful or inappropriate material from training data. The three core functions of data workers are: *training* AI by preparing data (e.g. labelling); *verifying* AI by checking the quality of outputs; and even *impersonating* AI by mimicking AI behaviour when systems are incomplete or malfunctioning (Eurofound, 2025c, p. 45).

p. 45). Therefore, not all workers involved in the AI production chain have high wages and good working conditions.

Interestingly, a recent OECD employer survey on their experience with AM reports high job satisfaction, driven by reductions in stress and repetitive work, which may also benefit workers through greater consistency and objectivity of decisions (OECD, 2025). However, four use cases of algorithmic management reviewed by Nurski and Hoffmann (2022) found that they tend to create more negative effects for job quality – especially if they are deployed as more prescriptive (as opposed to supportive) use cases[45]. These changes in job design affect the social and physical environment at work and put pressure on contractual employment conditions. However, these negative effects are not technologically predetermined but are the result of choices made by technology designers (AI developers) and job designers (managers) in response to economic, social and political incentives (cited in Nurski & Hoffmann, 2022). Deficient design may arise from either unreliable data or the designers' intentions to increase productivity and control.

One related example is the use of software to determine workers' schedules, which has expanded considerably to a wide range of jobs; for example, in 2020, 42% of US companies already used it (Cappelli & Rogovsky, 2023). The goal is to optimise the work scheduling process in order to minimise the total amount of labour needed to cover assignments and make sure that everyone is doing roughly the same amount of work allocated across similar schedules. Despite traditional approaches that work well when the employees themselves work out their schedules through a process of negotiation and social exchange, scheduling algorithms are found to cut both employees and supervisors out of the process and end up being rather rigid and unable to respond to last-minute adjustments. While a study in healthcare found that AI-based staff scheduling systems help reduce physician burnout by optimising shifts and balancing workloads, another study discovered that automated scheduling increased turnover and turnover costs while adding nothing to performance outcomes (cited in Cappelli & Rogovsky, 2023).

Another example is new ways of optimisation in the workplaces by AI tools: rather than having employees figure out what is wrong in their work processes – as exemplified by Toyota's lean production model, which involved empowering employees – some initiatives are now replacing them with software. This new software captures what employees are doing with cameras, constantly monitoring assembly line workers to make sure that they perform the tasks exactly as designed. Another type of software, called robotic process automation, takes those video images and figures out how to redesign tasks to make them more efficient. This is taking over the tasks the workers used to do in lean production, which may go towards redesigning jobs to push simpler tasks down to cheaper labour, a classic example of deskilling (Cappelli & Rogovsky, 2023).

Thus, AM increases not only the standardisation/routinisation and centralisation of knowledge, but also monitoring and managerial control over work processes. As such, it creates conditions to reduce autonomy and opportunities for discretion and intrinsic skill use, often with increased responsibility for both middle managers and workers. Evidence from platform work and logistics highlights the risks of intensified work and new sources of job insecurity (JRC, 2021b; Nurski, 2024). AI, in these contexts, does not just change the job – it changes the relationship between worker and employer. Moreover, using AM to automate tasks of core management functions reduces these firms' reliance on low-level managers and supervisors. As a result, the role of human managers focuses on 'executing decisions based on data analytics', thus reducing managerial agency (JRC, 2021b).

Perhaps the most dreaded scenario comes from increased workplace monitoring and surveillance with AI-supported tools, the so-called '*datafication of the workplace*', such as phone logs; recorded calls; monitored emails, files and browsing history; closed-circuit surveillance cameras; facial recognition; biometric data (iris, fingerprint, voice); voice analysis; analysis of workers' eye/body movements; wearable devices tracking biological data (heart rate, blood pressure); smart exoskeletons; and tracking of workers' digital activities. All this surveillance results in greater collection and analysis of

[45] Four use cases of algorithmic management identified and reviewed by Nurski and Hoffmann (2022) are algorithmic work-method instructions; algorithmic scheduling of shifts and tasks; algorithmic surveillance, evaluation and discipline; and algorithmic coordination across tasks.

workers' data (and job applicants), raising concerns about how this information might be used by organisations. After the COVID-19 pandemic, employee monitoring technologies further expanded as more people began working from home. While they aim to enhance security measures, improve user experience and optimise operational efficiencies, they also bring substantial ethical dilemmas, particularly for personal privacy and the security of the data being collected. The pervasive collection and analysis of personal and biometric data may ultimately lead to invasive surveillance and profiling (UNESCO/OECD/IDB, 2022).

Context is important when thinking about whether an AI monitoring system could benefit employees. For example, systems could monitor things like offensive social media posts or tweets by employees, or potential sexual harassment or racist activity that may flag in online activity. In manufacturing, predictive analytics supported by AI can enhance safety by identifying hazardous conditions and preventing accidents in real time. Nevertheless, excessive monitoring might generate risks surrounding worker autonomy, stress, self-esteem, anxiety and paranoia, and consequently decrease creativity levels. The increased pressure could also pose physical risks, such as a higher likelihood of repetitive strain injury, nerve disorders and high blood pressure, with evidence suggesting that overwork puts employees at greater risk of injury (UNESCO/OECD/IDB, 2022).

In conclusion, AI changes working conditions, but the direction of change depends on the workplace and the nature of the profession. In highly educated professions, AI is acting as a support tool: filtering information, automating routine processes, and giving workers more space for problem-solving and interpersonal tasks. These changes often improve satisfaction and reduce routine work (OECD, 2023b). However, the same technologies in low-autonomy jobs can have the opposite effect. In logistics, e-commerce and the gig economy, AI is being used to monitor performance, schedule shifts, and allocate tasks in real time. Digital workers in call centres and warehouses frequently report higher workloads and less predictability: conditions that challenge both physical and mental health. While efficient, this model often reduces worker control and increases stress, especially when algorithms determine work pace or track keystrokes and facial expressions (Piasna, 2024; Pot, 2024).

Overall, these monitoring systems alter the relationship and *increase power disparity between employers and employees*, especially if AI is used to track performance, determine pay and make decisions about promotions and/or dismissals. The risk is real in reducing the power and control of individual workers over the work process, although the impact always depends on the design and implementation of AM tools. It generates concerns about increased information asymmetry between employers and workers (including their representatives), work intensification, obscured employer accountability for workers' rights, and potential (automated or semi-automated) discrimination against specific segments of workers (Juego et al., 2024). There are already several court cases involving gig workers and work platforms in Spain, France, Italy, the UK and the US that challenge algorithmic control and call for greater transparency and employment protections.

The final critical aspect is dynamic feedback loops between humans and AI systems, a process known as *human-AI coevolution* – a continuous, reciprocal process in which human behaviours and AI systems mutually adapt and evolve (Pedreschi et al., 2024). AI systems learn from human behaviour and influence decision-making, while human decisions shape the training and outputs of AI. This dynamic can lead to both positive enhancements and unintended social consequences. Real-world examples from social media, online retail and urban mapping illustrate these co-evolutionary dynamics. The feedback loops introduced by online platforms can inadvertently amplify phenomena such as polarisation, echo chambers and inequality. As traditional (static) human-machine interaction models are inadequate for understanding the complexity introduced by iterative AI influences, monitoring how feedback loops – particularly in recommender systems – shape both individual choices and broader societal outcomes, is vital to preventing human capabilities from being reduced (Pedreschi et al., 2024).

3.4. Main lessons and key findings

There is an abundance of studies of AI's impact on the labour markets, covering both job quantity and quality. The studies employ many different methodologies, from measuring the theoretical exposure of occupations to AI (task-based framework) to empirical investigations of actual employment effects. Like every new technology, AI affects job demands and job resources, with consequences for jobs, employment conditions, employee safety and performance. While early studies focused a lot on job displacement with a gloomy picture, later more refined studies recognise job transformation – a shift in the task content of jobs – as the most common effect, where AI reorganises automatable and non-automatable tasks, and AM practices alter how work is performed and monitored and the way in which workers interact. Job transformation has much larger and heterogeneous effects by shifting the relative importance of tasks within each occupation and generating wage effects.

AI's impact on both job quantity and quality is mixed. The reasons are diverse: researchers use different methodologies and approaches, mostly theoretical with few empirical examples. It is a newly developed area where researchers cannot possibly grasp all the aspects and fully account for the job-creating effects of AI, such as the emergence of new industries and occupations. Thus, the AI-exposure studies often miss the system redesign perspective, since new technology can create new processes, handle coordination tasks and have decision-making capabilities with the potential of new management and operational models. Theoretical measurements often overestimate the extent of job displacement, as they tend to focus on the technical feasibility of automation rather than its economic viability or political acceptability[46]. The wide variation of results is also explained by the different contexts and work organisations under which firms adopt AI tools in the workplace.

AI's impact on both job quantity and quality is context dependent. Estimates of AI-related job losses and gains largely vary by type of economy, sector and occupation as well as how an AI tool is developed and implemented (OECD, 2021a). For example, many experts agree with the impact of job augmentation for high-wage/high-skilled occupations and of job displacement and/or precarity for routine-based occupations. The existing *institutional and regulatory environment* in which organisations adopt AI tools in the workplace shapes the responses. Depending on how governments and economies choose to govern its deployment, labour market institutions play a crucial role in mediating and moderating the effects of technology. Similarly, workplace dynamics and decisions made by managers and workers are vital in the final outcome, which in turn are shaped by industrial relations, work cultures and management styles. Following AI adoption, companies often develop adjustment mechanisms through job (re)design, organisational changes or internal mobility[47].

Employment trends in AI-exposed sectors and occupations reflect a mix of substitution and expansion effects. Despite a lack of net job destruction, occupations with a higher automation risk (e.g. office and admin roles, translators) saw lower labour demand and slower employment growth compared to low-risk occupations, yet within-occupation task reallocation and firm-wide AI-driven growth help sustain overall employment levels (Hampole et al., 2025). Meanwhile, employment trends in highly exposed occupations differ across skills and seniority levels: AI exposure often means augmentation in highly skilled work, but automation in low/medium-skilled work (Nurski, 2024; KPMG, 2023). Rather than leading to across-the-field job losses, AI appears to be reallocating labour across tasks and firms, although freelance platforms show early evidence of displacement in IT and writing jobs. Overall, AI seems to extend automation up the skill ladder in knowledge work, shifting routine

[46] A real-life example is the fintech firm Klarna, which replaced around 700 customer-service staff with AI-powered chatbots. While the move cut costs and improved some metrics, customer satisfaction declined due to the lack of personalised support. As a result, Klarna recalibrated its approach and rehired human customer service agents to balance efficiency with quality (cited in Tay et al., 2025).

[47] Job redesign strategies can be implemented from *the top down* (via management-led decisions that selectively automate tasks to maintain critical human oversight); from *the bottom up* (via worker-led adjustments using AI to offload tedious tasks); or through *job co-design* via co-determination where decisions are made together (Eurofound, 2025a, p. 17). *Job crafting* is the term used for employee-driven bottom-up processes, where employees take proactive steps to redesign what they do at work, changing tasks, relationships, and perceptions of their jobs. The outcome varies depending on whether the job is redesigned from the top down by managers or from the bottom up by workers.

analytical work down the value chain and substituting an even broader set of middle-skill jobs – this time in offices rather than factories.

Two opposing observations on the automation patterns of knowledge work. *The first observation* suggests that *AI may destroy entry-level jobs and break the career ladders of fresh graduates*. AI is better at low-complexity knowledge tasks, which are exactly what entry-level white-collar workers used to do. In this scenario, tasks like research, data analysis, report writing and document review – once requiring a larger number of junior employees – can now be handled by a few senior workers armed with an AI tool[48]. Thus, AI can take over the initial stages of research, medical, legal and financial analysis, but finalisation would still require specialist 'elite experts' . Demand for such high-skilled expertise would rise, while an even broader set of middle-skill jobs would be threatened by automation. Fresh graduates – who rely more on codified knowledge gained through formal education – are more vulnerable by AI systems, whereas experienced workers benefit from tacit, context-specific knowledge that is harder to automate (Eurofound, 2025c, p. 27).

The second observation sees AI as an *opportunity to augment and broaden expertise (cognitive extension), which could lift vocational jobs and bring back medium-skilled employment*. This is because lower-skilled and inexperienced workers are observed to benefit more from AI's support in tasks of writing, translation, financial and legal tasks, consultancy, customer services, software development and programming (Autor, 2024; Acemoglu et al., 2023). By improving quality and reducing time spent on tasks, AI could support and supplement judgement, enabling a larger set of non-elite workers to engage in high-skilled work (Tay et al., 2025). This could improve the quality of jobs for workers without university degrees, moderate earning inequality, and possibly lower the cost of key services such as healthcare, education and legal expertise (Autor, 2024). Dubbed the '*democratisation of expertise*', such increased access to expertise could enable organisations to shift tasks down from high- to low-skilled occupations, potentially creating more middle-class jobs.

AI's impact on total (aggregate) employment has been close to null. Empirical studies from actual workplaces that have adopted AI tools so far point to no visible change, sometimes with small decline or increase in some exposed occupations, as very few jobs are completely automatable. Even if they destroy some tasks, they also create new ones and transform many tasks (OECD, 2021a, 2023b, 2023c, 2023f; ECB, 2023; ILO, 2023; Eurofound, 2025c; JRC, 2025a). An analysis of historical data does not suggest that AI exposure has led to negative employment or wage outcomes on an aggregate level so far (OECD, 2024a). In another study covering 23 OECD countries, no clear relationship is found between AI exposure and employment growth, but in occupations where computer use is high, greater exposure to AI is linked to higher employment growth (Georgieff & Hyee, 2022). Some studies even suggest that AI exposure has been linked to positive outcomes among more educated and higher-income workers. Nevertheless, **the jury is still out** on AI's ultimate impact on job numbers.

Evidence exists of both positive and negative AI effects on job quality. AI can improve or reduce job quality through its effects on job intensity, autonomy, skill use and collaboration. Job quality improvements include more interesting tasks, improved physical safety, greater work engagement, increased complexity and responsibility, and higher job satisfaction, leading in some cases to job upgrading (OECD, 2023fg; Georgieff & Hyee, 2022; Webb, 2019; EY-Parthenon, 2024). On the contrary, examples of worsening working conditions include higher pace of work, reduced autonomy, cognitive underload, higher control and monitoring, skills underutilisation and psychosocial effects (increased anxiety, reduced motivation), leading in some cases to job downgrading (JRC, 2021b; Nurski & Hoffmann, 2022; ILO, 2023). In general, workers tend to benefit most when AI acts as a support tool giving workers more space for problem-solving and interpersonal tasks, in contrast to AI's

[48] These entry-level roles have historically served as the training ground for tomorrow's experts. Juniors don't arrive knowing how to read between the lines of client emails, navigate office politics, or make judgement calls during crises. They learn through repetition, mistakes and mentorship – starting with simple tasks that gradually build into complex responsibilities. AI disrupts this natural progression by eliminating the foundational experiences, while junior employees are losing opportunities to develop their skills (Walther, 2025).

use for replacing human judgement, controlling work processes and monitoring performance (Nurski, 2024).

AI adoption often increases work intensity by shifting human effort toward more cognitively and emotionally demanding tasks, though some applications do reduce workload and strain. Increased work intensity seems to be a common result across the board in diverse sectors, occupations and skill levels (Eurofound, 2024, 2025a, 2025b; Delfanti & Frey, 2021; JRC, 2025a). The use of AM at work directly contributes to this impact, by increasing the standardisation/routinisation and centralisation of knowledge and monitoring, and managerial control over work processes. Besides reshaping the existing content and structure of jobs, AM often creates conditions to reduce autonomy and opportunities for discretion and intrinsic skill use in the workplace, often with increased responsibility, but the final outcome is shaped by the management decisions of organisations.

What is striking is the opposite effects depending on skill level. Despite the mixed outcomes of AI for overall job quality, one can identify more positive effects of AI on highly skilled occupations. On the one hand, AI becomes a new productivity tool in these cases, supporting and speeding up the execution of some tasks in these occupations, where highly skilled and digitally literate workers benefit from it in terms of employment growth, wage gains, or transitions to higher value-added tasks. On the other hand, more negative effects are experienced in low-skilled occupations, where lower-wage workers face work intensification, loss of autonomy, stress, anxiety, burnout and decreased morale. This is particularly the case for location-based platform workers, logistics and warehouse workers or similar sectors where AM practices are common. In these cases, digital control and monitoring systems leave workers little room for negotiation or recourse, resulting in them facing a higher risk of displacement, reduced hours, or wage pressure.

AI tools lead to increased workplace monitoring and surveillance (*datafication of the workplace)*. There is a clear and increasing trend for using AI-supported tools to monitor all aspects of work and the workplace. These monitoring and surveillance tools collect and analyse large volumes of data on workers, which may be an invasion of their privacy (OECD, 2024c). The same technologies that can assist workers and bring safety carry a significant risk of privacy breaches and data security risks. By giving employers access to more and better data about workers, AI can lead to information asymmetries, especially when workers are unaware that they are interacting with AI. Therefore, the use of AI tools in the workplace has the potential to alter the traditional work relationship between workers and firms. Depending on how they are deployed, AI tools can *widen the power and agency gap between employees and employers* in favour of corporate business.

AI expands AM practices into traditional workplaces. The transformation is enabled by the digitisation of economic activities, the wider use of digital tools and digital monitoring, and other AM features linked to the gig economy (short-term contracts and freelance work). This is called the *platformisation of work*, with increasing risks of employment precarity and work control. With increased standardisation and remote work practices, most workers are now using digital devices that are often connected to platforms for management and coordination, which become control and monitoring tools (JRC, 2025a, 2025b). AI systems may further accelerate this platformisation process at work, before ultimately reaching the stage of increased productivity and greater benefits for workers and businesses (EPC, 2024; Eurofound, 2025c). It may also increase the proportion of gig workers in employment because the production of modern AI systems depends on digital platform labour performed by millions of gig workers – data labellers, content moderators – performing repetitive, low-wage tasks under heavy surveillance and often harmful conditions.

AI can either empower or overwhelm workers – depending on who is using it and how. Evidence from existing studies suggests that AI's effect on job quality is not fixed: it is constantly negotiated within the dynamics of the workplace. The negative outcomes on job quality often stem from organisational factors and management choices, rather than the technology itself (Eurofound, 2024, 2025c). This, in turn, is affected by *labour market institutions and regulations, as well as by the organisational structures of firms and work culture.* AI's impact on well-being, wages and opportunities depends on how it is implemented in the workplace and whether workers have any say on it. The existence of institutional and regulatory frameworks, with their moderating role, determines the outcome, as 'AI systems tend to replicate existing power dynamics in organisations' (Nurski & Hoffmann, 2022). Consequently, disadvantaged groups can suffer more of the negative effects of AI, risking further job-quality polarisation across socio-economic groups.

These contradictory effects may lead to further labour market polarisation within occupational groups. In a provocative study '*Automation and the fall and rise of servant economy*', Krenz and Strulik (2025) observe that in a world where algorithms write emails and robots build cars, household service jobs – domestic staff, couriers, pet carers and food delivery workers – are growing rapidly. Once on the decline, these roles now form a central part of the gig economy, partly explained by the technological change and inequality that are transforming labour markets in more traditional ways than one might expect. In many ways, '*this resembles a return to the servant economy in a 21st-century version— one shaped not by domestic necessity, but by the time constraints and wealth of a growing professional class*' (Krenz & Strulik, 2025). Highly educated high-income professionals have higher adoption and use of AI models, which in turn support further productivity and higher income. This is increasing the existing income gap with more disadvantaged workers.

Digitisation has enabled firms to access talent anywhere without having a traditional employment relationship, opening non-core activities to cost competition via outsourcing, franchising and the use of temporary work agencies and labour brokers – so-called *fissured employment relations* (cited in JRC, 2021b). The platformisation of work may accelerate and expand fissured employment relations, worsening access to decent work, fair remuneration and social protection. In the context of today's challenges of eroding job security, income stability and workers' rights, AI may further weaken the hands of workers (OECD, 2024c). By challenging traditional industrial relations, AI also challenges social dialogue itself. It alters the conditions under which social dialogue operates, as it introduces new layers of complexity (Eurofound, 2025c, p. 67). The opacity and decentralised deployment of AI systems raise questions about the ability of existing labour institutions to represent workers' interests effectively. Moreover, enabling task coordination at a global level may also give rise to the 24-hour economy, increasing the commodification of labour and globally competing labour markets, placing further downward pressure on wages in high-income economies (cited in Nurski & Hoffmann, 2022).

In an AI impact study covering Singapore, Vietnam and the Philippines, Tay et al. (2025) argue for an *augmented-intelligence approach*, such as the *democratisation of expertise*. Instead of automating tasks, AI can be used to enrich essential, practical work such as logistics, maintenance, care and customer service. These roles are not disappearing, but they remain low-skilled and offer limited pathways for progression. By embedding machine-generated insights into the workflows of these jobs, it can enable a broader segment of the workforce – particularly those in practical, hands-on roles – to perform higher-order tasks such as data interpretation, situational judgement and adaptive decision-making, to make roles more productive and meaningful. This requires '*restructuring work systems in ways that increase the amount of cognitive work that a broad segment of workers perform – elevating their value and rebuild a strong, inclusive middle*'. Example occupations include AI-styled beauty experimenters, social-robotics care technicians, smart-fabric engineers, AI-powered textile designers, precision agriculture technicians, aquaculture-data technicians and AI-driven surveillance specialists (Tay et al., 2025).

Unlocking AI's full potential requires deliberate *political will* in favour of job-augmenting strategies. Policies need to move beyond mere techno-centric solutions and consider the wider social structures (including power structures) in which AI is deployed. Ensuring that AI improves rather than degrades job quality will require new governance models aimed at transparency, inclusion and trust. Workers need to be treated as co-creators of technological solutions, rather than merely costs to be minimised. As nicely put by Acemoglu et al. (2023), '*nothing about the path of AI (or any) technology is inevitable*'. They believe that a better path is available, because GenAI offers an opportunity to complement workers' skills and expertise by providing them with better information and decision-support tools – including people without a university degree. Choosing a human-complementary path is feasible but will require changes in the direction of technological innovation, as well as in corporate norms and behaviour (Acemoglu et al., 2023).

CHAPTER 4. THE IMPACT OF AI ON EQUALITY AND INCLUSIVENESS

Labour market inclusiveness is about equal access to decent jobs and career progression for all socio-demographic groups (e.g. in recruitment, promotion, worker monitoring and evaluation, and dismissals). Of particular importance is ensuring equal access to quality jobs for socio-economically disadvantaged groups and regions, and preventing bias and discrimination linked to age, gender, race, education level, occupation, residence or socio-economic status (OECD, 2023e). As AI systems increasingly take on roles in recruitment, screening, job matching, monitoring performance, scheduling shifts, allocating tasks, determining pay, deciding on promotions, dismissals, and access to training, they increasingly influence who gets seen, selected, promoted, supported and dismissed in the labour market and how the work is done. Despite the promise of efficiency and objectivity, these tools can reinforce existing inequalities in performing these important tasks if they are built on biased data or designed without safeguards.

Most of the debate on inclusiveness focuses on biased data, because incomplete, unrepresentative or historically discriminatory patterns in datasets used to develop AI might perpetuate undesirable social outcomes. However, merely de-biasing datasets is not sufficient; as reminded by Nurski & Hoffmann (2022), historical experiences are full of deep socio-economic inequalities, and technological development is a product of power in organisations that replicates existing power dynamics in society. The power imbalance in technological development and implementation is pervasive across gender, race and socio-economic background, as highly educated managers and technology developers fund and design the AI software, often from their own perspectives and with their interests in mind. Consequently, disadvantaged groups tend to suffer more from the negative consequences of AI, risking further inequality across socio-economic groups.

Existing power dynamics; diverse economic structures, education and income levels; and gender norms shape how workers experience AI systems in a variety of ways. Several studies look at the potential influence of AI on the most important determinants of inclusiveness around the globe, such as age, gender, race, education, occupation, residence, income level and disability. This chapter is structured around three sections to review the findings of existing literature on these determinants of equality. The first section focuses on education, occupation and age; the second section discusses AI and gender inequality; and the third section looks at people with disabilities. Finally, the chapter ends with a short summary of key findings from the three sections. Overall, there is a risk of amplified inequality and exclusion, since AI disproportionately benefits highly skilled groups while further marginalising vulnerable groups and deepening social divides.

4.1. AI and education, occupation and age

Several OECD studies (2021a, 2022, 2024a) report that AI has an uneven impact on labour markets, highly dependent on workers' educational background, occupation and skill level. While AI creates new opportunities for high-skilled professionals with complementary 'bottleneck skills', it threatens to reduce demand for certain low/medium skills and managerial roles in algorithmically managed environments. Consequently, women, workers of colour and lower-educated workers may have less access to AI-related employment opportunities and to productivity-enhancing AI tools in the workplace. Furthermore, older workers face compounded challenges – from digital skills gaps to algorithmic screening tools that may filter out candidates who do not conform to standardised employment patterns or qualifications (Chen, 2023). These biases, which are often embedded in training datasets or unconsciously coded into algorithmic design, can lead to systematic exclusion.

Education is probably the most important determinant of AI exposure (OECD, 2024a). Occupations that are highly exposed to AI not only have a large proportion of highly educated workers, but education also mediates the relationship between AI exposure and other socio-demographic characteristics. Native-born and prime-age workers with higher education are considered among the groups most exposed to AI and most in line to gain from it. The level of impact escalates with income, predominantly influencing white-collar occupations. Setting aside automation technologies, the highest AI exposure brings more positive outcomes among more educated and higher-income workers[49]. If the process of adapting to AI overwhelmingly favours more educated and higher-income workers, then AI will probably deepen existing inequalities (OECD, 2024b).

Other studies also confirm education level as the key moderator of AI's employment impact, as highly skilled, high-computer-use and digitally literate workers are more likely to benefit from AI adoption, experiencing employment growth, wage gains, or transitions to higher value-added tasks (Georgieff & Hyee, 2022; Webb, 2019). In contrast, AI tools such as AM systems negatively affect the jobs of low-wage, low-skilled workers and increase job displacement and wage pressure risks (Chen, 2023; Brussevich et al., 2019; Kanagarla, 2024). This means that AI may widen the gap between high- and low-skilled employees, leading to further technology-driven labour income inequality and job polarisation (Drydakis, 2025).

If AI is destroying entry-level jobs, this may also affect young university graduates, making their school-to-work transition more difficult (Bloomberg, 2024; Walther, 2025). With decreasing junior roles, salaries would also decline for roles that are perceived as simpler and supported by AI. Even more important is the loss of training ground for fresh graduates in gaining foundational experience and expertise. Another important determinant is poor socio-economic background, which is often correlated with limited digital skills and internet connection. Some of this comes from the lack of education or cultural/social norms that lead to these people's exclusion from the digital world, all of which will deepen inequalities across social groups and gender (UNDP, 2025). Box 6 presents a summary of the comparison between advantaged and disadvantaged groups of workers in AI adoption.

Box 6: Advantaged versus disadvantaged groups of workers in AI adoption

Higher-educated, higher-income workers	Low-educated, low-income workers
STEM professions and chief executives	Elementary jobs, clerical/admin jobs, delivery services, logistics, transport, care work
White male workers	Older workers, women, workers of colour
Younger and prime-age workers – except fresh graduates in entry-level jobs	Marginalised groups (ethnicity, poverty, minority groups, migrants, etc.)
Higher socio-economic status	Low socio-economic status, without internet access and/or lacking digital skills
Access to internet and high-level digital skills	

The opposite effects of AI by skill level – i.e. a positive effect on highly skilled occupations versus a negative effect on low-skilled ones – have been established in Chapter 3. Beyond labour market access, a growing body of research suggests that AI may disproportionately benefit already-privileged groups. In a survey of 1 088 Dutch citizens regarding groups that are vulnerable to AI, Wang et al. (2024) identified the most vulnerable groups as being mostly older – with lower levels of education and digital safety skills – than the average user. In the information domain, researchers identify demographic disparities in algorithmic awareness and warn that those with a lower understanding, such as lower-income and less-educated groups, may be especially vulnerable to algorithmic manipulation and misinformation. Overall, the results of the study resonate with the existing findings on the *digital divide* and provide evidence for an *emerging AI divide* among users (ibid).

Another risk factor for inclusiveness is AI's use in algorithmic HR management. AI systems are not immune to bias and discrimination. If training data reflects existing societal prejudices and inequalities, AI-powered decision-making can perpetuate or even amplify these biases. Today, AI systems support

[49] Currently, the five most exposed occupations predominantly are prime-aged male workers employed as science and engineering professionals, chief executives, managers, business professionals, and ICT and technology professionals.

the initial recruitment and selection of a new employees (hiring), moving or reallocating existing employees to new functions (evaluation and promotion), removing employees (termination) and the upskilling of employees (learning and development). All these functions determine not only *who* gets a job within the organisation, but also what kind of position they get in the overall hierarchy, what kind of privileges and opportunities they receive, and what career options are made available to them (Nurski, 2024). The risk with algorithmic HR management is whether AI will select or deselect people into jobs fairly and whether it will favour certain groups of people.

Several cases of bias or discriminatory are identified when AM is used in recruitment, selection, evaluation, promotion, termination, and learning and development. Studies show that workers from marginalised communities may receive fewer job offers or lower compensation due to biases embedded in AI-driven ranking systems. Research into ride-hailing platforms has found that drivers with non-Western-sounding names are sometimes assigned fewer or lower-priority tasks, reflecting the discriminatory dynamics present in broader labour markets. When historical HR processes are biased towards certain demographic groups, then the data used to train HR algorithms will be biased too. By deciding how people are placed into jobs and how employees are assigned into organisational positions, AI could consequently redistribute the wages, privileges and career options of particular groups (Nurski, 2024). Despite these negative examples, AI can also contribute to improving ethical recruitments and HRM practices, if these tools are specially designed to prevent bias and discrimination against vulnerable groups.

Studies confirm increased wage inequality in previous waves of automation and offshoring, especially in routine jobs in the US and UK economies, although there are substantial differences in terms of labour market polarisation in European countries, which can be explained by country-specific institutions and policies (JRC, 2018). This recalls the softening impact of policies and institutions. With an AI governance model designed for transparency, inclusion and trust, AI can complement workers' skills and expertise by providing them with better information and decision-support tools, and lift the productivity gap of lower skilled workers. This has a huge potential to reverse the previous trend of job polarisation and to reduce wage inequality among workers by raising the productivity of low-skilled workers (KPMG, 2023). However, this alternative path is not an inevitable consequence of AI; it will require sustained political, economic and technological efforts.

4.2. AI and gender inequality

As AI systems become increasingly integrated into our daily lives, the question of who develops and operates these technologies becomes critical. A large volume of studies exists on the vicious cycle of digital and AI gender inequality. They often point to systemic inequalities cutting across all aspects of social, economic and political structures, forming a vicious cycle that is difficult to break. They also conclude that AI will not decrease gender inequality by itself unless this is deliberately aimed for; on the contrary, it may exacerbate gender inequality in labour markets, ranging from further horizontal and vertical occupational gender segregation to an increase in the gender pay gap (see Gomez-Herrera & Koeszegi, 2022; Brussevich et al., 2019; Lazaroni & Pal, 2024; Demirci et al., 2024; EPC, 2024; OECD, 2024b; and Arora & Huang, 2025). Cultural norms and gender stereotypes play a crucial role in perpetuating this imbalance.

AI developers are facing a critical diversity crisis, with women severely underrepresented across all seniority levels. An analysis based on the Revelio Labs dataset of nearly 1.6 million AI professionals worldwide in 2024 reveals stark gender imbalances (Lazaroni & Pal, 2024). Accordingly, women comprise only 22% of AI talent globally, with even lower representation at senior levels (less than 14% of senior executive roles in AI). The share of women in entry-level AI jobs is slightly higher (29%), but this disparity widens as seniority increases (Lazaroni & Pal, 2024). Systemic discrimination, unconscious bias, discriminatory practices in hiring, promotions, daily interactions, strongly male-dominated work environments, and sexual harassment are among the factors that lead women to prematurely end their STEM careers. The demanding nature of STEM careers often conflicts with family responsibilities, which affect women more (ibid).

As reported by Nurski, the lack of diversity among AI developers in the US is infamous along both gender and racial lines (Eurofound, 2025c, p. 44). Women make up just 18% of authors at major AI conferences and less than 20% of AI professors. Within the tech industry, the imbalance is even more pronounced: women account for only 15% of AI research staff at Facebook and 10% at Google. Racial disparities are even starker: black workers represent just 2.5% of Google's workforce, and 4% at both Facebook and Microsoft (Eurofound, 2025c, p. 44). This underrepresentation of women in AI potentially exacerbates biases in AI systems, thus limiting innovation. While having more women and underrepresented groups in AI won't automatically fix existing biased datasets, it will drive a push for more diverse and representative data collection over time. Diverse teams are more likely to question the status quo, recognise gaps in data collection, and advocate for more inclusive practices (Lazaroni & Pal, 2024).

Within the EU, France, Germany and the Netherlands have the highest absolute numbers of AI female talent. However, simply a higher number of females does not mean a gender-balanced AI workforce. While Latvia (45%), Finland (43%) and Italy (31%) are among the countries with the highest female share of AI talent, Austria, Germany and Greece have a lower female proportion of AI professionals, at around 20%. Eastern European countries generally outperform their western European counterparts in maintaining a balanced male-female ratio within the AI workforce, which can be partially attributed to the legacy of the Soviet Union, where women's participation in science was strongly encouraged (Lazaroni & Pal, 2024). In leading European AI hotspots, women's share is the highest in Milan (30.7%), Barcelona (26%) and Amsterdam (25%), while in Frankfurt, Munich and Zürich, just 19-20% of AI talent is female, while the figure is only 17% in Istanbul (Lazaroni & Pal, 2024).

Gender stereotypes and inequalities in societies are the root causes of the early segregation of genders in education systems, resulting in only a few girls and women opting for education in STEM and ICT. Uneven access to AI may reflect women's lower participation in science- and ICT-related tertiary education, as well as digital skill divides. Only a relatively small number of women enter lucrative ICT- and AI-related jobs, where women find themselves disadvantaged in employment opportunities: disparities in women's representation, remuneration and promotion make it extremely difficult for women to remain in technology-related fields. Many of them leave these jobs early in their career. The AI workforce (specific skills to develop and maintain AI systems) accounted for below 1% of employment in 2025 across OECD countries – almost all of which was made up of white male university graduates – while 81% of ICT specialists employed in the EU were male in 2022 (OECD, 2024b). Consequently, male-homogenous developer teams design AI systems and their applications, potentially neglecting the needs of diverse users and perpetuating gender stereotypes.

Gender bias in AI within education has been analysed by many studies (UNESCO/OECD/IDB, 2022; Arora & Huang, 2025; Gomez-Herrera & Koeszegi, 2022). The different role socialisations of boys and girls lead to an overall reduction of talent in STEM subjects, which only becomes visible in choices of secondary and tertiary education. Cultural beliefs about gender skew the perceptions of girls' competencies and constrain their career aspirations, while structural barriers and prevailing gender stereotypes and a lack of self-confidence lead to selective educational choices[50]. In addition, course recommendation algorithms exhibit gender bias towards female students, steering male students towards STEM fields and female students towards humanities and social sciences, reinforcing social stereotypes (Arora & Huang, 2025). The consequences of these biases limit the academic and career opportunities of women and minorities in high-paying and traditionally male-dominated fields.

Even if women aspire to and take up masculine jobs (e.g. engineering, ICT), social, cultural and structural barriers for women complicate careers in these occupations. Once in the field, women are again exposed to cultural biases within professions that contribute to low retention and high attrition. A Silicon Valley insider described how women face toxic workplaces with discrimination and sexual harassment, and how the *aggressive, misogynistic, work-at-all costs bro-culture* excludes women from

[50] As cited by Gomez-Herrera& Koeszegi (2022), the global proportion of female enrolments in education was 70%, while it was 69% in health and welfare, 61% in art and humanities, 56% in natural sciences (including biology), 36% in STEM and 29% in ICT in 2019. In Europe, the numbers were even lower: only 34% of STEM graduates and 17% of ICT graduates are female. Only 2.4% of female tertiary graduates earn ICT degrees, compared to 9.2% of male tertiary graduates (Gomez-Herrera & Koeszegi, 2022).

technology development (cited in Gomez-Herrera & Koeszegi, 2022). Besides horizontal segregation into specific occupations, women experience a glass ceiling effect resulting in vertical gender segregation. This means that women in STEM fields and the digital sector are less likely to hold high-level positions. According to UNESCO, only one in every four leadership positions in tech industries worldwide is occupied by a woman – including non-technical positions such as marketing and human-resource management (Gomez-Herrera & Koeszegi, 2022).

Brussevich et al. (2019) found that women, on average, perform more routine or codifiable tasks than men across all sectors and occupations. They perform fewer tasks requiring analytical thinking or abstraction (e.g. information-processing skills), resulting in a significantly higher risk of exposure to automation than men – albeit with significant country-by-country differences regarding women's exposure to automation. Female-dominated jobs, mixed-gender jobs and male-dominated jobs differ significantly in terms of their task profiles. Tasks associated with 'caring' (which involves low-technological content) are much more common in female-dominated jobs. In contrast, machine use (meaning high-technological content) is much more common in male-dominated work. Consequently, women are overrepresented in sectors such as education, office work, sales and paid care, which offer significantly lower wages than occupations predominantly carried out by men. This occupational (horizontal) gender segregation explains an important part of the existing gender pay gap (Brussevich et al., 2019).

Gender differences by task seem to occur even in the same occupation. Based on the 2022 EU LFS datasets (extra module on job skills), the recent Eurofound analysis confirmed the variation of task profiles even for the same occupation along gender and sector in the EU (Eurofound, 2025a). The EU data confirms that even when men and women perform the same occupation, women tend to do manual tasks 6.8% less often than men, cognitive tasks 9.1% less often than men, and social tasks at similar rate. They are 10% more likely than men to use digital devices in their work. Most importantly, women report around 13% less autonomy and 5% more routine than men in the same job. These differences indicate that it is not only tasks but also work organisation – which determines autonomy and routine – tends to adversely affect women on average (Eurofound, 2025a, p. 12).

Women are underrepresented in STEM occupations with the highest exposure to AI and overrepresented in clerical occupations with a high risk of automation (OECD, 2024b). An estimated 79% of women in the US are employed in occupations highly exposed to automation, particularly in clerical and administrative support roles, which stems from historical job segregation (McNelly & Smith, 2023)[51]. On top of this, women report less positive perceptions about AI than men, and they are also highly underrepresented among AI users – a broader category of workers who say that they interact with AI at work in one way or another (Demirci et al., 2024). Several studies confirm that female workers are less likely to adopt and use AI tools (such as ChatGPT) than male workers even in the same occupation, raising questions about how women's and men's experiences of AI at work may differ (Demirci et al., 2024). The OECD AI survey of workers confirmed that AI users were more likely to be younger, male and university-educated compared to non-users (41% of male workers were AI users compared to 29% of women) (OECD, 2024b).

While women have been historically discriminated against and disadvantaged in many fields, gender bias in AI applications can perpetuate gender discrimination and amplify these disparities. From digital healthcare misdiagnosing women to recruitment tools favouring male candidates and financial algorithms preventing female entrepreneurs from accessing investment, this gendered impact can be compounding (Arora & Huang, 2025). The rise of these biases is due to AI models being trained and optimised by existing large datasets that are full of missing and incomplete data on women and contain misrepresentations that often fail to consider their needs. The *'male norm' in datasets* is a default across contexts, skewing tools, services and policies towards male-centred experiences, often overlooking the distinct lived realities of other genders (Arora & Huang, 2025). The algorithmic biases

[51] Their analysis is based on data from Goldman Sachs' report 'The Potentially Large Effects of AI on Economic Growth', which identified several occupational groups with the highest exposure to AI. In Europe, women play a predominant role in fields such as office administration (70%), healthcare (79%), education (73%), and community and social services (67%) (EPC, 2024). While automation is highly likely in office work, the variety of roles that women play in these fields requires more research to fully grasp the gendered impact of AI-led automation.

include presentation bias, filter bias, selection bias, historical bias, aggregation bias and interaction bias – which widen the gender gap by limiting access to resources and opportunities for women and marginalised communities.

There are examples of how existing AI tools are gender-biased even without deliberate intention. Studies have revealed that many medical AI systems fail to accurately predict the health of people from economically disadvantaged backgrounds, because datasets for medical AI systems favour middle-class and high-income people in developed countries, resulting in a lack of gender and ethnic data in digital health records (cited in Arora & Huang, 2025). The underlying causes of pain in people of colour and myocardial infarctions in women cannot be effectively diagnosed, as AI systems are trained on data centred on white males. In tracking instances of bias in AI systems across industries from 1988 to 2021, the University of California, Berkeley's Haas Center for Equity, Gender and Leadership found that almost one in every two analysed systems demonstrated gender bias, and every fourth system exhibited both gender and racial discrimination (cited in Gomez-Herrera & Koeszegi, 2022). This gender bias results in low-quality service for women and non-binary individuals. For example, voice recognition systems, which increasingly used in many products and services, from autonomous cars to healthcare products, often work less well with women's voices[52].

AI systems have also exposed deep-rooted biases in recruitment and gig platforms. For example, female drivers in India who are from lower-income and marginalised communities often face obstacles such as cultural norms, a lack of necessary documents, and safety issues when using online ride-hailing platforms such as Uber and Ola for flexible income opportunities (Arora & Huang, 2025). This results in female drivers being pushed into lower-paid and less secure roles. This is on top of women and girls struggling to access public ICT facilities due to unsafe roads and facilities, limits on their freedom of movement, and lacking financial independence (UNDP, 2025). In another high-profile case, Amazon's now-discontinued AI recruitment tool penalised applicants whose CVs included the word 'women', reflecting the bias towards the male-dominated data on which it had been trained (Seattle Times, 2016). Similarly, LinkedIn's search algorithms once demonstrated preference for male names in professional networking suggestions, subtly skewing visibility in favour of men (ibid).

Box 7 summarises the key factors leading to a vicious cycle of digital gender inequality.

Box 7: Vicious cycle of digital and AI gender inequality

- Very few women have jobs in STEM and ICT occupations
- Very few women are AI users – female workers are less likely use AI tools than males, even in the same occupation
- Women report less positive perceptions about AI than men
- Very few women can enter and remain in the AI workforce
- Very few women are involved in designing AI systems and tools
- AI education and career guidance tools favour men for STEM and ICT studies, and women for humanities and social science studies
- Recruitment tools favour male candidates for AI and ICT occupations
- Digital healthcare tools misdiagnose women due to male-based datasets
- Financial AI tools prevent female entrepreneurs from funding
- The 'male norm' in training datasets is the default across AI development contexts

Result: Existing gender stereotypes and inequality are further exacerbated by algorithms.

The importance of diversity in AI development cannot be overstated, as AI systems are not neutral; they reflect the biases, perspectives and values of their creators. The homogeneity of the AI workforce has direct consequences on the technologies being developed, often reflecting and amplifying existing societal biases related to gender and race (Lazaroni & Pal, 2024). Gomez-Herrera and Koeszegi

[52] This creates an exclusion overhead for women and minorities, who may face more frequent misidentifications or system failures, leading to practical challenges in areas such as security checks and device access (Lazaroni & Pal, 2024).

(2022) argue that AI technologies are not gender-neutral by nature. The quality of AI applications depends on the training data (in data-driven systems), the modelling (algorithms), the design (voice, shape and other features of embodiment) and the actual implementation of the system in the specific context – which can be identified in several existing tools[53].

Hence, it is *AI system designers* who determine which data and parameters are relevant for training the system, and who decide on the performance indicators and goals – including the AI system's appearance, such as their names, voices and characters – and on the roles and tasks they should take on. Consequently, the initial social judgement of AI system designers is mathematically specified in the systems' algorithms, goals and indicators. The terms 'algorithm' and 'AI system' obscure the fact that cultural, societal and political values are inherent in AI systems – and with them, potential discrimination and bias. As cited in the study, '*An algorithm is nothing more than an opinion formulated in a programming language*' (Gomez-Herrera & Koeszegi, 2022).

It is crucial to address these gender biases when building AI systems by ensuring that models are trained on diverse, representative data that captures gender-specific needs, behaviours and disparities (Arora & Huang, 2025). The question is how AI can promote equity, rebalancing opportunity, surfacing hidden talent, removing barriers to entry, and expanding access for historically marginalised groups, including women. AI itself does not ensure inclusive access to work unless genuine efforts are made with stronger regulation, participatory governance and systematic monitoring. Technical solutions such as bias audits and transparency frameworks must be matched with social and institutional reforms that put fairness and inclusiveness at the core of AI adoption. The final verdict will not be determined by AI systems, but by the choices that societies make about how they are built and used.

4.3. AI and people with disabilities

Given the severe disadvantages that people with disabilities have in the labour market, there are concerns that AI could further exacerbate the disparities they experience (OECD, 2023d). The first group of risks are linked to how AI is developed: AI models trained on 'average' users may not work properly for people with disabilities, preventing them from accessing mainstream AI products. AI tools might exclude people with disabilities by design if user interfaces are inaccessible to them – such as incompatible screen readers for blind users; no captions for deaf users; and no alternatives to video interviews for people who are unable to have their facial expressions or speech analysed. Even if AI tools are designed 'for people with disabilities' they may overlook the wide diversity within this group. This is also linked to AI developers' low awareness of, and familiarity with, accessibility and disability needs. Investment decisions on which types of AI tools should be developed are biased toward marketable products for people without disabilities. Even if investment is made in disability-focused AI, commercialisation and scaling beyond prototypes are difficult.

People with disabilities are often underrepresented or excluded in training datasets, so limited and biased data on these people can lead to biased outcomes. If AI screening tools are trained on historical data that replicates past hiring patterns, the tools may exclude people with disabilities by overlooking candidates who differ from employees who were hired previously (EDF, 2023). Privacy risks are also heightened for people with disabilities, who may be more easily identifiable because of their uniqueness in the users' databases. People with disabilities are often from marginalised communities with multiple disadvantages such as low education and socio-economic status, and often lacking digital literacy, usability of tools, or integration issues. Moreover, they have less access to

[53] Often, 'obedient and compliant machines posing as women enter our homes, cars and offices with AI applications' (cited in Gomez-Herrera & Koeszegi, 2022). Apple's Siri, Amazon's Alexa, Microsoft's Cortana and many AI chatbots, GPS systems and virtual assistants serve us in the soft voice of females, because they are implicitly associated with being personal assistants. This hard-wired subservience in female voices affects how people speak to them and how women respond and express themselves in response to requests, while the online gaming industry is often questioned for its gender bias and other discriminatory features.

information on existing AI tools with poor market visibility. All these risks can be further amplified by the existing policy gaps in the field, which lacks regulations and standardisation on the topic.

Nevertheless, AI is not inherently discriminatory as a technology; it can also serve as a powerful force for including people with disabilities in the labour market, by creating more inclusive and accommodating environments and removing existing barriers through AI-powered solutions. Disability-centred solutions that aim at addressing individual impairments can facilitate the daily and professional lives of people with disabilities and increase their access to employment (OECD, 2023d; ILO, 2025b). The OECD has identified more than 140 AI-driven solutions pertinent to the education and labour market inclusion of people with disabilities. These solutions cater to various disabilities, with vision, hearing and motor impairments the most commonly addressed; however, only about 25% are designed to support multiple disabilities simultaneously (OECD, 2023d).

Assistive AI technologies for people with disabilities include live captioning algorithms for deaf and hard-of-hearing people; image recognition tools that provide audio descriptions for those who are blind or have limited vision; autonomous self-driving wheelchairs utilising computer vision; AI-driven prosthetics that aid in gait correction; speech-to-text applications designed for people with dysarthric voices or those unable to use a keyboard; and conversational AI for mental health support. Eye-gaze-control systems enable users to control their computer via eye tracking; voice-command applications can facilitate control of the work environment as well as other tools and equipment; while generalised natural language processing applications can also help support neurodiverse workers who struggle to read and/or write long texts (OECD, 2023d; EDF, 2023; ILO, 2025b). These and several other developments can support communication, productivity and social inclusion of people with disabilities[54].

Environment-adaptation solutions can make content and workplaces more accessible to people with disabilities, while AI-powered smart wheelchairs and self-driving cars can increase autonomy and independence and address the barriers that many people with disabilities face in commuting to work (EDF, 2023). Conversational chatbots that can read aloud and summarise the content of job offers, and AI-based interview coaching platforms tailored for neurodiverse individuals allow blind and/or neurodivergent users to access traditionally inaccessible jobs. AI-powered accessibility checkers help refine documents and websites to ensure that they can be accessed by people with disabilities. AI-powered job matching platforms can analyse a wider range of skills and experiences – beyond standard CVs – and can bring non-traditional candidates to the surface, supporting a more diverse hiring pool (OECD, 2023d). When designed ethically, AI can reduce subjectivity and even challenge entrenched biases in hiring.

AI-driven tools can also enhance accessibility indirectly on a broader scale by streamlining the process of making improvements and optimising reasonable accommodations, such as AI systems recommending suitable accommodations tailored to specific disabilities. They can also create new employment possibilities for people with disabilities – for example, certain data-labelling firms focus on hiring neurodiverse talent – while AI technology can enable forklifts to be operated remotely. According to the ILO (2025b), AI offers significant potential to improve access to employment for assistive technology users and is filling gaps in this area to support communication, transport, productivity and social inclusion in the workforce. Despite all these potentials, however, public policies are necessary to tackle the risks and seize the opportunities of AI to support people with disabilities in the labour market. The chances are lower if things are left solely to market forces.

4.4. Main lessons and key findings

[54] Another promising initiative is DISH (Disabilities Innovative Solutions Hub), an AI-powered platform developed by EnAble India in collaboration with the Zero Project to connect people with disabilities and stakeholders to assistive solutions, including products, processes and programmes. By using AI and integrating data from a wide range of sources, DISH enables users to search for, develop and replicate emerging solutions to a specific question, via both WhatsApp and a platform-based interface, making it easily accessible in multiple languages (see EDF, 2023).

AI systems increasingly influence decisions on access to jobs and career progression. As they take on roles in recruitment, screening, job matching, monitoring performance, scheduling shifts, allocating tasks, determining pay, deciding on promotions, dismissals, and access to training, they increasingly decide who gets seen, selected, promoted, supported and dismissed in the labour market, and how the work is done. This has implications for access to decent jobs and career progression for historically disadvantaged socio-demographic groups. Existing research points to biased data due to incomplete, unrepresentative or historically discriminatory patterns used in datasets to develop AI systems, hence amplifying existing inequalities. However, de-biasing datasets is not sufficient, since technological development often replicates the existing power dynamics in society.

The power imbalance in AI development and implementation is pervasive across gender, race and socio-economic background, as it is often highly educated managers and technology developers who decide on the features of AI systems from their own perspectives and in their own interests. A growing body of research suggests that AI may disproportionately benefit already-privileged groups and its impact on labour markets is uneven, highly dependent on workers' age, gender, race, education, occupation and income level. Empirical studies have identified that the most vulnerable groups to AI are mostly older and low-educated individuals in low-paid jobs and lacking digital safety skills. Several studies have cases of bias or discrimination when AM is used. Education is the key moderator of AI's employment impact, as highly skilled, digitally literate workers seem to benefit from AI adoption, experiencing employment growth, wage gains or transitions to higher value-added tasks.

Younger prime-age workers with higher education are the most exposed to AI and most in line to gain from it. The level of impact escalates with income, mainly influencing specialist white-collar occupations. Thus, AI creates new opportunities for high-skilled professionals, while it threatens to reduce demand for certain low/medium skills in algorithmically managed environments. Consequently, women, workers of colour and lower-educated workers may have less access to productivity-enhancing AI tools in the workplace. Furthermore, older and marginalised workers face compounded challenges – from digital skills gaps to algorithmic screening tools that may filter out candidates who do not conform to standardised backgrounds. Overall, the findings so far resonate with the existing *digital divide* and provide evidence for an *emerging AI divide* among users.

The vicious cycle of digital and AI gender inequality continues. While women have been historically discriminated against and disadvantaged in many fields, gender bias in AI applications can perpetuate gender discrimination and amplify these disparities. There are many examples of how existing AI tools are gender-biased even without deliberate intention, resulting in a vicious cycle. AI developers have a critical diversity crisis, with women severely underrepresented across all seniority levels, because very few women study and enter STEM and ICT occupations and even fewer are in the AI workforce. Moreover, women are overrepresented in clerical and admin roles with the highest risk of automation. Very few women are AI users, and women report less positive perceptions about AI than men. AI education and career guidance tools favour male candidates for STEM and ICT studies, while recruitment tools favour male candidates for AI and ICT occupations. AI systems cannot be gender-neutral when they reflect the initial social judgements of AI developers. All these trends result in the further exacerbation of gender inequality by algorithms.

AI could exacerbate the disparities experienced by people with disabilities in the labour market. People with disabilities are often from marginalised communities with multiple disadvantages, such as low education and socio-economic status, and they oft lack digital literacy. AI developers have low awareness of, and familiarity with, accessibility and disability needs, which are often excluded from training datasets. AI tools are trained for 'average' users with limited and biased data on disabilities; for example, AI screening tools trained on historical data would replicate past hiring patterns and exclude people with disabilities. Nevertheless, there are also examples where AI tools support the inclusion of people with disabilities by removing existing barriers and creating more inclusive environments (e.g. speech-to-text applications; live captioning algorithms for deaf people; image recognition tools for blind people, etc.). However, their commercialisation and scaling beyond prototypes are difficult due to the focus on marketable products for people without disabilities. Conscious effort is needed to seize AI's support in this area.

CHAPTER 5. THE IMPACT OF AI IN DEVELOPING COUNTRIES

While terms such as ‘developing countries’, ‘transition countries’, ‘emerging economies’ and the ‘Global South’ are often used interchangeably to describe this group of countries, the use of these terms often oversimplifies their complex realities and fails to account for their respective cultural and socio-economic diversity. Despite the generic use of the term ‘developing countries’ in this report for reasons of simplicity, the differences between low-income, lower-middle, higher-middle and high-income countries are kept in mind when reviewing impact studies[55].

The last four decades have seen expanded global value chains (GVCs) towards developing countries through offshoring, facilitated by new ICT technologies. The process has contributed to their economic growth, employed large numbers of workers, and reduced poverty. However, these opportunities are now decreasing due to lower foreign direct investment, increasing trade tensions and less manufacturing to offshoring. The COVID-19 pandemic was an ‘automation-forcing event’ shaking the established GVCs, which brought the prospect of ‘reshoring’ or ‘nearshoring’ – the opposite of offshoring – in which the production of labour-intensive manufacturing shifts from developing back towards developed countries (ILO, 2020). Despite limited reshoring so far, new automation technologies and robotics have implications for developing countries.

Another development is widening inequality between and within countries globally. According to the G20 South Africa (2025) report, globally between 2000 and 2024, the richest 1% captured 41% of all new wealth, in contrast to just 1% being captured by the poorest half of humanity. Nationally, 83% of countries – accounting for 90% of the world’s population – have high income inequality. One in four people globally (2.3 billion) face moderate or severe food insecurity (G20 South Africa, 2025). Global inequality impairs economic growth and social development (education and health) and undermines democracy. Digital divides are a natural consequence of this trend, while the arrival of AI on top of this make for a new ‘development wildcard’ (UNDP, 2025).

The majority of existing research into AI’s impact on labour markets focuses on advanced economies, with results based on the income levels and labour market structures of North America and western Europe. Less research into developing countries is available, which will be reviewed in this chapter. The previous chapters have established AI’s varying impact by sector, occupation and skills, favouring highly educated and high-wage professions in white-collar occupations. This means that the composition of the labour force – the broad occupational groups reflecting a country’s economic structure – is the main determining factor in AI’s exposure and complementarity.

The first section provides a brief overview of different starting conditions in developing countries for the AI age, often exacerbated by global digital divide. It presents a comparison of key aspects such as digital infrastructure, AI-related investments, research and development, and AI talent and education. Following this contextual background, the second section focuses on the existing studies regarding AI’s impact on jobs in low- and middle-income countries. The findings provide information on the risk of job automation in diverse economic and labour market structures, the most exposed occupations, complementarity, potential productivity gains, and institutional and regulatory environments.

[55] The World Bank classifies all countries according to 2024 gross national income (GNI) per capita, calculated using the World Bank Atlas method. The threshold of low-income countries is a GNI per capita ≤USD 1 135, and for high-income countries it is GNI per capita >USD 13 935. For middle-income countries, there are two sub-groups. The threshold for lower-middle-income countries is a GNI per capita of between USD 1 136 and USD 4 495, and for upper-middle-income countries it is a GNI per capita of between USD 4 496 and USD 13 935. See [How does the World Bank classify countries? – World Bank Data Help Desk](#).

5.1. Different starting point for AI in developing countries

Developing countries start the AI age with disadvantages, often exacerbated by the global digital divide. Access to AI and participation in its development and governance is concentrated among a few countries with advanced AI capabilities, while the global majority – from Africa to Latin America and south and south-east Asia – is largely excluded (Adan et al., 2024). As of October 2024, the number of internet users worldwide was 5.52 billion (Statistica, 2025), leaving 2.7 billion people out of reach of the internet. In the same period, northern Europe and North America were leading in terms of internet penetration rates worldwide, with around 97% of its populations have internet access. The US and India, the countries with the most internet users after China, are also the world's biggest English-speaking markets. This has led to most information online being created in English (Statistica, 2025).

Low- and middle-income countries face unique development challenges but also possess potential for leveraging AI to address critical societal needs such as agriculture, education, health and infrastructure (Okolo, 2024). However, they have large disparities in their ability to research, develop and adopt AI technologies, compounded by socio-economic deficits. Limited infrastructure – such as inadequate electricity supply, low internet penetration, high costs of accessing telecommunications services, and a lack of access to advanced computing infrastructure such as GPUs – hampers AI development and adoption (Adan et al., 2024). Similarly, gaps in skilled talent, amplified by weak education systems, limit opportunities to pursue secondary and tertiary training in AI-focused topics, while brain drain inhibits local innovation and capacity-building (Okolo, 2024).

The AI divide between low- and high-income countries is stark due to disparities in access to electricity, telecommunications infrastructure, cloud computing, quality education, and career opportunities in AI. Based on the International Energy Agency's 2024 estimates, while the global electricity access rate is 90.7%, only 49.3% of people in sub-Saharan Africa have access to electricity. The International Telecommunication Union reports that 67% of the world's population has access to the internet, but this statistic falls to 55% in middle-income countries and even lower – 27% – in low-income countries. Mobile broadband is a common avenue for people living in low-income countries to connect to the internet, with 84% of broadband connections occurring through mobile devices compared to 57% globally (Okolo, 2024).

Educational barriers in low-income countries significantly hinder the development of a skilled AI workforce. Many communities face challenges in accessing quality education, with 70% of children living in learning poverty – a metric indicating the inability to read and comprehend simple texts by age 10 (Okolo, 2024). Referring to UNESCO statistics, globally 244 million children and youth remain out of school, including 98 million in Africa, 85 million in central and southern Asia, and 9.6 million in Latin America and the Caribbean (ibid). These countries also experience disparities in science education, further amplified by a lack of assessment data on primary and secondary education and a limited offer of AI-related degree programmes (ibid). Many of the top AI universities are concentrated in the US and the UK (QS World University Rankings, 2025), with most formal AI programmes in English offered in the US, the UK and Canada[56].

Developing countries lack large investment and access to computing infrastructure, with a marginal share in the app market to generate user data. Three economies (US, China, EU) produce roughly 80% of all AI patents and computing power. The US is estimated to hold around 74% of global high-end AI computing capacity, with China and the EU trailing behind at roughly 14% and 4.8% respectively (Haag, 2025). Cumulative private AI investment in the US from 2013 to 2024 exceeded USD 470 billion, compared to roughly USD 50 billion across the EU Member States. The US also accounts for the majority of global venture capital investment in AI-related data start-ups and over 75% of reported funding in generative AI ventures.

[56] The top 10 universities in data science and AI are the Massachusetts Institute of Technology (MIT), Carnegie Mellon University, the University of Oxford, the University of California Berkeley, Nanyang Technological University (Singapore) and the National University of Singapore, Harvard University, ETH Zurich, Yale University and the University of Toronto. See QS World University Rankings for Data Science and Artificial Intelligence 2025 | TopUniversities.

According to Haag (2025), the US also has absolute leadership in hosting data centres, with an estimated 4 049 data centres as of 2024, far more than the EU (~2 250), the UK (484) and China (379). The US holds a significant advantage in data-centre construction too, leading to enormous disparity compared to developing countries: the US has built 19 times more leading cloud and co-location data centres than India, which has the most data centres among emerging-market economies (UN, 2024). Asia, Europe and North America have almost equal shares of the mobile app developer market, with South America and Africa accounting for just 7% in total (UN, 2024). Leadership in the app market is important, as apps generate additional user data that is then used to expand the database for training algorithms.

As technology adopters, developing countries also face a cultural and linguistic mismatch between suppliers and users of AI models who reflect the cultures where those models were developed. Many AI models (especially LLMs) embed Western-centric assumptions and promote stereotypes that make these models less suitable for use in other cultures, ignoring local values, ethics and cultural contexts (Okolo, 2024). As of October 2025, English was the dominant language for online content, used by nearly half of all websites worldwide (Statista, 2025). Spanish ranked second, accounting for around 6% of web content, followed by German with 5.9%. Among the top 20 languages are Russian (7th with 3.8%), Turkish (11th with 1.7%), Persian (12th), Vietnamese (14th), Indonesian (15th) and Ukrainian (18th) (Statista, 2025).

For many, ChatGPT responses are closer culturally to those of humans in high-income countries and distant from those in low-income countries. In this regard, a new Harvard study mapped ChatGPT's values against 60+ countries using World Values Survey data (Atari et al., 2024). The result showed that LLM's performance in cognitive psychological tasks most resembles that of people from Western, educated, industrialised, wealthy and democratic societies. In other words, ChatGPT thinks like western Europe and aligns more with the Netherlands and Germany than with China, India or Nigeria. When someone in Rwanda asks ChatGPT for advice and gets Dutch values with an American accent, this may have cultural bias implications, from hiring and lending to education, work and ethics, exporting not only intelligence but also culture (Atari et al., 2024).

Current AI large language models favour only a few language and cultural perspectives. The lack of linguistic diversity in models introduce biases that reflect Anglo-centric and North American viewpoints and undermine other cultural perspectives (Cohere Labs, 2024). Other language speakers and communities may be left behind as language models do not cover their language. Resources for AI language model development are biased towards English, and many non-English languages are considered 'low-resource', meaning they are less prominent within computer science research and lack the high-quality datasets necessary for training language models (Cohere Labs, 2024).[57] The result is a decreasing diversity of cultures and languages, and regression to Western and Anglo-centric language models.

Table 5 provides a comparative assessment of digital infrastructure readiness and AI talent availability in selected countries. While high-income countries such as the US, Germany, and China score above 80 in both dimensions, lower-middle-income countries lag significantly behind, with scores ranging from the mid-40s to the mid-70s. This disparity underscores the urgency of addressing digital and human capital gaps if these countries are to benefit from the AI revolution. According to Okolo (2024), there are some promising examples of AI projects in low-income countries, e.g. diagnosing poultry diseases in Tanzania, monitoring crop pests in Uganda, facilitating telemedicine services and diagnostic access in rural areas of Brazil and Angola, and the initiatives of *AI4Bharat, Masakhane, Ghana NLP,* and *Te Hiku Media* to increase the representation of low-resource languages in LLMs (Okolo, 2024). But these remain limited and isolated in scope. Limited interest is shown in AI policies by only 25 of the 55 African Union Member States that currently have one, according to the African Observatory on Responsible AI[58].

[57] There are several efforts around the world to develop the multilingual capabilities of AI language models, including Cohere Lab's Aya models and dataset — an open source, 3 massively multilingual language models that cover 101 languages — and Cohere's Command R+, a proprietary model with open weights that covers 23 languages (Cohere Labs, 2024).
[58] See https://policy.africanobservatory.ai/

Table 5: Digital infrastructure readiness and AI talent availability in selected countries

Country	Digital infrastructure score (0-100)	AI talent score (0-100)
USA	92	88
Germany	89	81
China	85	84
India	72	66
Brazil	70	59
South Africa	60	55
Kenya	52	50
Nigeria	45	48
Egypt	58	52
Türkiye	67	60
Uzbekistan	40	44

Source: Author's creation based on Stanford HAI Index, AI World.eu and regional datasets (World Bank, ITU).

AI talent disparity is probably the most striking aspect between high- and low-income countries. According to the AI talent-tracking firm ZEKI, around 36% of the top global AI talent is in the US, followed by about 6% in the UK and another 6% in Germany – numbers that have remained static during the past decade. However, India's share jumped from 4% to 7% in 2024 (ZEKI, 2024)[59]. Therefore, the US remains as top AI talent destination, India is transforming from talent provider to consumer, while Europe and the Gulf are intensifying their talent retention efforts. MacroPolo (2023) confirms the US's position for training top-tier AI talent to work. It is also a leading destination for the world's most elite AI talent (top ~2%) and remains home to 60% of top AI institutions. Beyond the US and China, the UK and South Korea, along with continental Europe, have slightly increased their share for top AI researchers to work. India is a significant exporter of top-tier AI researchers, but since 2022 one fifth of its talent has ended up staying to work in India (MacroPolo, 2023).

In terms of top 25 metropolitan areas by number of AI talent, the US also dominates the AI talent hubs, with San Jose, San Francisco, Seattle and New York City claiming the top positions globally. Europe (Amsterdam, London, Paris, Berlin) and Asia (Singapore, Beijing, Seoul) follow (Lazaroni & Pal, 2024). Despite the challenges, certain cities in low- and middle-income countries, such as Bangalore (India)[60], Kuala Lumpur (Malaysia), Johannesburg (South Africa), São Paulo (Brazil), Bangkok (Thailand), Jakarta (Indonesia) and Lagos (Nigeria), have also emerged as growing AI hubs (Okolo, 2024). These cities benefit from a mix of government support, private-sector investment and increasing access to educational resources. However, increasing global demand for AI expertise has resulted in significant talent migration, with 42% of top-tier AI researchers relocating to pursue career opportunities abroad, a brain drain disproportionately affecting low- and middle-income countries (MacroPolo, 2023).

An analysis based on the Revelio Labs global dataset of nearly 1.6 million AI professionals in 2024 shows a highly concentrated distribution of AI expertise in advanced economies (Lazaroni & Pal,

[59] See The State of AI Talent 2024 - Zeki. The firm publish annually an extensive analysis of AI talent trends, based on their proprietary dataset of 140,000 leading AI professionals from 94 countries, connected to 2,296 universities and more than 20,000 organisations worldwide.
[60] As an exception, India has many more AI hubs, such as Delhi, Hyderabad, Pune and Mumbai, besides Bangalore (Lazaroni & Pal, 2024).

2024). Singapore ranks at the top with the highest concentration of AI talent per capita in a list of 25 countries, closely followed by Luxembourg[61]. It then continues with Switzerland, Israel, the Netherlands, Ireland, Sweden, the US, Canada, Finland, Denmark, the UK and others, with no developing country making the list. If the absolute number of AI talent is taken by country, however, the US tops the list of 25 countries, with around 450 000 professionals. This is followed by India (~220K), the UK (~60K), Germany (~50K), France, Canada, China, the Netherlands, Spain, Italy, South Korea, Australia and others. Some emerging economies also appear in the list of top 25 countries, such as Brazil (14th), Türkiye (17th), Indonesia (19th), Iran (21st), Pakistan (22nd) (Lazaroni & Pal, 2024).

The emigration of AI talent severely undermines local AI capability-building. For example, in the EU, AI talent by country of origin indicates significant immigration from developing countries, with India leading at 12%, followed closely by China (11%) (Lazaroni & Pal, 2024). There is also AI talent coming from the US and UK to Europe (10% each), but these are probably linked to the mobility of EU nationals. The diversity of source countries in Europe, including Iran (7.6%), Russia (5%), Brazil (4%), Egypt (3.2%), Pakistan (2.7%) and Argentina (2.5%), highlights the EU's appeal as a destination for AI professionals worldwide (ibid). All these numbers show a clear picture of asymmetry between developing countries and advanced economies. Despite the global discourse on AI as a shared frontier, the actual flows of capital and innovation remain heavily skewed, concentrated in a handful of countries that share not only the pace but also the direction of AI development.

5.2. The impact of AI on jobs in developing countries

Against this contextual background, the few studies of AI's impact on jobs in developing countries largely agree that advanced economies are better positioned to leverage AI due to stronger and more mature digital infrastructures and higher digital literacy (ILO, 2023, 2025a; IMF, 2024; ILO & World Bank, 2024). Since AI complementarity is positively correlated with income levels, studies often make a distinction between low- and middle-income countries. These studies often cover three issues: (i) the risk of job automation in diverse economic and labour market structures; (ii) the most exposed occupations, and complementarity in diverse occupational structures; and (iii) potential productivity gains due to job augmentation. In most cases, the composition of the labour force in terms of broad occupational groups – reflecting countries' economic structure – explains most of the differences in exposure and complementarity across countries (IMF, 2024). AI adoption and productivity gains also depend on two preconditions: the use of digital devices at work and foundational digital skills.

Thus, AI systems have created conditions that favour advanced economies over others. For example, the UK has a significant portion of employment in professional and managerial occupations, which exhibit high exposure and high complementarity, and in clerical support worker and technician occupations, with high exposure and low complementarity (IMF, 2024). In contrast, workers in lower-income countries face structural barriers to adoption, from limited connectivity to underdeveloped digital skills. For example, in India most workers are craftspeople, skilled agricultural workers and low-skilled elementary workers; most of these are in the low-exposure category. Brazil is an intermediate case, with higher income and more diverse professional groups. Conversely, sub-Saharan Africa, which is often still reliant on manual labour and traditional agriculture, may initially face fewer AI-induced disruptions, but it may miss out on early AI-driven productivity gains. Overall, it risks increasing interregional and international income inequality around the globe, which may trigger the reallocation of capital and labour from less developed regions – which are not as prepared to harness AI – towards more technologically advanced and AI-ready countries (IMF, 2024).

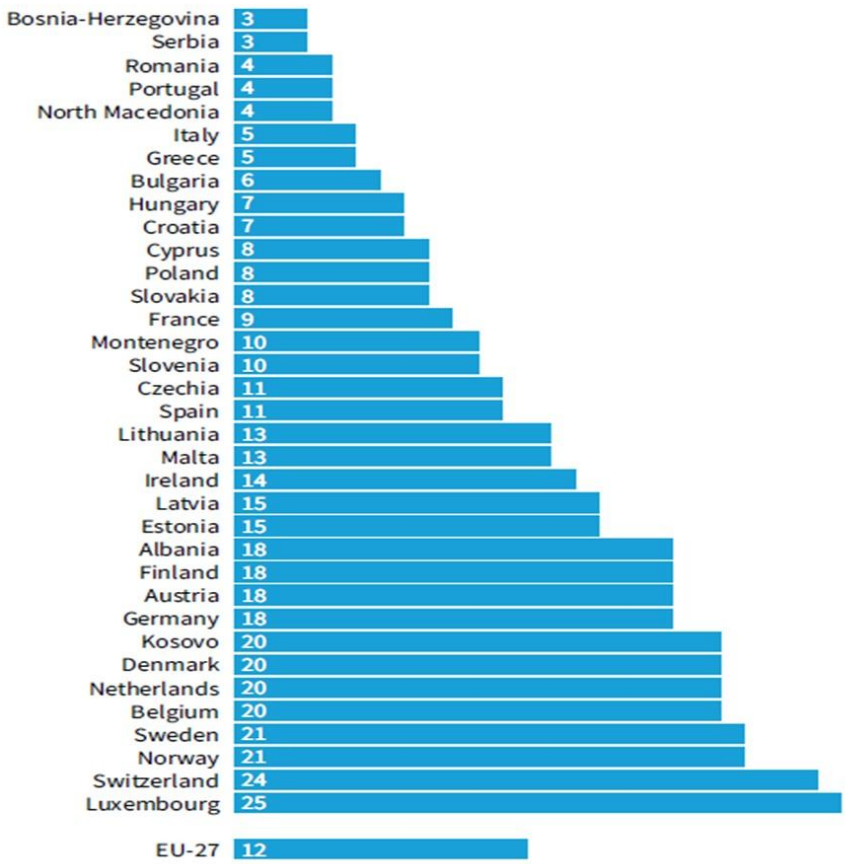
Differential AI impact arises not only from heterogeneous occupational structures, but also from the fact that occupations vary across countries in their composition of tasks (Carbonero et al., 2021). By developing and applying a new methodology to measure AI impact in developing countries, Carbonero et al. (2021) found that a larger share of individuals and occupations in Viet Nam are exposed to

[61] This is calculated as the number of AI talent per 1 000 people in a given country. The ranking changes when the absolute number of AI talent is taken by country.

labour-displacing ML technologies than in Lao PDR. This is probably linked to the differences in skills use between the two countries but also the fact that Viet Nam has already seen a larger transformation of its labour market through previous waves of mechanisation. The fact that a significant share of workers in Lao PDR is employed in subsistence crop farming reduces the threat of displacement, but at the same time casts doubt on the feasibility of leapfrogging the current development path by means of AI technologies in Lao PDR (Carbonero et al., 2021). These dynamics risk increasing interregional and international income inequality around the globe, which may trigger the reallocation of capital and labour from less developed regions – which are not as prepared to harness AI – towards more technologically advanced and AI-ready countries (IMF, 2024).

Variations of AI adoption rates are also visible among developed countries. For example, the results from the EWCS in 2024 clearly show large differences in the use of generative AI tools by workers across countries, even within the EU (Eurofound, 2025b). While one in five workers report using generative AI tools in their work in countries such as Luxembourg, Sweden, Belgium, the Netherlands and Denmark (which have a greater presence of knowledge-intensive sectors), Greece, Italy, Portugal and Romania have much lower rates (5% or lower) (Figure 6). Among the few non-EU countries included in the survey, the share of workers who reported using GenAI tools is 3% in Serbia and Bosnia and Herzegovina, 4% in North Macedonia and 20% in Kosovo (Eurofound, 2025b). In another more recent survey by the JRC (2025b), on average a third of EU workers report using AI for work-related purposes. As a result, these differences in AI adoption rates may lead to the country differences in terms of job transformation and productivity.

Figure 6: Use of generative AI tools, list of countries participating in the EWCS in 2024 (%)



Note: *Percentage of workers replying 'yes' to the question: 'And do you use the following equipment in your work? Artificial intelligence that simplifies complex mental tasks or makes recommendations on how you should be working? (ChatGPT, LLAMA, DALL-E, Midjourney, Jasper)'.*

Source: Taken from Eurofound 2025b, p. 21.

According to the ILO (2023), the share of jobs at high risk of full automation due to generative AI varies from 5.1% in high-income countries to 0.4% in low-income countries, with 2.4% in upper-middle-income countries and 1.3% in lower-middle-income countries. The IMF (2024) estimates that about 60% of jobs in advanced economies are exposed to AI due to the prevalence of cognitive-task-oriented jobs – 27% of which are in high-exposure/high-complementarity occupations and 33% in high-exposure/low-complementarity occupations. In emerging market economies, this share is 40% (with corresponding shares of 16% and 24%) and in low-income countries it is 26% (with corresponding shares of 8% and 18% respectively). While almost 70% and 60% of UK and US employment respectively is in high-exposure occupations, high-exposure employment in emerging market economies ranges from 41% in Brazil and 39% in Colombia to 35% in South Africa and 26% in India (IMF, 2024). Box 8 presents the factors shaping AI's impact on jobs in high-income and low/middle-income countries.

Box 8: Factors shaping AI's impact on jobs in high-income versus low/middle-income countries

- Good level of digital infrastructure – internet, data centres, leadership in app market
- More mature digitisation, diffused into all jobs
- High digital skills base, wide computer use
- High level of AI talent and high-quality education infrastructure in AI and data science
- Easier and more widespread adoption of AI models
- High share of white-collar occupations
- High share of highly educated workforce

- Poor digital infrastructure and energy sources
- High costs of broadband connectivity and software
- Low diffusion of digital technology in workplaces
- Low foundational digital skills base
- Low number of AI talent, and emigration thereof
- High share of elementary occupations
- High share of low-skilled workers in total employment
- Linguistic and cultural barriers and bias of AI models

The risk of increased divergence in productivity between high- and low-income countries due to a wider adoption of generative AI products is already pointed by the ILO (2023). Due to mature digitisation and AI adoption in advanced economies, larger shares of jobs fall into the augmentation category and GenAI systems are more likely to become productivity tools, supporting and speeding up the execution of some tasks within certain occupations (EY-Parthenon, 2024). The *digital divide* will determine how the benefits of such productivity tools are distributed among societies and countries, with high-income countries and privileged groups likely to reap the biggest rewards. While middle-income countries are more exposed to the automating effects of AI technologies, their digital infrastructure and skilled workforce may also be an asset for initiating the growth of complementary industries. For instance, although India and the Philippines are at risk of losing jobs in call centres, their dominance in business process outsourcing may provide the needed foundation for developing new industries in these emerging economies (ILO, 2023; UN, 2024).

The World Economic Forum (2025) also reminds us that AI and many other megatrends occur simultaneously at different speeds in every region and from different starting points across geographies. As a result, the extent of job disruption is not uniform across economies. In high-income countries, AI's impact is more likely to be offset by job creation in new sectors and roles in services, while in middle-income countries, the risk of displacement is higher, particularly for female, low-skilled and older workers. Another study shows that globally, 57% of occupations in emerging markets have a high to moderate exposure, while this is 67% in advanced economies (EY-Parthenon, 2024). In transition economies, uneven AI adoption could lead to pockets of rapid transformation, especially in sectors like manufacturing and logistics, while many areas remain unaffected (ILO, 2023). Thus, lower- and upper-middle-income countries are expected to experience greater disruption in jobs due to automation in their industrial employment shares – particularly in Egypt, Colombia, Portugal, Türkiye, Israel, Bahrain, Argentina, Malaysia, the UAE, Nigeria, Kazakhstan, Mexico and Serbia (WEF, 2025).

Low-income countries are at the highest risk of falling behind due to the widening digital divide and income disparity, although the immediate risk of job displacement is lower due to lower digital penetration. The augmentation potential will be hampered by the lack of reliable infrastructure, which depends on access to, and the cost of, broadband connectivity and electricity. This is about one third of the global population (2.7 billion people) who still did not have access to the internet. Among the two thirds that do have access, many would be unable to use GPT technologies due to limitations in the quality of their connection or the cost of the service (ILO, 2023). In its 2025 update, the ILO confirms income-based differences in exposure across country groups, with high-income countries having the highest share of employment exposed to AI (34%). The total share of exposed employment declines significantly as income levels decrease, reaching just 11% in low-income countries (ILO, 2025a).

Workers also need a minimum level of foundational skills to fully reap the benefits of AI technology, and such skills are scarce in low-income countries. As an AI's impact study in Latin America and the Caribbean by the ILO and World Bank (2024) showed, the rate of adoption and exposure to GenAI is slower in developing countries where less workers use digital technologies in their jobs. Alongside hard infrastructure, software costs are likely to impact the economic viability of adoption as well (e.g. the high licensing costs of ChatGPT or MS Copilot). The study in Latin America and the Caribbean by the ILO and World Bank (2024) also emphasise that considering the large proportion of the workforce in the informal sector and the small share of formal firms with limited technology adoption, workers displaced from formal-sector jobs may face more challenges in finding good-quality jobs (see Box 9 for more details of the study). Less GenAI exposure may act as an insulating buffer to automation risks in developing countries for now, but it also means untapped potential of augmentation and productivity gains with a risk of being left behind (ILO, 2023).

Box 9: Study of AI's impact on employment in Latin America and the Caribbean (LAC)

This employment exposure study by the ILO and the World Bank found that a total of 26-38% of jobs in the LAC may be exposed to GenAI (ILO and World Bank, 2024). The exposure is linked to the economic status of countries, confirming again that income levels are strongly correlated with GenAI's impact on labour markets. The findings indicate a higher exposure of urban-based formal jobs that require higher education and are held by individuals with higher relative incomes who can afford access to this technology. Younger and female workers tend to face greater automation exposure, particularly in the finance, insurance and public administration sectors. The share of jobs exposed to automation is relatively small but not trivial, at between 2% and 5% of total employment.

The study also found a higher potential of job augmentation than those with automation risks in all LAC countries, ranging between 8% and 14% of employment, especially in jobs in education, health and personal services. However, for this to happen, *workers must use computers at work:* in some countries, such as Mexico and Peru, the majority of workers in augmentation potential occupations do not use a computer at work and are thus unable to benefit from augmentation. The study confirms again that access to digital technologies is a critical determinant of the extent to which workers can harness the potential benefits of GenAI. Up to half of the jobs that could improve productivity with GenAI – about 17 million jobs – are hindered by gaps in digital access and infrastructure (ILO & World Bank, 2024).

One additional factor to consider in AI's impact on jobs in developing countries is the existence or lack of institutional and regulatory frameworks that mediate AI's impact in the workplace in some high-income countries. Promoting responsible AI development and adoption requires strong institutions and a strong regulatory environment. AI technologies carry much higher risks particularly in low- and middle-income countries, where existing social, economic and institutional inequalities can amplify their harms. According to Okolo (2024), deploying AI tools without adequate oversight and with weak policy frameworks would bring higher risks of harmful applications such as mass surveillance and worsening societal divides in developing countries. For example, governments in Africa have rapidly been acquiring AI-enabled surveillance technologies that have been deployed in ways that infringe on privacy and target vulnerable populations (Okolo, 2024).

In recent case studies, Rani et al. (2024) found a striking contrast between the impact of the algorithmic management of work in Italy and France on the one hand, and in India and South Africa on the other hand. The case studies conducted in Italy and France show benefits in terms of work coordination and improvements in the business models without pervasive negative consequences for job quality, or for worker monitoring and surveillance. In the case studies conducted in India and South Africa with similar types of work, besides productivity and efficiency gains and improvements in business models, a significant worsening of job quality and intrusive forms of worker monitoring and surveillance, including with disciplinary consequences, are observed (Rani et al., 2024). This means that a limited or lacking institutional and regulatory environment in developing countries can lead to more negative consequences of the same AI technology on labour market conditions.

Another example of lacking worker protection regulations in developing countries comes from the AI production value chain through platform work opportunities in developing countries. As already mentioned, the production of AI systems depends on ‘micro-workers’, whose contributions are often invisible and who are mediated through digital labour platforms as ‘independent contractors’. Content moderation, data annotation and data labelling work is at the low end of the AI value chain as it does not require high qualifications (besides literacy), digital skills or access to a computer (or mobile device) and the internet. In addition to platforms such as Amazon Mechanical Turk and Appen, data labellers sometimes work through third-party companies hired by leading tech firms, in a subcontracting relationship. Western companies increasingly outsource data annotation tasks to developing countries like Kenya, India, Venezuela and the Philippines, where workers are often exposed to graphic and traumatic content as part of their work, with a growing risk of exploitation (Tan & Cabato, 2023).

For example, more than 2 million people in the Philippines perform this type of ‘crowdwork’ according to informal government estimates, as part of AI’s vast underbelly (Tan & Cabato, 2023). As one of the world’s biggest destinations for outsourced digital work, at least 10 000 workers in the Philippines carry out data annotation on a platform called Remotasks, which is owned by the USD 7 billion San Francisco start-up Scale AI. The workers, known as ‘taskers’, often earn far below the minimum wage – which ranges from USD 6 to 10 per day depending on region in the Philippines – sometimes with delays and reduced or cancelled payments (Tan & Cabato, 2023). This is an industry fuelled by millions of gig workers performing repetitive, low-wage tasks under heavy surveillance, with underpaid and unstable jobs. These micro-tasking platforms can bypass labour regulations, such as a minimum wage and a fair contract. Without stronger labour protections and ethical oversight, such practices may worsen, undermining the prospective benefits of AI in developing countries.

The poor working conditions and precarious jobs in these locations have been labelled as a new digital underclass (Eurofound, 2025c, p. 44). Earnings are lower even in a developing country context, and the skill level of the workforce is typically higher with, many workers holding university or postgraduate degrees (UN, 2024). While no precise figure exists on the overall numbers of people working as data labellers, estimates range in the tens of millions, and demand for such work is likely to continue as AI datasets and training needs grow. The size of the market is estimated at between USD 1 and 3 billion and is likely to experience double-digit growth over the next five years (UN, 2024). Thus, data curation and annotation are not only a critical component of the AI value chain, but also an important source of employment creation for developing countries. Ensuring decent work in the AI value chain would help to spread the benefits of AI more evenly.

The current geopolitical tensions and the AI innovation race risk leaving many countries behind, while three key inputs of AI supply – computing power, data and talent – are highly concentrated in advanced economies. Given that only a handful of voices have power over AI, the majority of people and countries have no direct say over it, leaving them with the ‘take-it-or-leave-it’ terms of service agreements of multinational tech firms (UNDP, 2025). Although it is easy to be taken by the global AI hype, developing countries must adopt context-specific approaches that align with their unique socio-economic realities. They need to integrate local values and culture into AI systems, build robust mechanisms for oversight, and promote transparency and accountability in AI deployment (Okolo, 2024). Priority must be given to expanding internet connectivity, developing national data infrastructures, investing in AI education programmes, and strengthening regional collaboration (Adan et al., 2024).

5.3. Main lessons and key findings

Overall, developing countries are starting the AI age with disadvantages, often exacerbated by the global digital divide. Access to AI development and governance is concentrated among a few countries with advanced AI capabilities, while the global majority is largely excluded. The starting point for developing countries in AI includes stark disparities – access to electricity, telecommunications infrastructure, the internet, cloud computing, quality STEM education, and career opportunities in AI. Limited digital infrastructure and broadband access to the internet prevent the core preconditions for AI adoption and productivity gains in any country: the use of digital devices at work and foundational digital skills. As technology adopters, developing countries also face a cultural and linguistic obstacle, as the current AI large language models favour only a few linguistic and cultural perspectives. AI expertise is also highly concentrated in North America and western Europe, with few exceptions such as India, while the emigration of AI talent severely undermines local AI capability-building. The numbers reveal a picture of AI asymmetry between developing countries and advanced economies, further aggravated by the current geopolitical tensions and the AI innovation race.

There is a strong correlation between the share of occupational groups in a country and their exposition to AI, revealing the determining role of a country's economic structure and its income level for AI's impact. Full automation risk is higher for developed countries, while it gradually decreases in middle-income countries and falls to its lowest point in low-income countries. Mature digitisation creates favourable conditions for higher AI adoption in advanced economies, where larger shares of jobs fall into the augmentation category with AI systems becoming productivity tools (ILO, 2023; IMF, 2024). In middle-income countries, the risk of job displacement is higher in certain sectors such as manufacturing, but their digital infrastructure and skilled workforce can be an asset for initiating the growth of complementary industries. Low-income countries have the highest risk of falling behind due to the widening digital divide and income disparity, although the immediate risk of job displacement is lower due to lower digital penetration.

Limited institutional and regulatory frameworks in developing countries may create a higher risk of AI having a negative impact. There is evidence of the moderating role of institutional and regulatory frameworks in developed countries, but many developing countries lack effective implementation for these limited frameworks. AI technologies carry higher risks in low- and middle-income countries, where weak policy frameworks bring higher risks of harmful applications such as mass surveillance, and of worsening societal divides with higher socio-economic inequalities. An experimental impact study of AM practices in the same sectors across different countries found a higher negative impact on job quality and worker monitoring and surveillance in developing countries. Another example comes from the AI production value chain through platform work, which leads to poor working conditions and precarious jobs in developing countries. This is an industry with millions of gig workers performing repetitive and underpaid tasks under heavy surveillance, often outsourced to countries like Kenya, India, Venezuela, and the Philippines to bypass worker protection regulations. These conditions undermine the prospective benefits of AI in developing countries.

CHAPTER 6. CONCLUSIONS AND POLICY IMPLICATIONS

The integration of AI into the workplace represents a significant paradigm shift, with profound implications for both organisations and employees. In just a few years, AI has evolved from a niche capability performing repetitive tasks to a general-purpose technology with sweeping implications across sectors and geographies. From large language models like ChatGPT to AI-driven medical diagnostics, its reach is expanding rapidly. The future scope of AI in the workplace is vast and holds tremendous potential to revolutionise how organisations operate, innovate and compete in the global economy. As AI technologies continue to advance rapidly, they are poised to transform virtually every aspect of the modern workplace, from automation and decision-making to employee productivity and customer experience.

Yet it also poses challenges like any technological revolution. On the one hand, AI technologies have the potential to alleviate the burden of repetitive tasks, enhance creativity through intelligent tools, and even predict workplace hazards, thereby contributing to the physical and mental well-being of employees. However, privacy issues loom large as AI systems increasingly collect, process and analyse personal data. Job displacement remains a valid concern, while the constant connectivity enabled by AI-driven digital platforms can lead to burnout and reduce work-life balance if not managed wisely. On top of this, technologies are often not truly neutral, as software products are programmed by people with particular world views, premises and datasets that reflect particular normativity, managerial principles and interests.

An abundance of studies regarding AI's impact on the labour markets have been reviewed in this report. The report documents the wide-ranging ways in which AI is influencing employment, not just in terms of job quantity through creation, transformation and displacement, but also in relation to job quality and inclusiveness. What emerges is a complex picture: AI is neither inherently a threat nor a solution. Its impact will be shaped less by the technology's capabilities and much more by the choices made by governments, businesses and societies. Therefore, AI must not be assessed solely by its technical capacity, but also by the governance frameworks and institutional values that guide its deployment. As a general-purpose technology, *'stupid but powerful',* it is capable of immense societal benefit or harm, depending on how it is implemented, by whom and for what.

AI's impact on both job quantity and quality is mixed for diverse reasons. Researchers use different methodologies and approaches, mostly theoretical with few empirical examples. It is a newly developed area with a limited grasp of the job-creating effects of AI. Theoretical measurements often overestimate the extent of job displacement, as they often focus on the technical feasibility of automation rather than its economic viability or political acceptability. The studies often miss the system redesign perspective, since new technology can create new management and operational models.

AI's impact on both job quantity and quality is context-dependent. Estimates of AI-related job losses and gains largely vary by type of economy, sector and occupation, but experts agree with the job augmentation effect for high-wage/high-skilled occupations and with job displacement and/or precarity for routine-based occupations. The existing *institutional and regulatory environment* in which organisations adopt AI tools mediates the effects of technology. Labour market institutions play a crucial role in moderating negative impact, as do the workplace dynamics shaped by managers and workers within a given work culture and management style, and their adjustment mechanisms through job (re)design, organisational changes or internal mobility.

Employment trends in AI-exposed sectors and occupations reflect a mix of substitution and expansion effects. Occupations with higher automation risk (e.g. office and admin roles, translators) have seen slower employment growth compared to low-risk occupations, yet within-occupation task reallocation and firm-wide AI-driven growth help sustain overall employment levels. AI exposure often means augmentation in highly skilled work, but automation in low- and medium-skilled work. Rather than leading to broad job losses, AI appears to be reallocating labour across tasks and firms, although freelance platforms show early evidence of displacement in writing jobs. AI seems to extend automation up the skill ladder in knowledge work, shifting routine analytical work down the value chain and substituting a broader set of middle-skill jobs – this time in offices rather than factories.

Two opposing observations on the automation patterns of knowledge work. *The first observation* suggests *AI may destroy 'entry-level' jobs and break the career ladders of fresh graduates.* As AI is better at low-complexity tasks, entry-level tasks such as research, data analysis, report writing and document review can be automated. AI can take over the initial stages of research, medical, legal and financial analysis, but their finalisation would still require specialist 'elite experts'. Demand for high-skilled expertise would rise, while mid-level skills would be threatened by automation.

The second observation sees AI as an *opportunity to augment and broaden expertise, which could bring back medium-skilled employment* since lower-skilled and inexperienced workers are observed to benefit more from AI's support in simpler tasks. By improving the quality and reducing time spent on tasks, AI could support and supplement judgement, thus enabling a larger set of workers (without university degrees) to enter good jobs, moderating earning inequality, and lowering the cost of healthcare, education and legal services. Dubbed the '*democratisation of expertise*', such increased access to expertise could enable organisations to shift tasks down from high to low-skilled occupations, potentially creating more middle-class jobs.

AI's impact on total (aggregate) employment has been close to null. Studies point to no visible effect or only small decline or increase in some jobs, as very few jobs are completely automatable. Thus, employment trends in AI-exposed occupations and firms reflect a mix of substitution and expansion effects. Despite no indication of net job destruction, occupations with higher automation risk have seen slower employment growth compared to low-risk occupations, while employment trends in exposed occupations differ across skill levels. Nevertheless, the jury is still out on AI's ultimate impact on job numbers.

The is evidence of both positive and negative AI effects on job quality. AI can improve or reduce job quality through its effects on job intensity, autonomy, skill use and collaboration. Job quality improvements include more interesting tasks, improved physical safety, greater work engagement, increased complexity and responsibility, and higher job satisfaction, leading in some cases to job upgrading. Examples of worsening working conditions include higher pace of work, reduced autonomy, cognitive underload, higher control and monitoring, skills underutilisation and psychosocial effects, leading in some cases to job downgrading. Workers tend to benefit most when AI acts as a support tool for workers, in contrast to its use in controlling work processes and monitoring performance.

AI adoption often increases work intensity by shifting human effort toward more cognitively and emotionally demanding tasks. Increased work intensity seems to be a common result across the board in diverse sectors, occupations and skill levels. The use of AM at work directly contributes to this impact, by increasing standardisation/routinisation, centralisation of knowledge, and monitoring and managerial control over work processes. It also creates conditions to reduce autonomy, but the outcome is shaped by the management decisions of organisations.

Most striking is the opposite effects by skill level. AI has more positive effects on highly skilled occupations thanks to new productivity tools that support and speed up the execution of tasks, where highly skilled and digitally literate workers benefit from it in terms of employment growth, wage gains, or transition to higher value-added tasks. To the contrary, more negative effects are experienced in low-skilled occupations, where lower-wage workers face work intensification, loss of autonomy, stress, anxiety and burnout. This is particularly the case for location-based platform workers, logistics and warehouse workers, and similar sectors where AM practices are common.

AI tools lead to increased workplace monitoring and surveillance. New forms of AI-supported tools are increasingly used to monitor all work processes (*datafication of the workplace)*. They collect and analyse large volumes of data on workers, which may be an invasion of their privacy. The same technologies that can assist workers and bring safety carry a significant risk of privacy breaches and data security issues. By giving employers access to more and better data about workers, AI can lead to information and power asymmetries in favour of corporate business, with the potential of altering traditional work relationships between workers and firms.

AI expands AM practices into traditional workplaces. The logic of algorithmic management and surveillance is now extending into traditional workplaces –the so-called *platformisation of work*. With increased standardisation and remote work practices, the majority of workers are now using digital devices that are often connected to platforms for management and coordination; these devices then become control and monitoring tools. Moreover, the AI value chain depends on many low-skilled gig workers – such as data labellers and content moderators – performing repetitive, low-wage tasks under heavy surveillance. Gig work is expected to grow as demand for AI jobs grows, worsening access to decent work, fair remuneration and social protection.

AI's effect on job quality is not fixed; it is constantly negotiated within workplace dynamics. Depending on who is using it and how, AI can either empower or overwhelm workers. The negative outcomes on job quality often stem from organisational factors and management choices, rather than the technology itself. This, in turn, is affected by institutional and regulatory frameworks and by the organisational structures of firms and work culture. As AI systems tend to replicate existing power dynamics in organisations, their impact on worker well-being depends on how it is implemented in the workplace and whether workers have any say on it.

AI's impact is uneven by age, gender, education and occupation. AI's impact is particularly dependent on workers' educational background, occupation and skill level. It creates new opportunities for higher-educated and high-income professionals, who tend to be younger and prime-aged white male workers. However, for low-educated, low-income workers, it creates risks of job displacement, deteriorating working conditions, or less access to decent work and productivity-enhancing AI tools in the workplace. The latter tend to be women, older workers and marginalised groups. Education seems to be the key moderator of AI's employment impact.

AI may compromise the ability of disadvantaged groups to access decent jobs. Since technological development often replicates the existing power dynamics in society, AI may amplify inequality by favouring privileged groups over disadvantaged ones. Power imbalance in AI development and implementation is pervasive across gender, race and socio-economic background, and highly educated managers and technology developers often decide the features of AI systems from their own perspectives and in their own interests. AI influences who get seen, selected, promoted, supported or dismissed in the labour market through its increasing use in recruitment, performance monitoring and promotions. There are examples of biased data due to incomplete, unrepresentative or historically discriminatory patterns used to develop AI systems, hence leading to existing inequalities being amplified.

The vicious cycle of digital and AI gender inequality continues. There are many examples of how existing AI tools amplify existing gender inequality even without deliberate intention. This is a vicious cycle, because very few women study and enter STEM and ICT occupations, and there are even fewer in the AI workforce. Women are severely underrepresented among AI developers, so AI tools reflect the social judgements of developers. Very few women are AI users, and women report less positive perceptions about AI than men. Moreover, women are overrepresented in clerical and admin roles with a higher risk of automation. AI's education and career guidance tools favour boys for STEM studies, while recruitment tools favour male candidates for ICT occupations.

For AI to serve for inclusive employment, conscious effort and concrete policy actions are needed. There are cases where AI tools are developed for, and contribute to, more ethical recruitment across marginalised groups, or to include people with disabilities by removing barriers (e.g. speech-to-text applications, live captioning algorithms for deaf people, image recognition tools for blind people, etc.). However, their development does not occur automatically; they are often the result of a deliberate attention and effort. People with disabilities illustrate this well: typically, AI developers have low awareness of, and familiarity with, accessibility and disability needs, and AI tools are trained for 'average' users with limited and biased data on disabilities. Even when effort is made to developed special AI tools for people with disabilities, their commercialisation and scaling beyond prototypes are not easy if left to market forces.

Developing countries are starting the AI age with disadvantages, often exacerbated by the global digital divide. Access to AI development and governance is concentrated among a few countries with advanced AI capabilities, while developing countries have stark disparities – access to electricity, telecommunications infrastructure, internet, cloud computing and quality STEM education. Limited digital infrastructure leads to limited use of digital devices at work and foundational digital skills, which are key for AI productivity gains. AI expertise is also highly concentrated in North America and western Europe, with a few exceptions like India, while the emigration of AI talent severely undermines local AI capability-building. This asymmetry may be further aggravated by the current geopolitical tensions and the AI innovation race.

A country's economic structure and income level are the main determinants for AI's impact. There is a strong correlation between the share of occupational groups in a country and their exposure to AI. Full automation risk is higher for developed countries, while it gradually decreases in middle-income countries and falls to its lowest point in low-income countries. Mature digitisation creates favourable conditions for higher AI adoption in advanced economies, where larger shares of jobs fall into the augmentation category with AI systems becoming productivity tools. The risk of job displacement is higher in middle-income countries and lower in low-income countries, which have the highest risk of falling behind due to the widening digital divide and income disparity.

Limited institutional and regulatory frameworks in developing countries may lead to a higher risk of AI having a negative impact. There is evidence of the moderating role of institutional and regulatory frameworks in developed countries, but many developing countries lack effective implementation for these limited frameworks. AI technologies carry higher risks in low- and middle-income countries, where weak policy frameworks bring higher risks of harmful applications like mass surveillance and worsening societal divides with higher socio-economic inequalities. One example is the 'AI production value chain' through platform work, with millions of gig workers performing repetitive and underpaid tasks under heavy surveillance, often outsourced to countries like Kenya, India, Venezuela and the Philippines to bypass worker protection regulations. These conditions undermine the prospective benefits of AI in developing countries.

A final word …

Given the gradual erosion of job security, income stability and workers' rights in the last four decades, it is essential to monitor the effects of AI on the workplace and workers' well-being and to continuously research AI's impact on the labour markets in order for policies to be adapted accordingly. The integration of GenAI tools into labour market research must be approached critically too. As discussed in the Economist (2025), tools such as OpenAI's Deep Research, despite their impressive capabilities, can entrench dominant views, overlook niche but valuable data, and discourage deep, reflective analysis. Researchers must ensure that the use of such technologies augments rather than replaces human judgement, leaving space for methodological scrutiny, expert interpretation and alternative perspectives.

Ultimately, the future of work in an AI-driven world is not predetermined. AI can drive innovation, increase productivity and open new frontiers for economic growth. However, it can also reinforce exclusion, inequality and insecurity if left unchecked. Special attention is needed to avoid common pitfalls: AI hype, oversimplified promises of objectivity, and the disempowerment of users when algorithmic systems are deployed without transparency or recourse. Embedding these principles, including risk assessments and data governance, into the adoption of AI in the workplace is not merely a safeguard, it is essential to ensure that AI complements, rather than replaces, human agency. There is a need to actively shape the conditions of AI deployment so that it supports – not undermines – human dignity, equality and opportunity.

The key policy challenge is how to manage this transition and share equally the benefits of AI adoption in the workplace. The AI-related developments will depend on the regulations introduced at national and international level, and whether the development of AI systems is centralised or decentralised.

Leaving the development of AI to market forces (e.g. a small number of tech companies) with a short-term focus on increasing productivity and decreasing costs is a choice – and this seems to be current market-based approach. Regulating it to develop AI forms in ways that enhance human capacities and maximise human/AI benefits is another choice; not choosing anything is also a choice. Whatever is done or not done now will shape how AI makes its way into our lives.

This brings us to relevant policy initiatives on AI use in the workplace, which is more of a priority in Europe, and specifically at EU level, where initiatives have focused on preventing the potential misuse of AI systems, protecting the customers of online services and data protection via the *GDPR, DSA* and *the EU AI Act*. The latter classifies recruitment and worker management systems as 'high risk', and imposes mandatory impact assessments and ethical scrutiny, conformity checks and the establishment of risk management systems. Although these are under the EC's new simplification package for amendments, discussions have also start around a new general directive on AI in the workplace.

Alongside these regulations, European social partners signed a Framework Agreement on Digitalisation in 2020, while a Code of Practice for General-Purpose AI is currently being drafted. The EESC also adopted an Opinion on Pro-Worker AI in 2025. Other EU policy responses relevant to future-of-work concerns include the EU Directives on platform work, and on transparent and predictable working conditions in the EU. The Platform Work Directive regulates the use of algorithmic management and classifies the employment status and rights of gig workers, although enforcement remains a challenge in cross-border digital markets.

Yet regulation alone is not enough. A robust policy agenda must also address foundational needs: universal access to digital education, targeted upskilling and reskilling for vulnerable workers, and active labour market policies that support mobility and adaptation. The policy implications are clear: governments need to go beyond reactive regulation. Strategic foresight, inclusive planning and agile public-private collaboration are necessary to shape AI's labour market trajectory. The key areas for action include the following:

Ethical governance and regulations: Establishing clear rules for transparency, explainability and fairness in algorithmic decision-making is essential. Workplace governance structures are needed to negotiate the implementation and oversight of AI systems, including data security, encryption, anonymisation techniques and data access controls to enhance the security and privacy of data.

Inclusive skills development: Lifelong learning, upskilling and reskilling are no longer optional. Governments and employers must scale up access to digital education, AI literacy, technical training and soft skills development across the workforce. Particular attention must be given to most vulnerable groups to AI, including older, low-educated and low-wage workers.

Updating labour regulations: Regulations need to be revised to address the algorithmic management of work, the privacy and security of workers' data, remote work structures, and the hybridisation of roles. Worker consultation and social dialogue must remain central to the governance of AI at work.

Adapting social dialogue mechanisms: Workers' voices are essential for responsible and effective AI adoption. Participation helps align AI deployment with real work practices, drawing on workers' tacit knowledge and improving acceptance. Advocating for workers' data rights is one way to challenge knowledge asymmetry.

ANNEX: AI GLOSSARY

Artificial intelligence (AI)	A machine-based system that is designed to operate with varying levels of autonomy and that may exhibit adaptiveness after deployment, and that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments (EU AI Act, 2024).
Agentic AI	Agentic AI refers to the most recent AI systems that exhibit autonomy, goal-directed behaviour and adaptive decision-making, enabling them to operate independently and interact dynamically with their environment. Unlike traditional AI models that function based on pre-defined inputs and outputs, agentic AI can initiate actions, plan long-term strategies and self-improve over time, making it a transformative force in industries such as automation, robotics and digital assistants. Agentic AI is increasingly integrated in workplaces to automates routine and repetitive tasks, enabling employees to focus on higher-value, creative and strategic work. It can serve as intelligent virtual assistants, providing real-time insights and data-driven recommendations to support complex decision-making processes, effectively reducing cognitive load and fostering a more efficient work environment.
AI model	An AI model is actionable representation of all or part of the external context or environment of an AI system (encompassing processes, objects, ideas, people and/or interactions taking place in context). AI models use data and/or expert knowledge provided by humans and/or automated tools to represent, describe and interact with real or virtual environments. There are three types of AI models: symbolic AI models, statistical AI models and hybrid AI models.
AI model training techniques	AI models are trained by feeding them data to help them learn and refine their ability to produce accurate responses. This process, known as AI model training, involves using algorithms and techniques to analyse data and make predictions. The quality and depth of the input data are crucial for the success of AI model training. The main training techniques are: ▪ supervised learning: this involves training the model on labelled data, where the inputs and desired outputs are provided; ▪ unsupervised learning: training the model on unlabelled data, allowing it to discover patterns and structures within the data; ▪ reinforcement learning: training the model to make decisions in an environment, receiving rewards or penalties based on its actions; and ▪ deep learning: employing neural networks with multiple layers to learn complex patterns from data.
Algorithm	An algorithm is a set of instructions, or a step-by-step procedure, used to solve a problem, accomplish a task or perform a computation. It is essentially a recipe for how to do something, whether it is a computer program or a manual process. Algorithms form the basis of computer programming, providing the blueprint for how a program should execute, ranging from simple sorting and searching to complex tasks such as artificial intelligence and machine learning. An algorithm is a coded formula written into software that, when triggered, prompts the tech to take relevant action to solve a problem. Computer algorithms work via input and output. When data is entered, the system analyses the information given and executes the correct commands to produce the desired result. Algorithms are the foundation of artificial intelligence and machine learning and are used to develop intelligent systems that can perform tasks such as image recognition, natural language processing and decision-making.
Algorithmic management of work	Algorithmic management can be defined as the use of computer-programmed procedures to coordinate labour input in an organisation. It is a mode of control in which AI systems oversee, allocate and evaluate work. Unlike traditional managerial oversight, algorithmic management often replaces human judgement with automated decision-making processes. While these systems offer operational efficiency and real-time responsiveness, they also introduce new challenges related to transparency, fairness and worker autonomy. Algorithmic

	management is now widely applied in both traditional sectors – such as logistics, manufacturing and retail – and in digital labour platforms, reshaping the nature of work across diverse contexts.
Artificial general intelligence (AGI)	Also known as strong AI or full AI, AGI refers to a theoretical AI system with generalised cognitive abilities that match or surpass human intelligence by (i) analysing and processing data in human ways; and (ii) creating complex and human-like outputs. AGI would be capable of understanding, learning and applying knowledge across a wide range of tasks, making decisions, and solving problems in a manner indistinguishable from human intelligence. Unlike narrow AI, AGI would possess the ability to transfer knowledge and skills across different domains. Despite significant advancements in AI, AGI remains a concept and has not yet been realised. Some consider multimodal large language models (MLLMs) a first step towards AGI.
Artificial narrow intelligence (ANI)	Also known as weak AI, ANI is designed to perform specific and narrowly defined tasks. Narrow AI does not possess generalised cognitive abilities and cannot perform tasks outside its programmed scope. Examples are recommender systems (e.g. Netflix, Amazon), voice assistants like Siri and Alexa, self-driving cars, and modern chatbots (e.g. ChatGPT). These systems leverage machine learning and deep learning algorithms to excel in their designated areas but lack the ability to apply their intelligence to unrelated problems. Most current advanced AI applications fall into this category, such as those based on natural language processing and/or large language models and those that focus on generative AI.
Artificial superintelligence (ASI)	ASI would be potentially smarter than humans and surpass human intelligence in all domains, but it is currently a theoretical concept and remains within the realm of science fiction. Yet there is considerable debate about their (potential) nature, which provides future perspectives on the development of AI.
AI literacy	Sometimes referred to as a kind of 'driving licence' for operating in the digital age, AI literacy is increasingly recognised as a foundational skill – an essential enabler of human agency, resilience and inclusion in AI-augmented environments. It refers to the ability to understand, use, monitor and critically reflect on AI systems. More than technical familiarity, AI literacy encompasses awareness of how AI works, its potential and limitations, and its social, ethical and economic implications. In this sense, it builds on and extends existing notions of digital, data and media literacy.
AI-related skills	AI-related skills can be conceptualised along a spectrum, ranging from minimal task-based familiarity with AI tools to sophisticated development and engineering competencies. This complexity can be simplified through the three-tier model of AI roles: ▪ developers of AI systems, who are responsible for building and improving AI models and infrastructures; ▪ maintainers of AI systems, such as IT technicians and AI system integrators, who ensure the functionality, security and continuous improvement of AI technologies; ▪ users of AI systems, who engage with AI tools in varying degrees of complexity, from basic (e.g. operating AI-driven chat interfaces) to intermediate (e.g. configuring data inputs) and advanced (e.g. customising AI applications).
AI in predictive maintenance	AI in predictive maintenance uses data analysis to forecast equipment failures and optimise maintenance schedules, leading to increased efficiency and reduced downtime. AI algorithms analyse sensor data, historical performance and other relevant information to predict potential issues before they cause breakdowns, allowing for proactive maintenance and repairs. This approach helps companies avoid costly outages, improve worker safety, and extend the lifespan of equipment.
Autonomous driving	Autonomous driving is a specialist field of AI that combines AI and machine learning with sensors, cameras and radars to make a vehicle operate and navigate without human intervention. Autonomous vehicles can perceive their environment, make decisions, and control the vehicle's movement to safely

	transport passengers or cargo from one location to another. The goal of this sub-field is to increase safety and reduce human error, enhancing the efficiency of transportation systems.
Autonomous systems	Autonomous systems are AI-powered systems capable of operating with minimal or no human intervention, including self-driving vehicles, smart robots and automated industrial machinery.
AI-driven job matching	While traditional job search methods might require a jobseeker to filter numerous postings to find roles that fit her unique skill set, an AI-driven job matching platform can analyse a jobseeker's CV, identify and extract key competencies which may not be visible at first sight, and match her with several diverse positions. Simultaneously, employers seeking candidates with this combination of skills receive her profile as a top match, expediting the recruitment process.
Big data	While not a form of AI, big data is often a key input into AI tools, providing the fuel from which AI systems can learn and improve. First coined in the early 2000s, the term 'big data' was created to describe the boom in the quantity of available data – largely aided by advancements in the technology associated with data recording and storage. Big data differs from traditional data in that it can feature structured and/or unstructured data that cannot be managed, processed or analysed using traditional approaches. Big data is often described using the '5 Vs.': Volume (quantity and scale of data), Velocity (speed of data generation), Variety (scope and heterogeneity of data), Value (large benefits that big data can provide), and Veracity (data accuracy and reliability) (ETF, 2019). For example, the most relevant forms of big data for public employment services (PES) include job vacancy postings (text) and internally generated click data from clients' interactions with PES digital platforms.
Centralised learning	Centralised learning is one of the machine-learning systems that are trained centrally. In this model, all datasets are uploaded to a central processing environment to train an algorithm. All datasets are considered local to the training environment. Most current machine learning is centralised.
Cognitive computing	Cognitive computing aims to recreate the human thought process in a computer model that can learn, reason and interact with humans in a natural and meaningful way, similar to how humans think. It seeks to imitate and improve the interaction between humans and machines by understanding human language and the meaning of images. While traditional AI systems are often rule-based (programmed to follow specific instructions), cognitive computing systems can learn and adapt to new situations, allowing them to make decisions independently.
Computer vision	This is key to how computers interpret the visual world. Computer vision employs deep learning and pattern identification to interpret image content (graphs, tables, PDF pictures, and videos). Through computer vision and image processing, machines can identify objects in photos, scan handwriting, or guide robots through space. These applications are increasingly used in areas such as healthcare diagnostics, security, and industrial automation.
Data labelling	Data labelling, also known as data annotation or data tagging, is the process of assigning labels to raw data (such as images, text or audio) to provide context and categorisation for machine learning (ML) models. These labels help ML algorithms understand the data and learn patterns, enabling them to make accurate predictions or decisions. Data labelling is crucial for supervised machine learning, where models are trained on labelled data to learn how to map inputs to outputs. It is critical and requires some explainability in contexts such as content moderation, where assigning a label such as 'misinformation' or 'violent' is important.
Deep learning (DL)	Deep learning is a specialist branch of machine learning that uses large neural networks with many layers to process the data. The more layers a neural network has, the more complex it becomes, and it is defined as deep learning. The biggest challenge is that the functioning of the layers is largely a black box because exactly what happens in each layer is unknown, and models can learn and self-correct, which changes how data is processed and inputs for subsequent

	layers are generated. In other words, it is very hard to derive how final outputs follow from initial inputs, thus creating a black box. This can be partially overcome by correct training, analysis and interpretation processes, but these add costs to running the model, with no certainty that the higher accuracy is worth the investment. Deep learning powers modern advances in image classification, speech recognition and natural language understanding.
Digital twins	A digital twin is a virtual representation of a physical object, system or process, often mirroring its behaviour, characteristics and performance in real time. It is a dynamic model updated with real-time data, enabling the physical counterpart to be simulated, predicted and optimised. Digital twins are used for simulation, testing, monitoring, predictive maintenance, optimisation and decision-making, most often in manufacturing, healthcare and transportation. They allow scenarios to be tested virtually before they occur in the physical world, while real-time data streams from the physical object to the digital twin allow for the performance monitoring and identification of potential issues. By analysing data and running simulations, digital twins also help optimise performance, improve processes and make better-informed decisions.
Ethical AI	Ethical AI is the field that examines and sets principles for the responsible development and use of AI, focusing on fairness, transparency, accountability, the mitigation of bias and respect for human values, to ensure that AI benefits society and avoids harm. It encompasses a wide range of considerations, including data privacy, fairness, explainability, and the potential societal impacts of AI. Sometimes called 'AI ethics', it is a multidisciplinary field that studies how to optimise the beneficial impact of AI while reducing its risks and adverse outcomes.
Explainable AI (XAI)	Explainable AI (XAI) is a growing area of AI research focused on making machine learning models and AI decisions more transparent, interpretable and accountable. It refers to a set of techniques and processes that make AI model decisions understandable to humans. It addresses the 'black box' problem of complex AI models by providing explanations for their predictions, reasoning and impact, ultimately building trust and facilitating deeper understanding.
Federated (collaborative) learning	Federated (collaborative) learning is another type of machine-learning system that trains an algorithm across multiple processing environments, including edge devices or different data centres. Data samples are kept locally within each environment and are not copied across environments. There is no centralised, complete dataset with which the algorithm can train. Federated learning helps to address critical issues like privacy, data security and data access rights by building models without sharing data.
Foundation models	These are broad AI models, pre-trained on vast datasets that can be adapted to perform a wide range of downstream tasks. It is an AI model with general-purpose building blocks that serve as foundational base for building more specialised applications. It is distinguished by massive datasets, general-purpose orientation, adaptability and scalability. Examples include GPT-4, Copilot and Claude. These models are trained on massive, diverse datasets and fine-tuned for specific applications, including NLP, vision, and multi-modal tasks.
Generative AI (GenAI)	The term 'generative' in the context of AI refers to the capability of AI systems to recognise and utilise textual, visual or auditory patterns from extensive datasets to generate new content in response to prompts, and where this content cannot be distinguished from human content. GenAI employs deep learning models, such as neural networks and transformers, which are trained on vast amounts of curated data to produce human-like content in response to complex queries and diverse prompts. GenAI is typically based on large language models (LLMs) or generative adversarial networks (GANs) to produce output by modelling the statistical structure of large training datasets. There are several examples of generative AI that creates new text (e.g. ChatGPT-4, Claude, Gemini, Copilot), code (e.g. Code Interpreter, GitHub Copilot), audio (e.g. MusicLM by Google, AIVA, MusicGen), images (e.g. Stable Diffusion, DALL-E from OpenAI, Firefly from Adobe), videos (e.g., Synthesia, Runway) and various other applications.

GPT (Generative pre-trained transformers)	GPTs belong to the family of LLMs, a type of machine learning model based on neural networks. The term ‘generative’ refers to their ability to produce output of a creative nature, which in language models can take the form of sentences, paragraphs or entire text structures, with characteristics often undistinguishable from that produced by humans. ‘Pre-trained’ refers to the initial training on a large corpus of text data, typically through unsupervised or self-supervised learning, during which the model learns about the text structure by temporarily masking part of the content and trying to minimise errors in the prediction of the masked words. Following pre-training, these models are further fine-tuned with the use of labelled data and so-called ‘reinforcement learning’, making them more suitable for specific tasks. Its prerequisite is the production of vast amounts of labelled data, typically done by workers on crowdsourcing platforms. ‘Transformers’ refer to the underlying model architecture, which uses numerous mechanisms, such as attention and self-attention frameworks, to develop weights related to the importance of text elements, such as words in a sentence, which are subsequently used for predictions.
Human-centric AI	AI tools that prioritise and enhance the human experience by making them more intuitive, empathetic, and aligned with human values and needs. Human-centric AI tools understand and respond to human emotions, enabling natural and empathetic interactions, and respect ethical and social considerations in decision-making processes (Fenwick et al., 2024).
Human-AI coevolution	Human-AI coevolution is defined as the continuous, reciprocal process in which human behaviours and AI systems mutually adapt and evolve. It involves dynamic feedback loops where human decisions shape the training and outputs of AI, while AI-generated recommendations, in turn, influence human choices. This interdependence creates emergent, complex patterns that affect individual and societal outcomes. It challenges traditional static models of human-machine interaction by emphasising iterative co-adaptation. Understanding AI coevolution will help for developing ethical, transparent and resilient AI systems (Pedreschi et al., 2024).
Hybrid AI models	Many applied AI systems combine symbolic and statistical models into ‘hybrid’ models. For example, NLP algorithms often combine statistical approaches building on large amounts of data and symbolic approaches that consider issues such as grammar rules. Hybrid AI systems that combine models built on both data and human expertise are viewed as a promising alternative that addresses the limitations of both system and machine-learning approaches.
Large language models (LLMs)	LLMs are the latest development in the AI space, and are powerful AI models trained on massive text datasets to understand and generate human-like language. They analyse vast amounts of text data to learn the patterns and relationships between words and phrases. They do this by breaking words and sentences into numerical elements called vectors. These vectors can then be used for mathematical calculations, e.g. whether the words ‘apple’ and ‘fruit’ are often used in similar contexts (inferring that they are probably related). They are built using deep learning (especially transformer architectures) and are central to many NLP tasks.
Machine learning (ML)	Machine learning is an AI application that automatically learns and improves over time from previous sets of experiences without being explicitly programmed. These learning systems can improve their performance over time, whether they are sorting emails, recommending products or detecting fraud. As an AI application that automatically learns and improves over time from previous sets of experiences, ML underpins many modern AI applications and includes over 70 algorithms and tools that support data analysis, pattern recognition, prediction and automation. ML dramatically enhances productivity by automating tasks and supporting decision-making processes.
Multimodal large language models (MLLMs)	With the increasing size of large language models (LLMs) and the increasing amount of parameters (the term used to show the number of variables present in LLMs), MLLMs have emerged as a newer type of LLM. MLLMs do not just process text-based data, but also work with multiple modalities (e.g. audio, video) as inputs, and can create combined modalities based on these inputs. For example, Microsoft’s Kosmos can generate movies with dialogue and sound

	based on text, audio files and pictures. Some consider these MLLMs the first step towards AGI.
Natural language processing (NLP)	NLP combines machine learning, linguistics and computer science to enable machines to understand, interpret and generate human language and speech. NLP powers applications such as chatbots, voice assistants and automated text classification. Frameworks such as Hugging Face, and models such as BERT, are widely used in NLP. Thanks to NLP, virtual assistants can answer our questions, chatbots can provide support, and translation tools can instantly convert languages. Recent advances in large language models, such as those powering ChatGPT, have pushed these capabilities even further, enabling machines to generate human-like responses and even creative writing.
Neural networks (NNs)	This is a subset of machine learning programmes and models that are loosely modelled on neural connections in the human brain and the idea that data can be processed in different 'layers', where each layer looks at the similarities between certain values and their correlations with other values. By mimicking the way in which biological neurons work together, neural networks identify phenomena, assess different options and arrive at conclusions. In simplest terms, if a picture of an animal is uploaded, one layer could look at the colour of the picture and determine whether it is a uniform colour or a pattern, with the next layers looking at the size of the animal, its shape, etc. The aim is to establish relations (and correlations) between different inputs. This helps the NN to recognise the data inputs (the picture of the animal) and map these to certain output values (e.g. animal class, species). In this case, the model can be told to look for animals, which is part of training the model, where annotated pictures are fed to the system so that the model knows what it is looking for. NNs are a fundamental analysis technique in LLMs. NNs learn and recognise patterns to perform tasks such as image recognition, natural language processing and predictive modelling. They are widely used in a range of sectors, from finance to marketing and healthcare.
Retrieval-augmented generation (RAG)	Retrieval-augmented generation (RAG) enhances generative AI by combining a language model with a retrieval mechanism. It allows the model to access external data sources (e.g. documents or databases) in real time, improving factual accuracy and contextual relevance in generated outputs.
Robotics	Robotics is a specialist field that involves the design, construction, programming and operation of robots. This field brings together AI, computer programming, mechanics and electronics to carry out a series of actions autonomously or semi-autonomously, often mimicking human or animal behaviours. Tasks can range from simple repetitive actions to complex problem solving in diverse environments, with applications in a wide range of industries such as manufacturing, healthcare and transportation.
Robotic process automation (RPA)	Robotic process automation (RPA) is a software technology that uses virtual software 'robots' or 'bots' to automate repetitive, rule-based tasks that are typically done by humans. These bots mimic human actions, such as logging into applications, entering data, and moving data between systems, to streamline processes and increase efficiency. It is a form of business process automation that is based on software robots or artificial intelligence agents. RPA should not be confused with artificial intelligence, as it is based on automation technology following a predefined workflow. It is sometimes referred to as software robotics and is often used to complement more complex AI systems.
Small language models (SLMs)	Small language models (SLMs) are AI models that process and generate human language, but with a smaller size and scope compared to large language models (LLMs) like GPT-3. SLMs are designed to be more efficient, requiring less computational power and memory, making them suitable for tasks where resources are limited, such as on-device chatbots or edge computing. They are also easier to fine-tune for specific tasks, allowing for specialised applications with higher accuracy.
Symbolic AI models	Symbolic or knowledge-based AI uses human-generated logical representations to infer a conclusion from a set of constraints (variables). These constraints include rules, ontologies and search algorithms, and they rely on explicit

	descriptions of variables –agents such as humans, entities such as factories, objects such as machines; variables that can be stock conditions – and descriptions of the interrelations between these variables. Symbolic models are expressed in languages such as mathematical logic (‘if/then’ statements or more abstract ways of representing knowledge via mathematical formulae), agent-based models, event-driven models, etc. Symbolic AI is still in widespread use for optimisation and planning tools.
Statistical AI models	Statistical AI models (e.g. genetic algorithms, neural networks and deep learning) identify patterns based on data rather than expert human knowledge. They have seen increasing uptake recently. Statistical AI models were previously used primarily for recognition purposes (e.g. translating writing on cheques into machine-readable code). More recently, they are also being used for generation-like tasks, such as synthesising and generating images or audio. Models that rely on data are designed to effectively extract and represent knowledge from data rather than to contain ‘explicit’ knowledge – knowledge that is sharable and easily comprehensible.
Visual image recognition	Visual image recognition is a sub-field that includes all AI activities related to using computer algorithms to identify and analyse objects, patterns or features with digital images. With this technology, machines are able to interpret visual data by recognising specific elements within an image, such as faces, objects, text or scenes. Virtual image recognition typically involves techniques from computer vision, machine learning and AI to classify and make sense of visual inputs. It is commonly used in applications such as facial recognition, image search, medical imaging, autonomous driving and augmented reality.

ACRONYMS

AI	Artificial intelligence
AIG	Artificial general intelligence
AM	Algorithmic management
ARISA	Artificial Intelligence Skills Alliance
CV	Curriculum vitae
CEPS	Centre for European Policy Studies
DL	Deep learning
DSA	Digital Services Act
EC	European Commission
ECB	European Central Bank
e-CF	European e-Competence Framework
EESC	European Economic and Social Committee
EPC	European Policy Centre
ESCO	European Skills, Competences, Qualifications and Occupations
ETF	European Training Foundation
EU	European Union
EWCS	European Working Conditions Survey
GAN	Generative adversarial network
GDPR	General Data Protection Regulation
GenAI	Generative artificial intelligence
GPT	Generative pre-trained transformer

HR	Human resources
HRM	Human resources management
IAPs	Individual action plans
ICT	Information and communication technologies
IDB	Inter-American Development Bank
ILO	International Labour Organization
IMF	International Monetary Fund
ISCO	International Standard Classification of Occupations
JRC	Joint Research Centre of the EC
LAC	Latin America and the Caribbean
LLM	Large language model
LFS	Labour force survey
LMI	Labour market information
ML	Machine learning
MLOps	Machine learning operations
NLP	Natural language processing
NN	Neural networks
OECD	Organisation for Economic Co-operation and Development
OHS	Occupational health and safety
OJV	Online job vacancy
O*NET	Occupational Information Network
OSHA	European Agency for Safety and Health at Work

PES	Public employment services
RAG	Retrieval-augmented generation
RPA	Robotic process automation
SBERT	Sentence-BERT
STEM	Science, technology, engineering and mathematics
S4YE	Solutions for youth employment
UK	United Kingdom
UN	United Nations
US	United States
UX	User experience
WEF	World Economic Forum
XAI	Explainable artificial intelligence

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