WORKING PAPER

Working conditions and sustainable work

Implications of AI for work, employment and social dialogue: Literature review

Automation, digitisation and platforms: Implications for work and employment

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Introduction

Artificial intelligence (AI) is advancing at a pace that, for many observers, recalls earlier general purpose technologies such as electricity or the computer (Agrawal et al, 2023b). Recent research breakthroughs in deep learning, large language models and generative AI systems have been followed by rapid experimentation and adoption in the workplace, provoking renewed attention to their economic and social consequences by media, regulators, governments and social partners. For Eurofound, whose mandate is to inform balanced, evidence-based policymaking, a clear and comprehensive framing of AI's implications for work, employment and social dialogue is essential.

In parallel to this literature review, which focuses on AI, another review was carried out at the same time examining the closely related concept of algorithmic management (AM). AI can power and significantly increase the sophistication of AM systems, enabling more advanced and data-driven organisational and management practices. Together, the two reviews are intended to give direction to what is known and what remains uncertain about the implications of AI and AM for work, employment, and social dialogue. The insights will inform a revised version of Eurofound's conceptual framework for the digital age, guiding its research agenda for the upcoming 2025-2028 programming cycle.

Key concepts and definitions

Artificial intelligence

AI is defined as "the study of agents that receive precepts from the environment and perform actions" (Russell et al, 2016, p. viii), where the chosen action is "the best possible action in a situation" (Russell et al, 2016, p. 30). Several approaches have been used to build such automated decision-making, from **expert systems** based on formal rules and symbolic reasoning, to mathematical optimisation models and **machine learning** (ML) models that learn from data. A subset of ML, **deep learning** (DL), uses layered neural architectures to extract patterns from vast datasets.

In popular discourse, there tends to be some confusion between AI, ML and DL. The clarification below aims to guide the rest of the chapter:

Artificial Intelligence (AI) refers to the development of computer systems designed to perform tasks that typically require human intelligence: learning, reasoning, problem solving, perception, and using language.

Machine Learning (ML) is a subfield of AI that uses algorithms trained on data to identify patterns and make predictions or classifications. ML systems learn either through **supervised learning**, with models are trained on labelled datasets, or **unsupervised learning**, where they detect patterns in unlabelled data. Common applications include predicting numerical outcomes (e.g. stock prices), classifying binary outcomes (e.g. spam vs. not spam), and clustering data points based on similarities.

Deep Learning (DL) is a subfield of machine learning that uses multilayered artificial neural networks to model complex data relationships. Deep learning models are capable of processing large volumes of data to achieve high accuracy in tasks such as image recognition, speech-to-text, and language translation.

Recent advances in deep learning have given rise to **generative AI** (gen AI) models that can produce new content[1]**. Generative AI** is a class of deep learning systems designed to produce new content - such as text, images, audio, or code - in response to prompts. These systems, typically based on **large language models (LLMs)** or **generative adversarial networks (GANs)**, generate outputs by modelling the statistical structure of large training datasets.

Most AI applications today are examples of so-called **narrow AI**, which refers to systems designed and trained to perform specific tasks. These systems often perform their designated tasks very well, but they lack the ability to generalise beyond the tasks they were created for. Narrow AI is opposed to **strong AI**, which refers to a still-theoretical form of artificial intelligence capable of general reasoning, learning across domains, and performing any intellectual task that a human can do. There is nonetheless growing interest and investment in the development of artificial general intelligence (AGI), that is, AI systems capable of general reasoning and learning across domains, much like human intelligence. GPT-4, for instance, demonstrates broad, human-level performance across diverse and complex tasks without task-specific prompting, suggesting it may represent an early, though still incomplete, step toward AGI (Bubeck et al, 2023).

Several of the above elements can be found in definitions of AI used in policymaking. For example, the European Union's AI Act defines an AI system as: *"'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."* (Regulation (EU) 2024/1689, art 3)

This definition builds on the definition proposed by the EU's High-Level Expert Group on AI (AI HLEG): *"Artificial intelligence (AI) systems are 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. AI systems can either use symbolic rules or learn a numeric model, and they can also adapt their behaviour by analysing how the environment is affected by their previous actions."* (High-Level Expert Group on Artificial Intelligence, 2019)

These definitions share notable commonalities with ones from other global institutions, such as the OECD's AI Expert Group[2], but also with measures from national and EU statistical agencies (Montagnier et al, 2021). They all mention in one form or another AI in relation to these four elements: ***capabilities*** (AI is framed by the cognitive tasks it can perform, such as decisions or predictions), ***form*** (AI is described as a 'system/technology/machine/software'), ***environment*** (AI perceives and acts upon its surroundings) and ***autonomy*** (AI operates with

[1] For an accessible overview, see here: https://www.ibm.com/think/topics/artificial-intelligence.
[2] "An AI system is a machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations or decisions influencing real or virtual environments. It uses machine and/or human-based inputs to perceive real and/or virtual environments; abstract such perceptions into models (in an automated manner e.g. with machine learning or manually); and use model inference to formulate options for information or action. AI systems are designed to operate with varying levels of autonomy." (OECD, 2022)

varying degrees of independence). Three of these four elements are also recognized by the International Organisation for Standardisation in ISO/IEC 22989:2022(E) where an AI system is defined as an '*engineered system that generates outputs such as content, forecasts, recommendations or decisions for a given set of human-defined objectives'*, missing the environmental element.

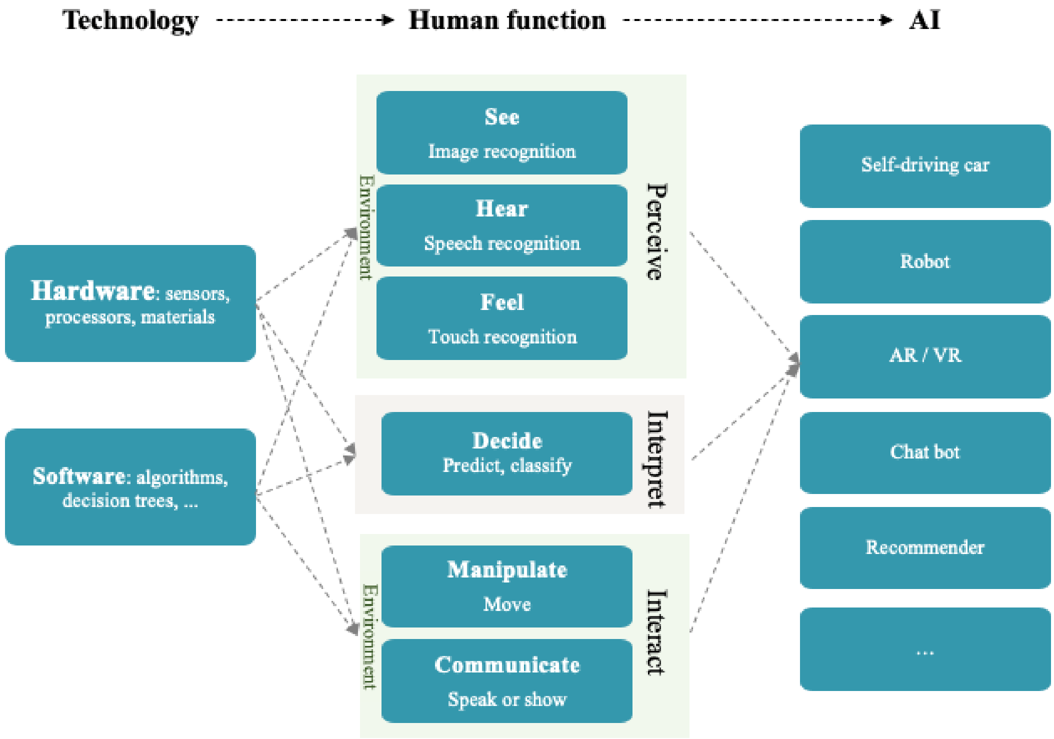
Notably, and importantly, none of these definitions restrict AI to the use of specific methods, although several sources note that it includes various approaches and techniques. The EU's AI HLEG, for example, expands its definition with: *"As a scientific discipline, AI includes several approaches and techniques, such as **machine learning** (of which deep learning and reinforcement learning are specific examples), **machine reasoning** (which includes planning, scheduling, knowledge representation and reasoning, search, and optimization), and **robotics** (which includes control, perception, sensors and actuators, as well as the integration of all other techniques into cyber-physical systems)."*

AI is thus not defined by the specific technique used for decision-making, which may therefore include non-ML- methods, such as logistic regression or optimisation algorithms in operations research. However, most current research on AI and work does focus on the ML, DL and generative types of AI. While the above definitions are broad enough to cover different AI technologies and applications, their lack of specificity allows researchers and statistical authorities to either focus on one specific subset of AI (such as gen AI), or otherwise group together diverse tools under a single AI umbrella. This makes it difficult to compare findings across studies.

This report delineates AI applications in its review of the literature in two ways. First, the type of technique does not matter, as long as some cognitive task is handled autonomously (i.e. generating decisions, predictions, recommendations or content). Second, physical systems can be included, as long as an accompanying cognitive decision is made. Good examples of this include visual inspection in quality control and predictive maintenance; both of these include extensive physical systems but mainly influence cognitive decisions (for instance detecting product defects or imminent machine failure).

Regardless of the decision techniques, the other elements of the AI definition do help to evaluate whether an application can be considered 'AI'. **Figure 1** visually illustrates this in three steps: (1) AI relies on both **hardware** (such as sensors, processors, and materials) and **software** (including algorithms and decision trees); (2) to emulate human sensory and cognitive functions across three broad stages: **perception** (seeing, hearing, feeling), **interpretation** (deciding or classifying based on inputs), and **interaction** (manipulating objects or communicating outputs); (3) allowing for the development of various **AI-enabled applications**, ranging from self-driving cars and robots to chatbots, augmented reality (AR/VR), and recommender systems.

Figure 1 Visual definition of AI



Source: Nurski and Hoffmann (2022) based it on High-Level Expert Group on Artificial Intelligence (2019)

Vectors of technological change

AI can be situated within the current debate on the impact of digital technologies on work and employment, through the lens of three vectors of technological change outlined in Eurofound's conceptual framework on the digital age (Eurofound, 2018):

- **Automation of work** is *"the replacement of labour input by machine input for some types of tasks within production and distribution processes."* (p. 16)
- **Digitisation of processes** is *"the use of sensors and rendering devices to translate parts of the physical production process into digital information […], and vice versa."* (p. 18)
- **Coordination by platforms** is the use of *"digital networks that coordinate transactions in an algorithmic way."* (p. 19)

AI interacts with – and increasingly integrates – each vector.

In **automation**, AI extends the frontier of tasks that can be fully or partly automated, shifting it from routine manual and cognitive tasks to nonroutine analytical, creative and interactive tasks. In manufacturing, for example, computer vision systems enable robots to handle irregular objects; in services, LLM powered chatbots can resolve complex customer queries.

In **digitisation**, AI scales up the extraction and analysis of granular data from sensors, documents or customer interactions, thereby converting tacit workplace knowledge into machine readable formats. This expanding pool of digital data not only enables data-driven decision-making but also fuels the training and fine-tuning of AI models, reinforcing the feedback loop between digital processes, model development, and continuous data driven improvement.

In **coordination by platforms**, AI supports real time matching of consumer demands and workers' labour supply, but also for dynamic price-setting and reputation scoring on online labour platforms. Several of these techniques can now also be found in traditional workplaces, which has been dubbed the 'platformisation of work' (Fernández-Macías et al, 2023).

These overlaps between AI and the existing vectors of change in the digital age caution against treating AI as an entirely new phenomenon in the world of work. Some authors argue that the exponential improvements in computing power, the explosion of digital data, and combinatorial innovations have ushered in a 'second machine age' (Brynjolfsson et al, 2014; McAfee et al, 2018), leading AI to be a new General Purpose Technology (GPT) (Agrawal et al, 2019). However, other researchers believe that AI does not constitute a *new* technological revolution, but mostly extends the current computer revolution, because it builds on and extends the digital infrastructure of the computer revolution (Perez, 2024).

AI vs algorithmic management

Algorithmic management (or AM) is the use of software algorithms to automate organisational functions traditionally carried out by human managers (Rani et al, 2024; Wood, 2021). While AM originated in the platform economy, its spread across the traditional labour market has been documented extensively and has been dubbed 'the platformisation of work' (Fernández-Macías et al, 2023). In the EU's directive on platform work (DIRECTIVE (EU) 2024/2831), AM is referred to as electronic systems that take or support decisions that materially shape platform workers' employment conditions, including hiring, promotion and termination, but also task allocation, earnings, schedules, safety, training opportunities.

Given that AI was defined above as a system that autonomously generates cognitive outputs, including decisions, (regardless of the specific technique used), AM can be considered the application of AI to a particular set of decisions within organisations. To delineate AI from AM, we separate the types of decisions and activities in organisations between their *production function* and their *governance function*.

The distinction between production and governance in organisations can be found in several social science disciplines (see box below). Transaction cost economics distinguishes between the *production function* and *governance function* (Williamson, 1981); sociotechnical systems theory, grounded in sociology, separates the *production structure* from the *control structure* (de Sitter et al, 1997); organisation design, developed within management studies, applies the principles of *division of labour* and *integration of effort* (Puranam, 2018), and labour process theory links these structures to power and control in the workplace (Braverman, 1974).

Box 1: the distinction between production and governance in different social science disciplines

In **transaction cost economics**, *governance costs* capture the coordination costs of planning, adapting, and monitoring of task completion under alternative governance structures (Williamson, 1981, pp. 552–553). Governance structures are mechanisms for managing economic transactions and include markets, hierarchies (or firms), and hybrid forms of the two such as franchising arrangements or labour platforms. These governance costs are set against the purely *production costs* of transforming inputs into outputs, i.e. the costs of capital, labour, materials and energy typically considered in an economic production function. While the costs of production might be lower when the transaction is handled by a market – as competition drives efficiency – governance costs are often cheaper inside a firm – as authority facilitates coordination and monitoring.

Sociotechnical systems theory dives further into the configurations of hierarchical structures by defining the *production structure* as the grouping and coupling of executing functions; and the *governance structure* as the allocation and coupling of control functions (de Sitter et al, 1997, p. 507). Features of the production structure include, for example, functional concentration and specialisation (e.g. grouping data scientists in a central data science unit as opposed to decentralising them in the business units). Features of the control structure include the separation of task execution and task control (e.g. splitting assembly and quality control across different functional roles) and control specialisation (e.g. creating specialised control functions for quality, maintenance, logistics, HR, IT, finance, …). Coupling refers to the degree of interdependence between each of those roles and work units. Higher interdependence increases coordination needs and reduces the scope for individual autonomy.

Organisation design, as developed within management studies, approaches the problem through the principles of division of labour and integration of effort (Puranam, 2018). The *division of labour* deals with the decomposition of organisational goals into tasks and their assignment to individuals or units. The *integration of effort* then refers to the mechanisms – rules, routines, authority, and information flows – used to integrate these distributed efforts so that the shared goal can be achieved. Minimising coordination costs – in terms of cognitive loads, delays, duplication and misalignment – is a fundamental problem of this discipline.

Labour process theory, grounded in critical sociology and Marxist analysis, focuses on the implications of production and governance structures for power and control in the workplace (Braverman, 1974). The production structure refers to the technical division of labour, while the governance structure is interpreted as the managerial control system imposed on workers. From this perspective, governance is not a neutral coordination mechanism but a vehicle for extracting surplus value, deskilling labour and controlling workers.

Combining the definitions on AI and AM, with those on the production and governance function of organisations and institutions, helps clarify the distinction between the two concepts - AI and AM - and highlights the need to treat them as analytically distinct phenomena.

In this framework, AI is understood as referring to applications within the production function, while AM refers to the use of applications of AI in the governance function. Some examples include:

- For work and employment:
  - AI (in production function): insurance claims validation
  - AM (in governance function): shift scheduling
- For social policy:
  - AI (in production function): validating eligibility for social housing
  - AM (in governance function): evaluating performance of public officials

Separating between the production and governance function also helps to align AI and AM with the vectors of change discussed above, as detailed in **Table 1**. AI-driven **automation** of tasks can be considered an application of AI in the production function of organisations. **Platformisation** is the algorithmic coordination of work and is therefore an application of AI in the governance of organisations, dubbed here algorithmic management (AM). Finally, **digitisation** of production processes generates massive amounts of data on products, services, processes, customers and workers, which could be used both for developing and finetuning AI and AM applications, who in turn generate and collect additional information. While the split between AI and AM is thus clear for automation and platformisation, digitisation will likely intersect between the two topics of the literature reviews.

Table 1: Linking the three vectors of change to AI and AM

Organisational function	Organisational element	Vector of change	AI	AM
Production function	Task	Automation	X	
	Process	Digitisation	X	X
Governance function	Structure	Platformisation		X

Source: based on Nurski (2024) and Eurofound (2018)

Work organisation and job quality

Eurofound defines **work organisation**[3] as '*the division of labour, the coordination and control of work: how work is divided into job tasks, bundling of tasks into jobs and assignments, interdependencies between workers, and how work is coordinated and controlled to fulfil the goals of the organisation.*'

This definition consists of two parts: (1) **the division of labour** - including how work is divided into tasks and how tasks are bundled into jobs, giving rise to interdependencies; and (2) **the coordination and control of work** – including how work is planned and scheduled, organised in terms of pace and procedures and managed. The first part of this definition can be considered the *production structure* while the second part can be considered the *governance structure*. The use of AI for the second part – the coordination and control of work – is what is referred to above as algorithmic management (AM). Given the accompanying literature review on AM, this report focuses exclusively on the first part of the definition, namely the division of labour in productive tasks.

Job quality is a multidimensional concept on which there is a lack of definitional consensus (Munoz De Bustillo et al, 2011). Eurofound defines job quality as '*the characteristics of work and employment that have been proven to have a causal relationship with health and well-being*'[4], considering seven dimensions: the physical environment, the social environment, work intensity, skills and discretion, working time quality, prospects and earnings. Each of these consists of further subdimensions and is surveyed in its European Working Conditions Survey (EWCS). An adapted version of this framework was used to guide the review and

[3] https://www.eurofound.europa.eu/en/topic/work-organisation

[4] https://www.eurofound.europa.eu/en/topic/job-quality

structure the findings on the impact of AI on job quality. It includes the following main elements of job quality: intrinsic quality of work (autonomy, skills and social support); health and safety (workplace-based physical and psychosocial risks); working time and work-life balance (duration, scheduling, flexibility and intensity), employment quality (career prospects, contractual stability and earnings).

There is some overlap between the two definitions of work organisation and job quality, as already noted in Eurofound (2021a), for example in the elements of decision latitude and organisational participation. This is only natural, as *work organisation is a predecessor and determinant of job quality*: the bundling of tasks into jobs (work organisation) directly shapes the cognitive dimension and decision latitude of jobs (job quality), see also the discussion below on the 'Structure of the report' and **Figure 2**.

Framing perspectives and theoretical approaches

Framing perspectives

The literature on AI and work is informed – explicitly or implicitly – by distinct framing perspectives on the role of technology in shaping work, organisations, and labour relations. This section highlights three overarching perspectives that recur across the literature reviewed in this report: the techno-optimist, socio-technical, and critical perspectives. Originally derived from a review of employee participation studies in Industry 4.0 (Vereycken et al, 2021), these perspectives are useful for situating not only the debate on social dialogue but also broader research strands on task transformation, work organisation, job quality, and labour market impacts.

The **techno-optimist view** sees AI as a key driver of economic growth, productivity, and innovation. From this vantage point, technological progress is largely beneficial, with any disruption framed as temporary and ultimately offset by gains in efficiency, new job creation, and improved services. Research aligned with this perspective often highlights the potential for AI to automate mundane or repetitive tasks, enabling workers to focus on higher-value activities. It also sees worker participation as a natural by-product of technological change, often assuming technology will naturally enhance or augment human work and align with managerial goals.

Examples can be found in reports by consultancy firms such as PwC (PwC, 2025) and McKinsey (Chui et al, 2023), as well as investment banks like Goldman Sachs (Goldman Sachs, 2023). This outlook is also prevalent in Silicon Valley, where leading technology firms and entrepreneurs regularly promote AI as a transformative force for human advancement and societal progress (Andreessen, 2023). Across scientific disciplines this perspective can be found in economic studies on task-level productivity increases (see next chapter) and computer science publications (see discussion in Vereycken et al, 2021). A similar outlook is shared by tech and innovation experts, who are optimistic about AI's potential to augment human capability and "make the world a better place" (Dries et al, 2024).

The **socio-technical perspective** (Cummings, 1978) assumes that successful and sustainable technology adoption depends on the careful alignment between technical systems and the social context in which they are embedded. This view stresses the need for human-centred design, participatory implementation, and organisational adaptation. Employee participation is seen as critical not only for increasing acceptance of AI but also for improving system performance, tapping into tacit knowledge, and fostering trust, thereby improving both worker and employer outcomes.

This perspective is prevalent in research on human-AI collaboration and AI-augmented decision-making (see next chapter). It is present in many institutional reports that stress the importance of social dialogue on technological change, such as Eurofound (2021a) and OECD (Milanez, 2023). While this perspective often stresses *workplace*-level participation, empirical evidence in the economic literature can also be found on unionisation and collective bargaining which has been associated with greater productivity gains from organisational change (Black et al, 2001).

The **critical** perspective focuses on power imbalances, warning that new technologies may be used to standardise work, reinforce managerial control and erode autonomy unless collective worker participation is ensured. From this viewpoint, technology is not neutral but shaped by power relations and economic interests. Participation, within this frame, is not just a means of improving outcomes but a political imperative to safeguard worker agency and distribute the benefits of innovation more equitably.

This perspective features prominently in literature on algorithmic management, surveillance, and datafication of work, including in platform work. It is also reflected in critiques by trade unions and their associations, which warn of the growing imbalance of power between employers and workers.

Theoretical economic approaches to technological change

The impact of technology on work has long been framed through economic theories that analyse how innovations reshape the demand for labour. Two of the most influential frameworks are Skill-Biased Technological Change (SBTC) and its refinement, Routine-Biased Technological Change (RBTC).

SBTC posits that technological progress increases the relative demand for skilled workers by raising their productivity more than that of unskilled workers. The introduction of computers from the 1980s onward was seen as favouring workers with higher levels of education and abstract problem-solving capabilities. This 'skill bias' in the evolution of labour demand was linked to widening wage gaps (Katz et al, 1992). This framework helped explain growing wage inequality in the US and other advanced economies. However, SBTC faced criticism as it struggled to explain stagnation in middle-skill wages and its focus on occupational skill levels overlooked the importance of task content within jobs.

RBTC, introduced by Author et al (2003) and developed further by Goos and Manning (2007) and Autor and Dorn (2013), addresses these limitations by shifting the focus from occupation-based skill levels to task-level analysis. It distinguishes between *routine tasks* – those governed by explicit procedures and thus more easily codified and automated by computers – and *non-routine* tasks that require judgement, adaptability, or human interaction. The RBTC hypothesis predicts that digital technologies replace routine cognitive and manual tasks (often in middle-income occupations) while complementing non-routine tasks found at both the high and low ends of the wage spectrum. The result is a predicted job polarisation: declining demand for middle-skilled work and rising demand for high-paid professional and low-paid service jobs.

RBTC gained significant empirical support at first, particularly in the United States and Western Europe between the 1990s and early 2000s (Goos et al, 2014, 2009). Yet its relevance has been debated in recent years. Eurofound research highlights that **job upgrading**, not polarisation, has characterised more recent employment trends in many EU Member States – particularly since the Great Recession (Eurofound, 2024b, 2015; Fernández-Macías et al, 2016; Torrejón Pérez et al, 2023). Furthermore, some occupations traditionally viewed as ‘routine’ contain both routinised and non-routinised elements, making the association between mid-paid jobs and routine tasks less clear-cut. Drawing on Cedefop’s European Skills and Jobs Survey, McGuinness et al (2023) provide micro-evidence that skill-displacing technological change is associated with dynamic worker upskilling rather than polarisation.

Both SBTC and RBTC, while influential, come with **limitations**, as they rely on assumptions that are increasingly questioned in the AI era. Both frameworks assume that labour tasks are fixed characteristics of occupations, easily separable, and can be reassigned to capital purely based on efficiency. In practice, task interdependencies as well as institutional factors, such as labour laws, union strength, job design strategies, and sectoral regulations, heavily influence whether and how technology substitutes or complements labour. Moreover, the measurement of routine intensity often relies on fixed occupational taxonomies such as O*NET, which assume task content is stable over time and fail to account for the actual use of digital tools at work (Sebastian et al, 2018). While most empirical analyses are based on such static sources, jobs often evolve dynamically through processes like job crafting (Tims et al, 2010) and active or passive assembly (Cohen, 2013).

Recent research addresses some of these gaps by incorporating dynamic mechanisms of **task creation** alongside automation. Acemoglu and Restrepo (2019, 2018) distinguish between a *displacement effect* (from automation of existing tasks) and a *reinstatement effect* (from creation of new tasks suited to human skills). Whether AI reduces or augments labour demand depends on the balance between these forces. Early results from the 2024 EWCS support this dynamic view: workers are more likely to report the creation of tasks due to technology than their elimination (Eurofound, 2025a). The existence of this reinstatement effect has also been documented using data from Cedefop’s European Skills and Jobs Survey (McGuinness et al, 2023).

Taken together, these theoretical approaches provide useful, but limited, tools for understanding AI’s impact on work. While they help identify which tasks and jobs are most exposed to technological change, they remain a mere heuristic for task-level substitution. Given the dynamic and context-specific ways in which AI technologies are now transforming work, these approaches must be complemented with institutional and organisational perspectives that account for how AI adoption is mediated in real workplaces.

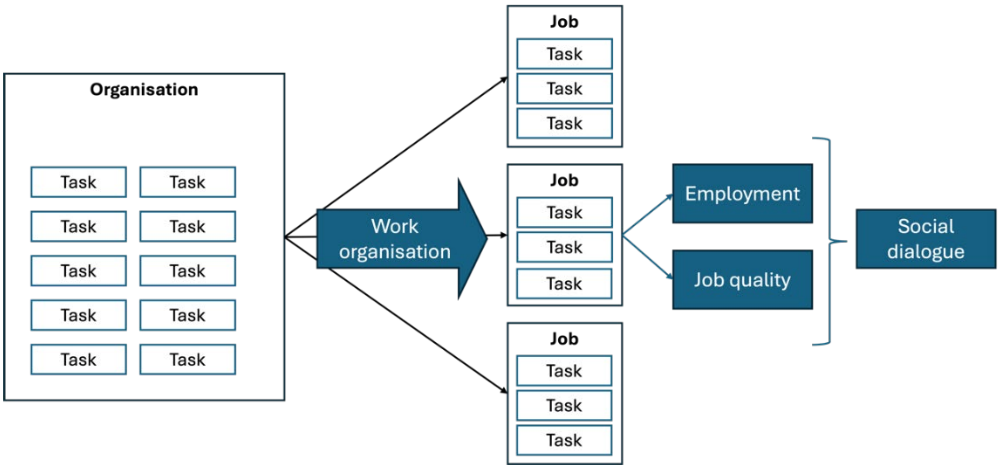
Structure of the report

This literature review primarily examines the applications of AI within the production function of organisations, where tasks are executed to transform inputs into outputs. The way these tasks are grouped and allocated to individual jobs constitutes the division of labour, which is a key aspect of **work organisation**. This, in turn, shapes the occupational structure of labour demand and **employment** opportunities for workers, as well as various aspects of **job quality**. This review only incidentally addresses the application of AI in governance functions within organisations, those involving decision-making to coordinate and control tasks, as these aspects are explored in a separate literature review.

Figure 2 provides a conceptual map for how the remainder of this literature review is structured. AI affects work first and foremost at the level of **tasks**, by enabling the automation, augmentation or creation of new work activities. This task-level lens offers valuable insight into what AI *can* do. However, understanding what AI *will* do in workplaces requires going further. The figure shows that jobs are not static collections of tasks: they are shaped by how organisations divide, coordinate and manage work. The division and specialisation of labour is both a product of technological change and serves as a key enabler of it (Eurofound, 2018). AI adoption may therefore not only alter task content, but also reorganise how tasks are bundled into jobs, how responsibilities are distributed across roles and hierarchies, and how decisions are made and supervised. This report considers the *allocation of tasks to jobs* (i.e. the division of labour) a design choice that is made **in work organisation**, while the resulting *task composition of jobs* (i.e. job content) is an outcome of that process, and a strong determinant of **job quality**.

This conceptual pathway informs the structure of the report. **Chapter 2** starts from the impact of AI at the task level and analyses implications for work organisation. **Chapter 3** starts from the resulting changes in the task content of jobs and analyses implications for job quality. **Chapter 4** reviews the evidence on the employment impact of AI. Finally, **Chapter 5** reviews the role of social dialogue and industrial relations in the impact of AI on the world of work.

Figure 2 Tasks, work organisation, employment and job quality



Source: Author's own elaboration

Box 2: Methodological note

This literature review is based on a structured search of peer-reviewed and institutional publications examining the impact of artificial intelligence (AI) on work, employment, and social dialogue. To ensure broad and high-quality coverage across disciplines, several sources and strategies were used.

Web of Science and **Scopus**, two comprehensive academic databases, served as a primary sources for peer-reviewed research in economics, sociology, management, and computer science. Search queries combined keywords related to AI (e.g. “artificial intelligence”, “machine learning”, “generative AI”) with terms related to work and employment (e.g. “job quality”, “working conditions”, “employment”, “social dialogue”). The **Topic** field — which includes titles, abstracts, and keywords — was used for these searches. No time restrictions were imposed, but emphasis was placed on studies published in the past five years.

Google Scholar was used as a supplementary source to identify relevant publications not indexed in Web of Science or Scopus. While the use of Google Scholar was less systematic, it was helpful in capturing grey literature and newly published work, especially in fast-evolving domains like generative AI.

Elicit.org, an AI-assisted academic search tool, further complemented these searches by retrieving studies based on semantic relevance rather than exact keyword matches.

In addition to these systematic and semi-systematic searches, the review incorporates a selection of sources from the author’s personal academic library and references suggested by peer reviewers. These include both foundational studies and recently released institutional reports by organisations such as Eurofound, the ILO, the European Commission’s Joint Research Centre (JRC) and the OECD.

Final inclusion was based on the contribution of each source to understanding AI’s implications for work organisation, job quality, and labour market dynamics.

Implications for tasks and work organisation

Human-AI augmentation vs synergy

A growing body of research reviewed in this section tests whether AI can improve the speed or quality of individual tasks in experimental set-ups, either in (online) laboratory settings or in quasi-experimental workplace settings. These studies zoom in on discrete tasks – such as writing code or analysing chest X-rays – among a treatment group that uses AI and a control group that does not use AI. While experimental studies offer strong causal identification, their findings should be interpreted with caution, as they often capture short-term effects and may overlook how workers learn to use AI tools over time, potentially underestimating long-term augmentation or skill development.

A systematic review and meta-analysis published in Nature Human Behaviour (Vaccaro et al, 2024) compares task performance between humans alone, AI alone, and human-AI combinations across a range of different tasks and different types of AI. The meta-analysis sought to answer two fundamental, interrelated questions, that arose from the many contradictory findings in the literature: first, does AI help humans perform better (**augmentation**)? And second, can human-AI collaboration outperform both humans and AI performing a task alone (**synergy**)?

To provide a clarifying example, augmentation occurs if AI scores 80/100, humans 70/100, and the combined human-AI team 75/100; by contrast, synergy occurs if the human-AI team scored 85/100, outperforming both individual scores. After analysing 106 experimental task-level studies, the authors found no evidence of synergy in general, but did find evidence of augmentation. To explain the heterogeneity in findings, the authors looked at different task types (decision vs. creation), the type of data (numeric, image, text) and output of the task (e.g. binary choice, open response).

They found that heterogeneity in findings could be explained by the following elements:

Relative performance of AI vs human: On average, there was not much evidence of synergy. Additionally, when the *AI alone outperformed the human alone*, human-AI collaboration led to performance losses. By contrast, when the human alone outperformed the AI alone, human-AI collaboration resulted in performance gains.

Type of task: humans generally performed worse than AI with respect to *decision tasks*, i.e. choosing between a finite set of options, such as validating (yes/no) the eligibility of insurance claims. In these cases, AI-human teams were no better than AI alone (meaning no synergy), even though human performance improved with the use of AI (so there was augmentation). In contrast, gains from AI-human collaboration were significantly greater for *creation tasks,* i.e. open-ended content creation, and showed signs of synergy, as well as augmentation.

Type of data: humans generally performed worse than AI alone in tasks that involved working with *numeric data*; in those cases, human-AI collaboration led to performance losses. For tasks based on images, human-AI collaboration showed lower performance losses, but still no statistically significant effects for synergy.

In terms of what the authors refer to as '**types of AI'** (deep learning, shallow learning, and wizard of Oz), the meta-analysis found that shallow learning was associated with a performance loss when measuring for human-AI synergy, i.e. the combined human-AI team performed worse than the best individual performer (human or AI) working alone. However, there was no significant loss or gain for deep learning and wizard of Oz in terms of synergy.

Notably, while synergy findings thus varied across all these splits (relative human/AI performance and type of task/data/AI), significant augmentation of humans by AI was consistently found.

This study suggests that yes/no decision tasks (especially number-heavy ML-based ones), are more suited for a human alone or an AI alone, rather than a joint human-AI decision system. Either the entire task (with all its instances) is allocated to an AI or a human alone, or a stream of task instances needs to be sorted between AI and humans, which is dubbed '**triage'** (Raghu et al, 2019). Triage involves sending some cases of a task to the humans and some cases to the AI, depending on the complexity or uncertainty of the task. Examples include customer service chatbots handling simple customer queries, while human operators handle the difficult ones; or automated quality control tools sorting out obviously faulty products but sending doubtful cases to a human inspector.

Given this significant difference between *decision* and *creation* tasks, the task-level evidence below is presented in these two categories. For decision tasks, several medical diagnostic tasks are considered, while for creation tasks the experiments focus on generative AI applications including text, code, image and ideas generation.

Decision tasks with ML/DL

To better understand the lack of AI-human synergy in decision tasks, this section zooms in on medical diagnosis as a well-studied case that highlights the need for — and strategies behind — triaging task instances between humans and AI. Medical diagnosis, especially image-based, is a heavily studied application of AI in decision tasks: a systematic review and meta-analysis found 82 studies published between 2012 and 2019 testing the performance of deep learning models on medical image classification tasks (X. Liu et al, 2019). Among the 69 studies that provided enough data to construct contingency tables, the review found that diagnostic performance of deep learning models was equivalent to that of health-care professionals (though synergy or augmentation was not studied). That makes medical diagnosis a good case study for understanding the need for triage, i.e. sorting instances of tasks between humans and AI as opposed to joint human-AI decision-making.

ML/DL based AI systems have shown high accuracy in diagnostic tasks based on images, such as radiology (Hosny et al, 2018), dermatology and pathology. Beyond image-based diagnosis, differential diagnosis is heavily text-based and also here LLM's can outperform human doctors in family, internal and emergency medicine (Goh et al, 2024) and additionally in neurology, paediatrics and psychiatry (McDuff et al, 2023).

Multiple studies now show that AI systems can outperform doctors acting alone and, notably, even outperform doctors who are supported by AI recommendations. For example, in a 2023 study on chest X-rays, the AI alone achieved higher diagnostic accuracy than both the human radiologists and the humans using AI assistance (Agarwal et al, 2023). Similarly, in a randomized clinical trial, LLM-assistance did not significantly enhance diagnostic performance of the physicians, while the LLM alone did score 16 percentage points higher than the physicians alone (Goh et al, 2024). Also in differential diagnosis, a specialised LLM outperformed both the clinicians alone and the clinicians assisted by the very same LLM (McDuff et al, 2023)

These results, as well as Vaccaro et al (2024)'s review study above, suggest that human-AI teaming is often not the optimal configuration. Instead, some form of *task triage* may be needed: determining whether a given diagnostic task should be handled by a human or an AI system. In a recent NYT op-ed, Dr. Pranav Rajpurkar and Dr. Eric J. Topol stated:

"The solution, we believe, is a deliberate division of labor. Instead of forcing both human doctors and AI to review every case side by side and trying to turn A.I. into a kind of shadow physician, a more effective approach is to let A.I. operate independently on suitable tasks so that physicians can focus their expertise where it matters most." (Rajpurkar et al, 2025).

To be able to affectively triage instances of tasks between humans and AI systems, it is imperative to understand which cases are best suited for the AI system. But even that decision – allocating cases to humans or AI – could potentially be handled by AI itself. Raghu et al (2019) propose a hybrid framework in which an algorithm decides, for each case, whether to delegate it to an AI or a human based on predicted competence. This kind of triage mechanism represents a new layer of work organisation, where task instances are dynamically allocated between humans or AIs with different capabilities. Early empirical evidence suggests this can work well in certain contexts, such as signalling unremarkable chest radiographs (Plesner et al, 2024), or the opposite, signalling when a double reading was required by two radiologists (Lång et al, 2023). However, given the risky setting of human health, further research is necessary on the wider applicability of this solution.

Radiology specifically has attracted a lot of attention in the AI-automation debate. Already in 2016 British computer scientist and Turing Award winner Geoffrey Hinton stated that "we should stop training radiologists now" as AI would outperform radiologists within 5 years[5]. Today, already three-fourths of the more than 1000 AI applications for use in medicine, approved by the US Food and Drug Administration, are in radiology (Rochester et al, 2025). Yet, radiologist employment in the US has grown steadily between 2005 and 2023 and projections anticipate further growth through 2055 (Christensen et al, 2025). These projections, however, are based on past trends and do not factor in future advances in AI capabilities. Likewise, predictions of full automation based on performance in specific sub-tasks — such as "Interpreting the outcomes of diagnostic imaging procedures" — may overstate the impact on employment, as this is only one of the 30 tasks listed for Radiologists in the O*NET database[6]. Other tasks, such as "treat complications during and after procedures" and "provide counselling to radiologic patients" remain far less amenable to automation. Taken together, both task-level predictions and employment forecasts should be treated with caution — neither can fully account for the uncertainties surrounding technological development and occupational transformation.

Finally, when triage between humans and AI is not possible or desirable, human-AI decision-making can be improved by mitigating some well-known automation risks, such as *'automation confusion'* (poor understanding of the system functioning), *'irony of*

[5] Geoff Hinton: On radiology. Available from: https://www.youtube.com/watch?v=2HMPRXstSvQ
[6] https://www.onetonline.org/link/summary/29-1224.00

automation' (becoming bored or occupied with other tasks as long as automation works well), *poor situational awareness* and *out-of-the-loop performance degradation*, *human decision biasing*, and *degradation of skills* (National Academies of Sciences, Engineering, and Medicine, 2022). Ways of mitigating these risks include transparency and explainability, building and maintaining trust in the AI, supporting shared situation awareness, bias detection and mitigation, and training (National Academies of Sciences, Engineering, and Medicine, 2022).

Creation tasks with genAI

While the research on decision tasks includes both ML, DL and generative AI, studies on creation tasks necessarily only involve generative AI, based on text, code or images.

Text-based genAI: Writing and translation

LLM's are an evident application for tasks involving text: both **text generation** (i.e. writing), and **text translation**. Studies show consistent time savings and quality gains of AI assistance for humans in these tasks.

One of the most cited studies on **writing** tasks is the online experiment by Noy and Zhang (2023), which assigned 453 mid-level professionals (marketers, grant writers, consultants, data analysts, HR professionals, and managers) to complete occupation-specific writing tasks, such as press releases, short reports, analysis plans, and sensitive emails. The group with access to ChatGPT produced higher-quality output (an 18% improvement in evaluator ratings) while completing tasks 40% faster, compared to the non-AI control group. Task composition shifted, as the treatment group spent less time brainstorming and rough-drafting, but more time editing. Importantly, these gains were largest for lower-skilled participants. Improvement in writing quality can have large real-world impacts, as a large-scale field experiment with nearly half a million job seekers in an online labour market showed: job seekers who received algorithmic writing assistance on their resumes saw an 8% increase in their hiring probability and even 10% higher wages (Wiles et al, 2025).

Another experimental study examining the cognitive and behavioural effects of using LLM's, specifically ChatGPT, for writing employed a mixed-methods approach that included EEG brain activity monitoring, natural language processing (NLP) analysis of essays, human and AI-based scoring, and post-task interviews (Kosmyna et al, 2025). The study found that reliance on ChatGPT for essay writing significantly reduced neural engagement, with EEG data revealing weaker brain connectivity in participants who used only ChatGPT compared to those who used a traditional search engine or relied solely on their own knowledge ('brain-only'). Furthermore, LLM users demonstrated poorer memory recall, lower perceived ownership of their essays, and produced content that was more homogenous and less original. In contrast, brain-only participants exhibited stronger cognitive engagement, more diverse writing, better recall, and a heightened sense of authorship. These findings suggest that while LLMs may improve short-term productivity in writing, they may also impair deeper learning and cognitive development. However, more and larger studies in different contexts are needed to assess the generalisability of these effects.

In the domain of **translation**, a pre-registered online experiment with 300 professional translators showed that access to larger LLMs improved professional translators' productivity by over 30%, with 4x greater gains for translators with an initially slower baseline speed (Merali, 2024). Furthermore, larger AI-models meant greater productivity increases as a tenfold increase in model compute improved task completion speed by 12.3% and quality by 0.25 points on a 7-point scale. Again, improvements in translation speed and quality have economic implications: On eBay, the introduction of a new machine translation system significantly increased increasing trade on the platform by 10.9% (Brynjolfsson et al, 2019).

Text-based genAI: Communication with colleagues and customers

Information handling through text summarisation and generation is a large part of **workplace communication** in knowledge work. AI assistance that is integrated in those workplace information and communication tools (such as MS Copilot in MS Outlook, Teams, SharePoint and Word) can leverage on company-specific information. In an early set of controlled experiments, Microsoft research documented that users with access to Microsoft 365 Copilot completed tasks such as finding information in documents and emails, summarising meeting transcripts, and drafting marketing content significantly faster (time savings ranged from 27% to 30%), with no reduction in accuracy (Edelman et al, 2023).

18 months later, researchers from Harvard Business School and Microsoft Research studied real-world Copilot deployments, confirming and extending these findings. In a six-month field experiment involving 6,000 workers across multiple firms, access to Copilot reduced the time spent on email by nearly three hours per week for active users, equivalent to a 25% decrease (Dillon et al, 2025). Notably, changes were most pronounced in areas where users had discretion over their workflow and tasks were relatively simple, such as managing their inbox, rather than in more complex activities requiring team coordination, such as meetings.

Customer support is also heavily dependent on information retrieval and interpersonal communication. LLM's have been shown to be able to effectively assess customer experience (Sidaoui et al, 2020) and chatbots improve customer experience as long as they are usable and responsive (J.-S. Chen et al, 2021). While customer support has already been partly automated through 'self-service chatbots', human call centre operators currently still handle the more complex customer queries. A study examining the impact of a gen AI assistant (trained on a history of previous chats in the firm) on 5,172 customer-support agents found an increase in worker productivity by 15% on average, as measured by issues resolved per hour (Brynjolfsson et al, 2025). This productivity increase was particularly strong for less experienced and lower-skilled workers.

Text-based genAI: Idea generation and product innovation

Given that text is not only a mode of communication, but also a carrier for ideas, knowledge and strategies, several studies have investigated the capabilities of LLM's for idea generation and product innovation.

In a study evaluating over 400 **business ideas**, ChatGPT-4 outperformed business students at an elite university in generating ideas for new consumer products, with higher average quality and higher variance in quality, meaning that most of the best ideas came from the LLM (Girotra et al, 2023). Even in more specialised areas, such as research ideas in the field of Natural Language Processing (NLP), ideas generated by AI agents were found to be more novel than those of human experts (Si et al, 2024).

A study with 758 BCG consultants found that gen-AI assistance significantly improved tasks related to **product innovation**, including brainstorming, market segmentation, writing marketing copy, and persuasive communication. Consultants with access to GPT-4 completed 12.2% more tasks and finished them 25.1% faster on average than those who did not. However, for business problem-solving tasks requiring analytical reasoning on quantitative and qualitative data, consultants using AI were 19 percentage points less likely to produce correct solutions, despite spending less time on the task (Dell'Acqua et al, 2023). This underscores again the importance of task type in determining the effectiveness of AI assistance. The authors thus describe a "jagged technological frontier," where AI enhances performance in some tasks while undermining it in others. Participants were found to integrate AI in their workflows in two opposing ways: *centaur types* neatly divided the tasks between the AI and themselves, while *cyborg types*, continuously and iteratively interacted with the AI throughout all the tasks. The adoption of the different behaviours seemed to be driven by different skill levels, previous gen-AI experience, and perceptions of the relationship between humans and AI. The analysis of these behaviours, as well as their impact on performance, is still ongoing though.

In a follow up product innovation study with 776 R&D and sales professionals from Proctor & Gamble (Dell'Acqua et al, 2025), participants were sorted in 4 groups: a human alone (R&D or commercial), a human with AI, a multi-disciplinary team (R&D + commercial) or a multidisciplinary team with AI. They found significant gains from GPT-4 support in the quality of the product innovations: having an AI team member proved to be as beneficial as having a cross-disciplinary human team member because AI was able to replicate key benefits traditionally attributed to human collaboration, particularly in terms of performance, expertise sharing, and social engagement. The AI support led to time savings for both the single humans and the teams. Both a human teammate and an AI teammate increased positive emotions (such as enthusiasm about the work) and decreased negative ones (such as frustration). Interestingly, the AI-supported teams produced more discipline-balanced proposals, containing a better mix of technical and commercial innovations, than the duo's without AI whose proposals either leaned on the technical side or the commercial side. The cross disciplinary teams with AI support were also more likely to generate innovations that scored in the top 10%.

Text-based genAI: Financial and legal analysis

A final text-based application includes the summary and analysis of large bodies of text, including financial and legal analysis.

Several types of AI are prominently applied in **finance** across areas such as valuation, pricing, and portfolio management, market prediction and forecasting, algorithmic trading and strategy optimization, risk and fraud detection, and – specifically for genAI – sentiment and text analysis of financial information (Cao, 2022). ChatGPT can now outperform specialised domain-specific language models like BloombergGPT, on a wide range of financial text analytic tasks, including the most common use case of sentiment analysis to predict investment behaviours and trends in equity markets from news and social media data (X. Li et al, 2023). Grennan and Michaely (2020) analyse what happens to security analysts that hold portfolios exposed to such AI-automated prediction – i.e. stocks for which large amounts of social media data are available. When the AI exposure of their portfolio increases, analysts' accuracy increases and their bias decreases, thereby improving the quality of their work.

Legal analysis is another non-routine cognitive task that is hypothesised to be suitable for AI. Studies have documented the success of ChatGPT-support in legal exams (Choi and Schwarcz, 2023), and law students perform better across legal writing and reasoning tasks (such as issue spotting essays and legal memos) (Choi, Monahan et al, 2023). However, few real-world studies with professionals have documented the effects of use in actual workplaces. One case study (Milanez, 2023) documents how a U.S.-based risk management firm implemented an AI tool that scans lengthy legal contracts to extract relevant passages related to liability and compliance, replacing a previously manual task. As initial document screening was entirely automated, lawyers could focus on the actual risk assessment. The automation also enabled the firm to scale up its review processes, expanding from selective assessments to a full analysis of all current and historical contracts.

Text-based genAI: Programming and development

As LLM's are trained not only on human-language texts, but also on computer-language code, programming is another type of task that is highly suitable for AI. Programming assistance for Python is available in several LLM's, such as ChatGPT, Claude and Gemini (Coello et al, 2024) and ChatGPT is also able to provide support in Hardware Description Language (HDL) used for the design of integrated circuits (Blocklove et al, 2023).

Peng et al (2023) conducted one of the most widely cited studies on the productivity gains of AI coding assistance. Their randomised controlled trial involved 95 professional programmers tasked with implementing an HTTP server in JavaScript. Those with access to GitHub Copilot (LLM-code assistance embedded in integrated development environments) completed the task 55.8% faster than those in the control group. Less experienced programmers benefitted the most.

Complementing the above lab results in a real-world context, two field experiments at Microsoft and Accenture involved nearly 2,000 professional software developers. Developers granted access to GitHub Copilot showed increased productivity, measured by the number of pull requests[7] submitted per week. At Microsoft, productivity rose between 12.9% and 21.8%, while at Accenture the increase ranged from 7.5% to 8.7%, depending on the estimation method (Cui et al, 2024). The study suffered from some methodological challenges and limitations however, including low initial uptake and short observation windows at Microsoft and internal reorganisation limiting the usable set of experimental data at Accenture.

The observation that productivity gains from AI-coding assistance are harder to measure in controlled experiments in the workplace than in the lab, could be due to the **type of programming** that is assisted – as lab studies tend to focus on simple, generic programming tasks that are not company-specific. A study assessing ChatGPT's ability to solve 240 programming problems across three difficulty levels, showed that ChatGPT performed well on easy and medium tasks, with initial success rates of up to 90%, but it struggled with hard problems, highlighting the current limitations of LLMs in handling more complex software engineering tasks (Bucaioni et al, 2024).

Large real-world impact LLM coding assistance could be observed when Italy temporarily banned ChatGPT in 2023. In the first two business days, coding activity on GitHub by Italian

[7] A pull request is a formal proposal by a software developer to merge their code into a larger project. It represents a self-contained, often pre-defined, unit of work, such as adding a new feature or fixing a bug.

developers dropped by roughly 50% compared to control countries (Kreitmeir et al, 2023). Productivity later rebounded, but this was accompanied by a surge in VPN-related Google searches and Tor usage (an open-source software for enabling anonymous communication), indicating active efforts of Italian developers to circumvent the ban.

Image-based genAI: Creative and design tasks

Besides text and code generation, a third type of genAI involves the generation of images, video or audio. Applications of AI in creative industries include among others content creation and enhancement, post production workflows and data compression, besides more widely (cross-sector) applications like information extraction and analysis (Anantrasirichai et al, 2022). Many industry-standard tools like Photoshop[8] and Canva[9] now include integrated tools for editing images and designing graphics with generative AI.

Ju and Aral (2025) set-up an online experiment in which 2300 humans where blindly matched either to another human or to an autonomous AI agent. Both groups worked together in a virtual environment and were tasked with creating advertising images and text. Producing over 11.000 ads together, the researchers found that, compared to human-human teams, human-AI teams communicated more in the chat window, allowing the humans in those AI-teams to focus 23% more on text and image content generation and 20% less on direct text editing. Analysing the types of communication, the authors found that the AI sent more task-oriented messages (on the process and the content), while humans sent more relationship-oriented messages (social and emotional). Despite these differences in communication types, the quality of the teamwork was judged equally. Finally, running the ads on the social media platform X revealed that both types of teams performed equally well. The human-AI teams achieved this equal performance with one less human, as they consisted of one human and one AI agent, while the human teams consisted of two humans – implying a doubling of human productivity.

Implications for work organisation

The preceding analysis of tasks impacted by AI, particularly in light of recent developments in generative AI, naturally leads to a discussion of the implications for work organisation, given that the task is the basic unit of work. Insights from Eurofound research on digitalisation show that the adoption of transformative technologies often leads to a reshaping of existing tasks and the emergence of new roles, driven by workflow reorganisation and increased work standardisation (Eurofound, 2024a, 2021b).

According to Bresnahan (2021), AI technologies are not fundamentally different from earlier information and communication technologies in that they do not primarily replace human labour at the task level. Instead, they contribute to capital deepening, raising productivity by increasing the use of capital rather than directly substituting workers. Their impact emerges at the system level, gradually shifting production towards more capital- and skill-intensive models, rather than reducing labour demand through task-based automation.

However, it is important to recognise that tasks are not fixed characteristics of occupations. The division and specialisation of labour is both shaped by technological change and serves as a key enabler of it (Eurofound, 2018). As such, while technological progress may change

[8] https://www.adobe.com/uk/products/photoshop/generative-fill.html
[9] https://www.canva.com/ai-assistant/

the task and skill content of work (Autor et al, 2003), tasks might also shift across roles and seniority levels.

As task-level effects are more easily detected in individual-based experiments and laboratory settings, they were among the first to be extensively documented. A reallocation of tasks, however, is less immediately observable and often more subtle, so this section draws on more theoretical, indirect and speculative research. Before turning to AI specifically, the following section reviews past waves of technological progress to draw lessons on how technology and work organisation have evolved in tandem.

Complementarity between technology and work organisation

Historical examples offer valuable insights into the organisational shifts that may be required to fully harness the potential of new technologies. Technology adoption is most effective when it is accompanied by complementary changes in organisational structures and practices. These complementarities help explain why certain organisational innovations tend to co-occur together. For example, the transition from mass production to flexible, multi-product manufacturing relied not only on new technologies but also on new practices and strategies, such as smaller batches, just-in-time delivery of input materials, higher quality and broader product offerings and various forms of employee involvement in decision-making (Milgrom et al, 1990). These joint changes allowed 'modern manufacturers' to adapt quickly to diverse and changing consumer demands.

To acquire these organisational complements necessary for profitable technology adoption, firms must invest in complementary intangible assets, both firm-specific human capital and "organisational capital" – i.e. the redesign of business processes, workflows, and job roles (Brynjolfsson et al, 2000). Research on past waves of general-purpose technologies, not specific to AI, shows that these complementary investments often **lag behind** the acquisition of technology itself, delaying productivity gains by at least half a decade (Brynjolfsson et al, 2003). Such investments are also **intangible**, and due to accounting rules are usually expensed instead of capitalised[10], leading to a hidden intangible capital stock (Brynjolfsson et al, 2021). Finally, complementarities exist between multiple aspects of the firm, not only between technology and organisation, but also between both of these and the strategy of the firm (Milgrom et al, 1995). This means that the empirical relationship between technology, organisation, and productivity is likely **non-linear** (Bertschek et al, 2004). These three complexities make it difficult to detect effects of reorganisation using basic statistical methods (for example simple dummy variables in linear models), and point to the need for systems thinking (Meadows, 2008) in analysing and managing technological change.

The lack of detectable aggregate productivity gains from ICT investment in the 1970's and 1980's became known as the ***productivity paradox***, when heavy ICT investment coexisted with productivity stagnation. The organisational adaptation to ICT adoption only took place during the 1990's wave of business process reengineering (Brynjolfsson et al, 2000). Micro-econometric studies confirmed that workplace reorganisation played a central role in translating ICT investments into productivity gains (Black et al, 2001; 2004) and that these IT-supported flatter hierarchies tended to use more skilled labour (Bresnahan et al, 2002).

[10] Meaning they do not appear as investment in balance sheets, but as expenses in profit-loss statements.

However, **not all digital technologies have the same implications** for the organisation of work. Analysing 1000 U.S. and EU manufacturing firms, Bloom et al (2014) found that *information technologies* (IT) are associated with greater autonomy – i.e. they decentralise decision-making by providing frontline workers and plant managers with better data at the bottom of the hierarchy. In contrast, *communication technologies* (CT) tended to reduce autonomy for the plant manager – i.e. they centralise control by facilitating oversight and coordination from the central headquarters. Interestingly, while CT reduced autonomy for the plant manager, this was not the case for frontline workers. A plausible explanation is that CT centralised decision-making from the plant manager up to the headquarters but still supported horizontal coordination among frontline workers.

Zooming out even further, over the long run organisational models have always evolved alongside major technological waves. Since the 1750's, each wave of technological revolution has been accompanied by the rise of a new organisational paradigm and associated management models – each with a revolutionary cycle and a balancing cycle (Bodrožić et al, 2018), see **Table 2**. These paradigms develop through cycles of problem-solving and adaptation, in which new models emerge to solve the dysfunctions of the previous ones, are shaped by managerial theories and practical experimentation, and finally diffused across different industries by consultants, authors and public-sector organisations.

Table 2: Technological revolutions, organizational paradigms and management models

Period	Technology revolution	Organizational paradigm	Management models	
			Revolutionizing cycle	**Balancing cycle**
1790-1890	Steam power and railways	Professionally managed firm	Line and staff	Industrial betterment
1850-1940	Steel and electric power	Factory	Scientific management	Human relations
1880-1980	Automobile and oil	Corporation	Strategy-and-structure	Quality management
1950-...	Computers and telecom	Network	Business process	Knowledge management

Source: Bodrožić et al (2018)

Complementarity between AI and work organisation

While some authors argue that AI is a new General Purpose Technology (GPT) (Agrawal et al, 2019), others believe it mostly extends the digital infrastructure of the fifth wave (Perez, 2024). As such, its impact on work organisation could be similar to other information technologies (IT), i.e. leading to further decentralisation of decision-making in organisations. Whether AI is viewed as a transformative general-purpose technology or as a continuation of existing digital infrastructure, its impact on work organisation ultimately depends on how it is adopted and integrated within firms.

Some studies suggest that the effective adoption of AI is strongly dependent on complementary technologies and existing organisational capabilities. Lee et al (2022), using firm-level survey and administrative data from 300 high-tech ventures in South Korea, show that AI adoption - conceptualised broadly without reference to specific tools or technologies - only leads to significant revenue growth when it reaches high intensity and is supported by investments in complementary technologies such as cloud computing and database systems, as well as firm-specific internal R&D strategies.

Similarly, Li and Jin (2024), based on an empirical analysis of 451 survey responses from employees in Chinese manufacturing firms, find that AI adoption - also not tied to particular applications - enhances corporate sustainability performance across economic, environmental, and social dimensions, but only when accompanied by internal organisational change, which plays a key role in translating AI use into better sustainability outcomes. They also find that this link is stronger in firms with more advanced digital capabilities.

Likewise, a 2025 OECD report (Kergroach et al, 2025), based on comparative statistical analysis of OECD-Eurostat business survey data, reveals that differences in AI uptake across regions, firms, and sectors are influenced by the presence of enabling conditions such as digital infrastructure, data ecosystems, and the integration of AI with business intelligence software and smart robotics. In the OECD study, AI is referred to as a general-purpose technology encompassing a broad spectrum of tools and applications, including machine learning, natural language processing, and robotics. An analysis of the European Enterprise Survey also showed that internal barriers such as skills, financial resources, data and infrastructure are the main barriers to AI adoption (Hoffmann et al, 2021).

Beyond these organisational preconditions, the specific functions of AI also shape how it integrates into existing production systems. In its role as a decision and prediction technology (**ML** and **DL**), AI is expected to complement modularised production systems by enhancing coordination and responsiveness across discrete components. Modular systems consist of components that can be independently designed, produced, and replaced, as long as they conform to a set of design rules or interfaces (Baldwin et al, 2000). Applied to work organisation, a modular work system is one in which work is broken down into semi-independent units, making a hierarchical system composed of nearly decomposable subsystems (Simon, 1962). Such loosely coupled work systems offer greater adaptability than tightly integrated structures, making them well-suited to environments with high variability or rapid change. Across a number of case studies, including Amazon, Google, Netflix and Facebook, Bresnahan (2021) illustrates that AI adoption is indeed facilitated by such modularisation. At Amazon for example, using AI for more targeted recommendations did not require changing other elements of the online bookstore extensively. Similarly, as Google's user interface design was already heavily modularised, using AI for Voice UI (i.e. voice control of Gmail) did not require substantive changes in its underlying services.

In some cases, too much modularisation can also limit the effectiveness of AI-driven decision-making, as illustrated in a 10-month ethnographic study of the implementation of an Inventory Assortment Planning Algorithm at a large online retailer (Valentine et al, 2024). Pre-AI, purchasing decisions were divided across multiple buyer roles to reduce information-processing requirements in each role and them achievable by a single human – a common principle in organisational design that accounts for the cognitive limits, or *bounded rationality*, of human decision-makers. During the study, the retailer adopted a mathematical optimisation model to recommend styles and volumes to purchase in each clothing segment. However, the AI worked better if it could reason over broader decision spaces (i.e. multiple clothing segments at once) that cut horizontally through these role boundaries. For example, inventory decisions were originally divided by product segments and allocated to different roles (e.g. men’s denim buyer, women’s denim buyer, etc), but the AI could suggest better inventory plans (in terms of established performance metrics such as margins and ‘keep rates’) if it was allowed to jointly optimize across all segments, because it could identify cross-segment opportunities (e.g. masculine-styled clothes for women).

Agrawal et al (2023a) develop a formal (symbolic) model to analyse these trade-offs between modularisation, coordination and AI adoption in a model where multiple tasks are part of an interdependent system. They show theoretically that AI as a prediction tool increases decision variation, which raises coordination challenges if decisions interact across the organisation. They also show that AI adoption will be enhanced when the work organisation is redesigned concurrently, highlighting two types of organisational redesign. The *first* option is to reduce interdependencies between decisions, through increased modularisation of the organisation: in a more loosely coupled work system, AI can be applied to individual decisions without disrupting decisions in other parts of the organisation. The *second* option is to increase mechanisms for inter-decision coordination: keeping a tightly coupled work system, AI’s impact on one decision must be communicated to others for alignment.

Beyond ML/DL applications, **genAI** is also driving broader organisational transformations across sectors, as documented in a review of the literature on generative AI conducted by the European Commission’s Joint Research Centre (Abendroth Dias et al, 2025). GenAI enables autonomous manufacturing, personalized retail experiences, early diagnosis and tailored treatment in healthcare, enhanced cybersecurity, AI-driven content creation in creative industries, and improved service delivery and administrative efficiency in the public sector. According to the review, GenAI is also increasingly reshaping workflows through the emergence of AI agents, systems capable of executing complex tasks autonomously. These agentic systems are transforming knowledge production by acting as ‘co-scientists’ in research and as ‘co-workers’ in enterprise settings. Their growing use raises important questions about how we define work and the role of the employee in increasingly autonomous organisational environments (Abendroth Dias et al, 2025).

AI and a new division of labour

The further diffusion of AI will likely be accompanied by a changing work organisation, potentially decentralising decision-making (if access to expertise can be organised lower in the hierarchy) or centralising it (if decisions are highly interdependent). The resulting effect on the division of labour will mostly depend on the types of tasks that are affected and on the types of humans currently executing those tasks. **Two recent sets of findings suggest potential opposing directions,** though arguments on both sides are very preliminary, and evidence is scarce:

- Several recent studies on genAI support at the task level have documented that AI-support **benefits lower-skilled, juniors or novices** more than seniors or experts (Brynjolfsson et al, 2025; Noy et al, 2023; Peng et al, 2023). These observations have led to speculation of a potential ‘**democratisation of expertise’** that would make high-skilled work more accessible to low-skilled workers. Such increased access to expertise would, in turn, allow organisations to shift tasks down from high to low-skilled occupations and potentially creating more middle-class jobs (Autor, 2024).

- At the same time, evidence is emerging that AI can currently handle **low-complexity tasks** better than high-complexity tasks (Bucaioni et al, 2024; Demirci et al, 2025; Teutloff et al, 2025). Those tend to be tasks in entry-level jobs, rather than in managerial roles (Kinder, 2024). The automation of entry-level tasks would mostly displace novices and **break the career ladder** (O'Connor, 2025). Such an evolution would require an intentional redesign of career development in organisations in order not to dry up the junior-to-senior pipeline. Brynjolfsson et al (2025) provide further evidence that generative AI disproportionately impacts entry-level employment in AI-exposed occupations. Using high-frequency payroll data, they find that, since the release of ChatGPT in late 2022, employment among young workers (ages 22-25) has declined sharply in roles such as software development and customer service, while older workers in the same occupations have remained unaffected or even seen employment gains. This divergence appears particularly pronounced in occupations where AI is used to automate, rather than augment, work. The authors suggest that younger workers – who rely more on codified knowledge gained through formal education – are more easily substituted by AI systems, whereas experienced workers benefit from tacit, context-specific knowledge that is harder to automate. Résumé and vacancy data from 62 million workers across 285,000 firms appear to confirm these findings, as junior hiring slowed sharply from Q1 2023 onwards in AI adopting firms, while senior employment continued to grow (Lichtinger and Hosseini Maasoum, 2025).

Combining these insights allows the formulation of potential scenarios for the future of the division of labour and valuation of expertise (National Academies of Sciences, Engineering, and Medicine, 2024):

Scenario 1: Sustained reduction in middle-skilled employment. In this scenario, leaning heavily on the second finding above, AI extends the reach of automation up the skill ladder, and substitutes for an even broader set of middle-skill tasks. While AI takes over the initial stages of medical, legal and financial analysis, finalisation would still require specialised 'elite experts'. Demand for such high-skilled expertise would rise, while mid-level skills would be threatened by automation. This scenario is also called 'RBTC on steroids' (Tyson et al, 2022).

Two empirical studies find preliminary, indicative support for this scenario. Arntz et al (2024) survey 2,032 German manufacturing and service firms about their adoption of frontier technologies (such as AI, augmented reality, smart factories, or cloud computing) and combine this with firm-level employment histories between 2011 and 2016. They find that the adoption of these technologies significantly – but modestly – reduces routine employment and increases non-routine cognitive employment in those firms. While not directly measuring changes in the organisation of work, these results do support scenario 1.

Babina et al (2023) measure work organisation more directly, by deducing U.S. firms' hierarchical structures and workforce composition from their employees' online resumes. They find that firms who invest in AI (measured by the number of vacancies requesting AI skills), transition to workforces with more advanced degrees, and more specialisation in STEM fields and IT skills. Furthermore, these AI investments are associated with a flattening of the firms' hierarchical structure[11], increasing the share of workers in non-managerial positions and decreasing them in middle-management and leadership roles. This study suggests that AI adopters shift their workforce to more educated and technically specialised workers but employ them in flatter organisational structures. This study supports employment scenario 1 as well, while also providing evidence for the decentralisation hypothesis in work organisation - echoing earlier findings by Bloom et al (2014) that IT adoption tends to decentralise decision-making.

Two other theoretical scenarios are possible (National Academies of Sciences, Engineering, and Medicine, 2024):

Scenario 2: The elimination of expertise. In this scenario, which extends the first to the entire skill ladder, AI and robots become so capable and inexpensive that they outcompete humans across every domain, reducing the value of human labour to near zero. While this scenario is unlikely in the near future, it is considered economically coherent and has been discussed in academic debates. Several American AI companies, such as OpenAI, Meta, Google DeepMind and Anthropic have explicitly committed to creating such general artificial intelligence, defined as 'highly autonomous systems that outperform humans at most economically valuable work'[12].

Scenario 3: The reinstatement of middle-skilled employment. In this third scenario, leaning heavily on the first finding above, AI makes elite expertise accessible to middle-skilled workers. As AI substitutes for technical knowledge, it reduces the level of expertise needed in expert jobs and it complements the soft skills of workers in those tasks. AI could provide technical guidance and safeguards to less-expert workers, allowing them to handle a broader range of expert tasks, reversing a long-standing trend of reductions in middle-skilled employment.

While no evidence is available yet for scenario 3, this does not rule out the possibility that such a shift could still occur over time, given that organisational changes often lag a significant amount of time behind technological adoption. If that were the case, AI-adopting firms could initially hire more high-skilled labour to develop and implement the technology, while in a later phase shifting AI-supported tasks to middle-skilled labour. However, more research and a longer observation period is needed are needed to assess whether and under what conditions such effects eventually materialise.

[11] The paper refers to the hierarchical positions as 'seniority levels', but they must be understood as such from the organizational – not the individual worker's – perspective. Indeed, an experienced worker (with high individual seniority) can be employed in a non-managerial position (with low organizational seniority). The paper finds that while AI adopting firms request more work experience in vacancies, their structure shifts to fewer managerial positions. 'Expertise' must therefore be decomposed into at least Three categories: (1) level of education, (2) field of education and (3) years of work experience. Indeed, expertise is defined as domain-specific hierarchical knowledge structures developed by an individual over time, acquired through education, training, study and in-depth practice. Within this definition, studies show that the quality of practice and learning experiences are particularly important in developing expertise (Rousseau et al, 2025).

[12] See for example *OpenAI Charter*. https://openai.com/charter/

Summary points

On task-level productivity gains:

- **Different types of tasks require different AI-human configurations.** Meta-analyses show that AI-human collaboration works better for open-ended creation tasks than for binary decision tasks, where either AI or human alone often performs best. This suggests the need for "triage" mechanisms that dynamically allocate task instances to the most competent agent – human or AI – rather than relying on joint decision-making by default.
- **In decision tasks, particularly in healthcare diagnostics, AI often outperforms both unaided and AI-assisted human workers.** Studies in radiology and differential diagnosis show higher accuracy when AI operates independently, reinforcing the case for selective automation. However, safe and effective triage systems – potentially AI-driven – are needed to route cases appropriately, and risks like automation bias and skill degradation must be carefully managed.
- **In creation tasks such as writing, translation, and workplace communication, genAI consistently boosts productivity and quality.** Experiments show significant time savings and improved output, especially for lower-skilled users. AI shifts human effort from drafting to editing and enhances effectiveness in real-world settings, such as customer support, and email management.
- **genAI also enhances idea generation, innovation, and complex text analysis, including financial and legal tasks.** AI-generated product ideas often outperform those of professionals, and combining AI with human teams yields especially strong results. In financial and legal domains, AI improves text summarisation, risk identification, and decision support, enabling humans to focus on higher-level judgment.
- **In programming and design, genAI tools accelerate task completion and boost productivity, especially for simpler tasks and less experienced workers.** While lab studies show large time savings, real-world productivity gains are more modest and context dependent. In creative design, human-AI teams can match or exceed human-only teams with less manpower, reallocating effort toward content creation and away from editing.

On implications for work organisation:

- **Technology adoption often requires complementary changes in work organisation.** Past productivity gains from ICT emerged only after firms adapted workflows, hierarchies, and skills. These complementarities between technology, organisation, and strategy are often hard to detect but critical in practice. Without investments in human and organisational capital, the benefits of new technologies can be delayed or remain unrealised.
- **Adoption of AI as a decision-technology is more effective in modular work systems or when coordination mechanisms are improved.** Modular structures allow AI to be integrated into discrete tasks without disrupting the whole system, while tightly coupled systems require mechanisms for aligning decisions across roles. Redesigning

work to either reduce interdependencies or enable cross-functional coordination enhances AI's impact, but overly fragmented roles may limit performance.

- **genAI may reshape the division of labour by shifting tasks across roles and skill levels.** On the one hand, AI can automate entry-level tasks, potentially displacing junior workers. On the other, it can amplify the performance of lower-skilled employees, making expert tasks more accessible. The outcome depends on how organisations reassign tasks to jobs, structure career development, and invest in human-AI collaboration.

Implications for job quality

Job quality concerns are increasingly prominent in debates on AI in the workplace. While fears of mass displacement have dominated earlier discussions (see for example Monaco & Nurski (2025)), many scholars now argue that AI's impact is more likely to unfold through changes in how jobs are performed rather than whether they exist at all. As such '*the robo-apocalypse plays out in the quality, not the quantity of work*' (Riemer et al, 2020). Algorithmic management might have the more direct impact on specific aspects of job quality, but also AI-driven automation and augmentation can affect job quality by reshaping design – i.e. the content and structure – of jobs (Parent-Rocheleau et al, 2022; Parker et al, 2022).

While there is substantial research on AI's impact at the task level and on overall employment effects, less attention has been paid to how AI reshapes the quality of work itself. The available evidence often points to diverging outcomes. These mixed findings likely reflect differences in how AI is deployed across sectors, occupations, and organisational contexts, as well as the variety of AI systems and job quality measures used.

This chapter begins by examining how the task-level transformations discussed in the previous chapter result in a changed job content, which in itself is an important determinant of the four dimensions of job quality explored next: intrinsic quality of work, working time and work-life balance, safety and health, and employment quality.

Changing task content of jobs

As discussed in the opening chapter, AI can theoretically change the task composition of jobs in a number of 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) (Acemoglu et al, 2019). 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 (Milanez, 2023).

In a representative sample (n=5,342 employees) of the adult workforce in 11 EU Member States, Cedefop (2025)'s AI skills survey finds that *complementary task change* was the most prevalent effect in the spring of 2024. Namely, 67% of workers using AI at work reported that AI helped increase the speed with which they carry out their tasks. 41% reported handling new or different tasks due to AI – which is the reinstatement effect – while only 30% reported that AI displaced some of their tasks completely.

Two years earlier, the OECD surveyed 5,000 workers and 2,000 firms in the manufacturing and financial sectors in Austria, Canada, France, Germany, Ireland, the United Kingdom and the United States (Lane et al, 2023).[13] In contrast to the Cedefop survey, this survey 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

[13] While the CATI employer survey was aimed to be representative for the population in those two sectors, the worker survey was a non-representative sample using online access panels.

workers, while only about half in each sector said AI had created new tasks. Around one-third of employers noted that AI had both automated and created tasks.

While the OECD survey only distinguished between task automation and creation, a set of 96 accompanying case studies in the same two sectors studied task change in more detail (Milanez, 2023). Across these cases, *complementary task change* was again the most prevalent, particularly in manufacturing, but also in finance. Examples in manufacturing included AI-assisted visual inspection tools that helped assembly workers improve accuracy, reducing scrap rates. In finance, a Japanese insurer used an AI system that listens to customer calls and suggests solutions in real time, helping representatives improve response quality.

Full and partial task automation was less common in the case studies but still observed. Examples of *full task automation* included an AI system that automatically monitors inventory and orders parts, replacing workers' role in stock management. Similarly, automated inspection of turbine blades using AI and robotics, eliminated technicians' involvement in defect detection. In finance, full task automation was less common, but one example covered the screening of legal documents for identifying sections potentially causing liability issues. The majority of *partial task automation*, which automates only the simple versions of tasks, did occurred in finance. For example, chatbots handle routine customer queries, while human agents manage complex issues. Or AI tools that classify emails or process standard insurance deal with predictable issues, and humans address exceptions. In the OECD case studies, *task creation* was the least observed form of change. Most new tasks emerged in the creation and use of the AI systems, such as algorithm training, machine parameter setting and monitoring of AI outputs.

Research conducted by Autor and Thompson (2025) suggests that it matters not only whether tasks are added or removed, but also whether these tasks are expert or inexpert ones. The study introduces a novel framework to understand how task changes alter the expertise required in occupations. Drawing on semantic analysis of historical task descriptions and a new linguistic metric of expertise, the researchers demonstrate empirically that shifts in occupational expertise (via changes in task composition) predict wage and employment trends in the U.S. between 1980 and 2018. Their findings show that automation can either raise or lower occupational entry barriers depending on whether it targets expert or inexpert tasks. When automation removes expert tasks (or adds inexpert ones), the threshold for entry into an occupation drops, increasing employment but depressing wages; conversely, when inexpert tasks are automated (or expert ones are added), the occupation becomes more expertise-intensive, raising wages but reducing employment.

Intrinsic quality of work

In Eurofound's job quality framework, intrinsic job quality can be understood as a measure of the richness of work as a creative human activity. It is shaped by three main components: autonomy, skills, and social support. Autonomy refers to the extent to which workers can make decisions about how and at what pace they perform their tasks. The skills component relates to how diverse, engaging, and intellectually stimulating the job requirements are. Social support reflects the quality of the interpersonal environment at work, including how supportive and enriching interactions with colleagues and supervisors are.

Much of Eurofound's research on digitalisation (Eurofound, 2021a, 2023, 2024a) finds that the impact of digital technologies in the workplace is not predetermined, but rather largely shaped by deliberate management choices made during the change process. In the same vein, drawing on work design theory and evidence from previous waves of technological change, Parker and Grote (2022) examine both the positive and negative impacts of AI on intrinsic aspects of job quality, emphasising that these outcomes depend heavily on how AI systems are designed, implemented, and integrated into work environments. They argue that AI can either empower or disempower workers, depending on whether it is used to augment or replace human judgment.

Job autonomy

Insights into the diverging impacts of AI use on **autonomy** emerge from an OECD survey of over 5,000 workers in the manufacturing and financial sectors, conducted in 2021 across Austria, Canada, France, Germany, Ireland, the United Kingdom, and the United States (Lane et al, 2023). The survey found that more than half of respondents reported that AI had increased their control over the sequence in which they perform tasks, a key dimension of worker autonomy that can act as a buffer against high-intensity work. However, workers managed by AI were significantly more likely to report a loss of control: 31% in manufacturing and 23% in finance said AI had decreased their task autonomy. These results suggest that AI management systems, depending on how they are implemented, may undermine worker autonomy and, in turn, reduce job quality. This draws attention to the need to design and deploy AI tools in ways that complement rather than replace human judgment, helping to sustain meaningful and empowering work environments.

The firm-level case studies conducted alongside the OECD worker survey (Milanez, 2023) revealed mixed evidence regarding job control. In some instances, AI occasionally removed autonomy over both low- and high-level decisions (e.g. when to reorder supplies or pre-empt equipment failure), though many workers welcomed the reduced responsibility. Most workers appreciated AI decision support, especially when they retained some autonomy, such as in scheduling their tasks. Workers who reported such autonomy were more likely to describe positive outcomes. Taken together these findings suggest that when workers retain some control over their tasks, including with AI support, they are more likely to report positive experiences.

Skill use and development

The critical role of implementation choices in shaping the impact of AI extends to other aspects of the intrinsic quality of work. Research suggests that AI's impact on **skill use** hinges on task allocation: when AI complements human capabilities, it can free workers from repetitive or hazardous tasks, enabling them to focus on more complex, meaningful work (Parker et al, 2022). By contrast, cognitive automation, where AI fully takes over tasks like diagnostics or monitoring, 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, restricting learning and professional development (Beane, 2019). However, in other healthcare settings, AI-based triage tools and robotic assistants have enabled clinical staff to focus on high-level decision-making, illustrating the potential for skill enhancement.

Other empirical evidence paints a more nuanced picture. Drawing on the European Skills and Jobs Survey, McGuinness et al (2023) investigate the effects of skills-displacing technological change (SDT), defined as technological change that renders some existing worker skills obsolete. They find that, contrary to the deskilling hypothesis, workers exposed to SDT tend to engage in **dynamic upskilling**, adapting to evolving technologies through the acquisition of new competences. Rather than simplifying work, SDT is often associated with an **increase in task and skill complexity**, suggesting that technological change can simultaneously displace older skills and stimulate the development of new ones. The study also finds that workers experiencing SDT report heightened job insecurity due to anticipated skill obsolescence. While not universal, there is evidence that technological change can be associated with higher wages, as increased task complexity and skill development often correlate with better pay.

Yet, these adaptive outcomes are not evenly distributed, as the differentiated impacts of AI are also evident when looking at intrinsic job quality across skill levels. A Danish TASK survey conducted in 2019 on a representative sample of 1,244 employees found that AI-based decision support was associated with enhanced job control in high-skilled roles, such as increased learning opportunities, reduced monotony, and greater responsibility for quality (Holm et al, 2022). 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.

The use of AI also drives changes in **skill demands**, as shown in Cedefop survey of over 5,300 employees conducted in 2024 across 11 EU countries (Cedefop, 2025). According to the survey, six in 10 respondents believe that AI will create new skill needs in their work in the next 5 years, and four out of 10 state a need to develop their knowledge and skills in using AI for their job. Despite this, only 15% of workers participated in AI-related education or training in the previous year.

Findings from OECD firm-level case studies in finance and manufacturing sectors suggest that these perceived changes in skill needs may not always materialise in practice (Milanez, 2023). In nearly two-thirds of the cases studied, AI adoption did not lead to new skill requirements, as workers continued performing the same tasks or tasks were simply redistributed. Where new skill needs were observed, in about one-third of cases, they included analytical, interpersonal, and domain-specific skills. An accompanying OECD survey conducted in 2021 among 2,000 firms in the same sectors as the case studies also highlighted a growing demand for 'human' skills, such as problem-solving, empathy, and collaborative decision-making (Lane et al, 2023).

Drawing on granular labour market data and LinkedIn information, the most recent OECD Skills Studies report (2025) provides further evidence on the impact of AI - defined as disruptive digital technologies, including machine learning and generative AI systems - showing that AI simultaneously drives demand for new competencies and risks displacing traditional roles. Demand for programming, software development, and human-computer interaction is projected to increase markedly through 2030, while transversal skills such as problem-solving, creativity, and interpersonal abilities are becoming increasingly important complements to technical expertise.

Social support

In the area of **social support**, available evidence suggests that digital technologies, including AI, do not necessarily alienate or isolate workers. According to the seventh EWCS, 48% of workers [14] who reported using at least one of the technologies covered indicated that it facilitates increased interaction among colleagues, either to a large extent or to some extent (Eurofound, 2025). Case study research (Milanez, 2023) found mixed effects of AI use on peer collaboration and interaction. 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. These mixed findings suggest that effects depend on which types of tasks are automated: individual, administrative ones or interactional, instructional ones.

Further evidence on the impact of AI on social interactions comes from two experimental task-level studies that were introduced in the previous chapter. In a large-scale randomised controlled field experiment with 2,310 participants randomly assigned to Human-Human or Human-AI teams, Human-AI teams were found to communicate more frequently than human-only teams, with AI agents predominantly contributed task-oriented (process and content) messages and humans offering relationship-oriented (social and emotional) communication (Ju and Aral, 2025). Despite these differences, the perceived quality of teamwork was equivalent between human-AI and human-human teams, suggesting that relational balance can be maintained even when AI is part of the group and even as performance increases[15]. In another field experiment on product innovation at Proctor & Gamble, emotional experiences also appeared to improve with AI collaboration (Dell'Acqua et al, 2025). Working with an AI teammate increased positive emotions (e.g., enthusiasm) and reduced negative ones (e.g., frustration), both for individuals and teams. These emotional benefits from AI support were on par with those observed when working with a human teammate. AI also facilitated more balanced disciplinary collaboration, suggesting that AI can help equalise participation in teams[16].

Working time and work-life balance

Working time

While productivity gains have not historically led to shorter working hours, AI-driven productivity improvements could create new opportunities to enhance working time quality, if such gains are more equitably shared (Ernst et al, 2019). While the reduction in working time is gaining traction in the media[17] and some companies have announced four-day work

[14] 79% of EU27 workers report at least one type of technology use in their main jobs (respondents who indicate that their job involves computer use / tech wearable use at least 1/4 of the time or who answer positively to any of the other technology use questions (cobots, platforms, generative AI, remote meeting software).

[15] See earlier discussion on the productivity findings in this experiment in 'Image-based genAI: Creative and design tasks' on 19

[16] See earlier discussion on the productivity findings in this experiment in 'Text-based genAI: Idea generation and product innovation' on page 17.

17 See for example https://www.bbc.com/worklife/article/20240223-ai-could-make-the-four-day-workweek-inevitable.

weeks citing substantial (and partly AI-driven) productivity gains[18], there is currently no evidence of widespread adoption, and the concept continues to face political resistance in many contexts.

Beyond shortening working hours, AI-enabled virtual/remote forms of flexible work can also allow workers greater choice over when and where to work, but expectations for constant connectivity could negatively impact these choices (Parker et al, 2022). In healthcare, a study of 559 nurses and physicians found that AI-supported systems for remote monitoring of patients (and also better scheduling) improved work-life balance by increasing flexibility in both time and location (Bienefeld et al, 2025). The analysis showed that without AI, clinical staff had very limited control over when or where to carry out their work due to the constraints of shift-based physical presence. Automating tasks such as patient monitoring and documentation allowed staff to step away from the bedside without missing critical events and enabled earlier, more coordinated interventions. This enhanced clinicians' ability to plan their work and integrate it with other life domains.

Work intensity

In Eurofound's EWCS, work intensity measures the level of demands in a job, both quantitative and qualitative demands. When these demands are very high - requiring excessive cognitive, emotional or physical effort - they can hinder performance and negatively impact workers' well-being and health. The available evidence on work intensity in the context of AI use points to opposite outcomes, largely depending on the type of application used, how it is implemented and various contextual factors.

As the theory of routine-biased technical change (RBTC) predicts, AI adoption mostly tends to increase the **cognitive intensity** of work by automating routine cognitive tasks and redirecting human attention to more complex responsibilities. OECD case study research in the manufacturing and finance sectors found that AI adoption tended to raise cognitive demands by automating routine tasks and shifting human effort to more complex or exception-based work (Milanez, 2023). For example, chatbots and document automation tools reduced routine form-filling and client triage in finance, while ML/DL for predictive maintenance and visual inspection shifted workers' focus to interpreting alerts and troubleshooting.

According to accompanying worker and employer surveys conducted by the OECD in the same sectors, work intensity generally increased with AI use (Lane et al, 2023). The case studies showed that even when AI reduced workloads, such as by clearing backlogs or eliminating repetitive tasks, workers were typically expected to accomplish more in the same amount of time (Milanez, 2023). Employers sometimes attempted to mitigate this – such as by deliberately preserving some routine tasks to provide breaks – but developers generally viewed AI's impact more positively than frontline workers.

This shift from routine to more complex and cognitively demanding tasks due to AI use is not limited to traditional employment settings. Evidence from research on freelance markets in online digital labour platforms shows that demand for short, junior-level assignments declined the most after the launch of ChatGPT (Teutloff et al, 2025), while the remaining

[18] AFAS notes 650% productivity increase over 25 years: https://www.computerweekly.com/news/366613352/Afas-leads-the-way-with-four-day-work-week-in-the-Netherlands

projects became more complex and skill-intensive, with budgets increasing by 6% to 15% (Demirci et al, 2025; J. Liu et al, 2024). These shifts are discussed in more detail in the chapter on Implications for employment.

A study that used empirical econometric analysis leveraging a panel dataset at the analyst-stock-quarter level showed that security analysts that hold portfolios highly exposed to AI-driven earnings predictions, reallocated their efforts towards more complex tasks, like interpreting intangible metrics like brand influence (Grennan et al, 2020). In a natural experiment arising from the deployment of GitHub Copilot on the GitHub platform, leveraging millions of panel observations, software developers with access to GitHub Copilot reallocated time away from administrative project management and toward core coding tasks, driven by increased independent and exploratory work (Hoffmann et al, 2025).

Other research suggests, however, that depending on how they are applied, AI systems can reduce **cognitive demands** and help alleviate workload. For instance, in a case study investigated by EU-OSHA of a German manufacturer, an AI system for product inspection (a cognitive task, albeit highly standardised) was put in place to evaluate tests on soldering points and detect errors. This system was able to reduce the rate of false positives, thereby reducing the workload and cognitive strain of the worker who was tasked with confirming the error (European Agency for Safety and Health at Work, 2023b).

Another study in manufacturing, that combined expert interviews with company case studies, found that AI can positively influence cognitive demands and enhance various aspects of employee engagement, including physical, mental, and emotional involvement, particularly in human-centred work environments (Tortorella et al, 2024). In these lean manufacturing organisations, AI was used to reduce wasteful or unnecessary activities and to improve communication and teamwork, thereby saving employees time and effort. However, the authors also acknowledge potential negative effects of AI on employee engagement. One concern is that AI implementation may require new skills, creating a perceived capability gap. If employees feel unprepared or unable to meet these demands, their confidence may suffer, leading to emotional insecurity and negatively affecting their wellbeing. Also, the productivity gains introduced by AI could result in job cuts, and the resulting fear of redundancy may undermine employees' sense of stability and engagement.

The insights from these studies are complemented by further evidence on genAI. An online survey of 319 knowledge workers who regularly use tools such as ChatGPT or Copilot found that GenAI can indeed save time and reduce mental effort (Lee et al, 2025). Productivity and efficiency gains emerged as the primary self-reported motivations for adopting these tools. However, the study also highlights a potential trade-off: while GenAI may enhance users' perceptions of productivity, this ease can reduce engagement in deeper, critical thinking. The authors caution that excessive reliance on AI may weaken reflective judgment, suggesting that efficiency gains could come at the expense of critical reflection.

Automating routine cognitive work also shifts the task composition of jobs toward more interactive and social tasks, which may, in turn, increase **emotional demands**. The study mentioned above on security analysts (Grennan et al, 2020) also found that analysts whose stock portfolios are heavily exposed to AI-driven prediction and analysis, reallocated their time towards spending more time in meetings with management and institutional investors. These interactions require emotional intelligence, persuasion, rapport-building, and adaptability, all of which are emotionally demanding compared to solitary data analysis.

Mixed evidence was found in studies on AI use in customer support services. Focusing on generative AI support tools, a study examining the staggered rollout of a generative AI chat assistant across 5,172 customer support agents found that task-level AI support improved customer sentiment and reduced escalations: the number of instances where customers asked to speak with a manager decreased by 25% following the introduction of AI assistance in support chats (Brynjolfsson et al, 2025). In contrast, another study combining large-scale surveys of contact centre workers in the US (n=2,891) and Canada (n=385) with comparative case studies across four countries (US, Canada, Germany, and Norway) found that employees reporting higher-intensity AI use – defined as experience with a greater number of eight different AI-based tools – on average experienced increased work intensity, heightened monitoring, and more frequent mistreatment by frustrated or angry customers (Doellgast et al, 2023). In the OECD case studies, emotional demands were not systematically studied, but some customer-facing AI tools (such as chatbots and predictive prioritisation of incoming calls) were reported to reduce emotional strain by improving client interactions and defusing frustration earlier in the service process (Milanez, 2023).

Safety and health

Physical risks

AI technologies are expected to positively impact the physical conditions of work, by automating tasks that are repetitive, dangerous, or taxing and reducing physical demands (Parker et al, 2022). Many 'Operator 4.0' technologies are designed with the goal of enhancing physical well-being and safety, including ‘smart’ exoskeletons, AR/VR applications and biometric wearables (Berg et al, 2023). According to an OECD employer survey (Lane et al, 2023) conducted among 2,000 firms in selected countries AI is widely perceived by employers to improve safety by automating dangerous or repetitive tasks. OECD case study research (Milanez, 2023) conducted in parallel to this survey provide more insights on this: in steel and metal plants, AI-controlled systems reduced exposure to heat, sharp tools, and heavy materials. Predictive maintenance further mitigated indirect risks by detecting faults early. However, residual safety concerns remain, particularly where AI increases the speed of operations or where less experienced workers underestimate new physical risks introduced by the faster, AI-controlled processes.

A systematic review of 24 papers documents how AI and robotics can indeed do dangerous work; for example, in iron and steel manufacturing where chemicals and high temperatures are used in production, AI and robotics systems can detect and classify surface defects of the metal (Intahchomphoo et al, 2024). Even for computer workers, AI-automated data entry reduces eye strain and repetitive wrists injuries compared to the constant keyboard and mouse movements for manual data entry (Bell, 2023). However, at the same time, the above-documented increase in work intensity and pace can create higher work injury rates (Bell, 2023).

In studying the implications for health and safety, EU-OSHA distinguishes between the use of AI for automating cognitive versus physical tasks: cognitive automation mainly targets routine, information-related tasks like diagnostic support and chatbots, while physical automation focuses on repetitive, object-related tasks such as lifting, cleaning or hazardous inspections. The agency notes that AI adoption can reduce physical strain and monotony but also raise OSH risks including job insecurity, work intensification, reduced oversight, and loss of control. The outcome depends on the design and implementation choices, such as the types of tasks that are automated, the degree of autonomy preserved, the adequacy of OSH risk assessment and worker training, and the management's approach to performance targets and monitoring (European Agency for Safety and Health at Work, 2022).

EU-OSHA conducted case studies on the implementation of AI and cobots in workplaces and their effects on workers, interviewing up to five employees in each case. A comparative report of 11 such cases notes that advanced robotics and AI-based automation offer substantial opportunities to improve physical health and safety by reducing workload, removing workers from hazardous environments, enhancing ergonomics, and lowering injury risks (European Agency for Safety and Health at Work, 2023a). These technologies also support inclusion of workers with different needs and relieve the mental load associated with physical risks. However, managing residual safety risks requires updated risk assessment tools and strong worker involvement in advanced automation.

Similar findings emerged from Eurofound case study research, which however also highlighted that the use of AI-enabled robotic systems in warehouse settings, designed to simplify and standardise tasks, may lead to **cognitive underload** (Eurofound, 2024a). This, in turn, can reduce workers’ attention and engagement, ultimately increasing the risk of workplace injuries despite the original intention to enhance safety. These insights call for job redesign to counter monotony and under-stimulation, ensuring that workers remain cognitively engaged while still benefiting from the efficiencies of automation.

Other case studies collected by EU-OSHA also emphasise how AI-supported smart systems can be used to improve OSH management itself, by both proactively detecting and preventing risks as well as reactively managing incidents (European Agency for Safety and Health at Work, 2024). AI, in combination with wearables, and Internet of Things (IoT) enable early identification of hazards, reduce physical strain through ergonomic support, and prevent accidents with systems like fatigue monitoring or automatic alerts. They also allow for continuous data collection, offering insights into physical risks and worker wellbeing. These systems support faster, data-driven decision-making, streamline OSH management and compliance, and improve training and guidance.

Psychosocial risks

The adoption of AI-powered technologies can give rise to the emergence of psychosocial risks that may adversely affect workers’ mental well-being. Based on in-depth qualitative research, including interviews and observations, conducted across multiple logistics departments and warehouses implementing digital (often AI-enabled) order-picking technologies, a study found that although these systems are designed to replace physically demanding or repetitive tasks and provide ergonomic benefits, they frequently lead to intensified work demands (Lager et al, 2021). In several instances, the efficiencies gained through automation were used to increase output or speed, rather than to improve job satisfaction or reduce strain.

Another case examined in the research focused on a high-tech manufacturing facility, where the adoption of interconnected systems had shifted the role of shopfloor workers from manual assembly to monitoring machine performance and troubleshooting issues (Eurofound, 2024a) . While this transition reduced physical strain and promoted more cognitively demanding, problem-solving work, the machine-paced environment and constant digital prompts regarding productivity can lead to **mental fatigue**, despite the intellectually stimulating nature of the tasks.

Survey-based studies offer further insights into emerging psychosocial risks associated with AI use. Drawing on data from a three-wave survey conducted in 2023 with a sample of 600 employees from publicly listed companies in Taiwan that had adopted AI technologies, (Chuang et al, 2025) found that generative AI is more effective than non-generative AI, which is typically used for support, automation, or simple interactions, in helping employees cope with the stress associated with new technologies, referred to as 'technostress'. AI efficacy - defined as how useful and reliable employees perceive the AI to be - also plays a key role in boosting productivity: the more effective the AI is perceived to be, the better employees tend to perform. Although AI use can be stressful and mentally draining, a certain level of stress may still drive productivity by encouraging employees to work harder. However, this benefit comes at a cost, as technostress increases emotional exhaustion, which in turn reduces job satisfaction and contributes to work–family conflict.

Aside from work organisation and the nature of the task performed, individual differences in **preferences or psychological predispositions can affect how beneficial AI adoption is** for workers. In another three-wave survey of 332 employees across eight Chinese companies, employees with an internal locus of control - the belief that life events are largely within one's own control perceived organisational AI adoption as a challenging yet rewarding opportunity for growth. In contrast, employees with an external locus of control - the belief that outcomes are determined by external forces beyond one's influence - viewed AI adoption as a hindering stressor. These differing appraisals influenced how employees adapted their work behaviour: those seeing AI as a challenge were more likely to engage in promotion-focused job crafting (seeking growth and development), while those perceiving it as a hindrance tended toward prevention-focused job crafting (aiming to avoid risks and maintain stability) (Cheng et al, 2023). These findings imply that organisations should tailor AI-related change management strategies to account for individual differences in personality, for instance by framing AI initiatives as opportunities, offering personalised support, and fostering an internal locus of control through training and leadership development.

A new strand of research has started to unpack the psychological and behavioural consequences of employee-AI collaboration. Tang et al (2023), using a multimethod approach across four studies (surveys, field experiment, and simulations; n=794), showed that frequent interaction with AI simultaneously fosters adaptive outcomes, such as heightened need for affiliation that promotes helping coworkers, and maladaptive outcomes, including loneliness that spills over into poorer after-work well-being, with effects amplified among employees high in attachment anxiety. Extending this line of inquiry, Hai et al. (2025), using an experience sampling method with longitudinal data from 229 service industry employees (1,050 matched daily observations), found that on days when employees collaborated more with generative AI, they reported greater work alienation, which in turn increased expedient behaviours, particularly under conditions of high digital job demands. Similarly, Meng et al (2025), using an experimental vignette design (2×2 manipulation; n=167), demonstrated that **AI collaboration elevates loneliness**, which leads to emotional fatigue and ultimately counterproductive work behaviours; importantly, leader emotional support buffered these negative effects. These findings suggest that while AI can support task accomplishment, its integration into work routines also introduces psychosocial strains that manifest both at work and beyond, contingent on individual and contextual factors.

Employment quality

Previous research by (Eurofound, 2023) identified **fear of job loss** as one of the most frequently reported concerns in surveys examining public attitudes toward AI adoption. While the most recent Eurobarometer survey (n= 26,415) confirms that this concern persists, it also indicates a slight decline compared to the 2017 survey wave. In 2024, 66% of general population respondents in the EU believe that more jobs will disappear than will be created as a result of AI and robotics, although this proportion has decreased since 2017 (-8 percentage points and -6 percentage points, respectively) (European Commission, 2025). Similarly, 66% agree that AI and robots ‘steal jobs’, though this perception has also seen a modest decline since 2017 (-6 percentage points).

In a 2024 survey conducted by Cedefop among 5,342 adults in employment across 11 EU countries, 15% of respondents expressed fear of losing their job due to automation or AI in the next 5 years (Cedefop, 2025). This concern was particularly pronounced among workers with low digital skills and those employed in occupations at higher risk of automation. According to the survey, approximately one in three workers (35%) believe their employer will use AI to replace workers whenever possible, while six in ten (60%) think it is unlikely that their employer will consider employees’ views when making decisions about the implementation of AI.

These findings somewhat align with evidence from the German Socio-Economic Panel (SOEP), which surveyed 16,000 individuals. That study found that since 2015, workers exposed to AI have become more, not less, concerned about job security and their personal economic situation compared to non-exposed workers. This suggests that direct experience with AI in the workplace may reinforce or amplify personal economic anxieties, even if aggregate fear levels appear lower in some surveys (Giuntella et al, 2023).

While these findings point to growing anxiety among certain segments of the workforce, there is so far no evidence of widespread job destruction or reduced employment levels at the broader labour market level, with the exception of specific segments of online freelance work. This pattern is echoed in recent OECD research on AI adoption, which found that job losses were relatively rare and largely managed through attrition or internal redeployment (Milanez, 2023). However, concerns about future job security persist, particularly among AI users, younger workers, and women. About 15–20% of workers in AI-adopting firms knew someone who lost their job due to AI, while 24–29% reported internal job transitions (Lane et al, 2023). Employers responded by reassuring staff and shifting affected workers to more cognitively demanding or judgment-based roles (Milanez, 2023).

Beyond job instability, another key dimension of job quality are **wages**. Wage effects from AI adoption, these are hard to study due to the lack of comprehensive micro-level data on both AI implementation and wage outcomes. Hampole et al (2025) finds that firms with high AI utilisation tend to be larger, more productive, and pay higher wages. However, this is likely not a causal effect, but a selection effect – as firms paying high wages are more likely to adopt AI (Acemoglu et al, 2023). Bessen et al (2025) find that automation (beyond just AI) increases the probability of workers separating from their employers, leading to a decrease in days worked and a five-year cumulative wage income loss of 9% of one year's earnings. Finally, several studies document wage premia for AI skills, but AI adoption is unlikely to generate AI skills in the workers affected by the adoption as the case studies above have shown.

OECD survey research (Lane et al, 2023) showed that workers worried about potential pressure on wages due to AI adoption: twice as many workers expected AI to decrease wages in their sector in the next 10 years as to increase them. However, the accompanying case studies (Milanez, 2023) found that actual wage changes in workplaces adopting AI were uncommon. In most case studies investigated, AI-induced task changes were insufficient to trigger reclassification or affect pay. A similar finding emerges from case study research by Eurofound (2024), which examines the implementation of robotics, in some instances supported by AI technologies, and the resulting changes in human-robot collaboration.

In the OECD case studies where wage increases did occur, this was largely in Austria, where strong collective agreements linked pay to upskilling or job reclassification. Some firms tied bonuses or future pay adjustments to workers' AI use or performance data, but formal mechanisms were often absent. Conversely, wage reductions were occasionally reported for new hires performing simplified, AI-assisted tasks.

Job quality in the AI production chain

So far, we have documented (potential) impact of the introduction of AI adoption on those jobs whose tasks are directly impacted by the technology. While these jobs are likely the most numerous, the impact of AI remains relatively modest at this stage. However, AI also creates demand for a distinct set of jobs involved in the development and deployment of the technology itself – what we refer to here as the *AI production chain*.

The AI production chain includes all types of activities required to build, train, test, and maintain AI systems. It includes high-skilled professionals such as data scientists and machine learning engineers, who develop and fine-tune in-house AI models or provide tailored AI products and services to clients. Less visible, but equally essential in the production of AI systems, are low-skilled data workers who label training data, evaluate AI outputs, or moderate harmful content. We discuss both segments of this workforce in turn.

High-skilled AI specialists

The OECD documented the characteristics and labour market dynamics of the AI workforce (defined as workers who have the skills to develop and maintain AI systems) in OECD countries. Finding that almost 0.5% of vacancies requested AI skills in 2021-2022, this study identified the AI workforce as a small but rapidly growing group concentrated in high-skilled technical roles such as software engineering and statistics (Green et al, 2023). These AI workers in OECD are highly educated – over 60% have tertiary education, rising to nearly 80% in AI-intensive occupations – and earn disproportionately high wages, with half of them earning above the 80th percentile.

The wage premium for AI skills is documented in other studies as well. For example, Stephany and Teutloff show that AI skills increase worker wages by 21 % on average, because of their strong complementarities with other skills and because of their rising demand in recent years (Stephany et al, 2024). Drawing on Cedefop's second European skills and jobs survey, Pouliakas and Santangelo (2025) find that AI developers earn significantly more than similarly educated or skilled workers, such as programmers who do not yet use AI tools in their coding tasks. A wage decomposition analysis reveals that a substantial portion of this pay gap remains unexplained. However, part of the higher wage dispersion among AI developers appears linked to greater performance-based pay elements and more demanding job-skill requirements.

The high education and high wages of AI-specialists suggest overall good job quality (Green et al, 2023; Stephany et al, 2024). However, several studies document the large lack of diversity in these jobs (Green, 2024; Pal et al, 2024; West et al, 2019). The OECD documented that fewer than 40% of the AI workforce are women, compared to over 50% of the tertiary-educated workforce more broadly. However, given that the study does not directly measure AI specialists but infers their share in the larger occupational groups from online job vacancies, this is likely even an underestimation.

Indeed, the lack of diversity among US AI developers found by the AI Now institute is much larger (West et al, 2019), both along gender and racial lines. Women remain underrepresented, making 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.

More recent 'big data' evidence shows that the gender gap in AI development has not decreased. Analysing nearly 1.6 million online resumes, Pal et al (2024) highlight significant gender disparities in the global AI workforce. Women represent just 22% of AI talent worldwide, and under 14% in AI-related senior executive roles. Within the EU, the contrast is striking: highly gender-equal countries like Sweden and Germany show some of the lowest female representation in AI – 20% and 22% respectively. Similarly, countries with near parity in the general labour force, such as Portugal and Estonia, exhibit AI gender gaps as high as 51%. These gaps are also evident in Europe's AI hubs, where female representation remains below parity – ranging from 19% in Frankfurt to 31% in Milan.

Such underrepresentation has serious consequences, both in terms of restricted access to 'good jobs' and untapped potential for fulfilling high labour demand. But potentially even more importantly, non-diverse workforces potentially amplify biases in AI systems, thereby creating a 'discrimination feedback loop' (West et al, 2019). While increasing diversity alone won't eliminate biased datasets, a more inclusive AI workforce is better positioned to question existing norms, identify data shortcomings, and promote more equitable practices over time (Pal et al, 2024).

Low-skilled data annotators

Recent advances in generative AI depend heavily on manual human input. 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.

Tubaro et al (2020) identify three core functions of these workers: *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. Drawing on qualitative evidence, the authors argue that micro-work is not a temporary scaffold but a structural feature of AI production. Even end-users of digital tools unknowingly and without compensation contribute to training AI systems through microtasks, for example when solving reCAPTCHA puzzles to gain access to a website (Casilli, 2025) or when having to select the ‘best answer’ out of two ChatGPT generated texts.

The production of modern AI systems is thus underpinned by digital platform labour, performed by “micro-workers” whose contributions are often invisible and mediated through specialised outsourcing platforms. Much of this micro-labour is outsourced to countries in the Global South, such as Kenya, India, the Philippines, and Venezuela (Monaco et al, 2025). The poor working conditions and precarious jobs in these locations have been called out by both the popular press and AI ethics researchers stating that AI ‘factories’ are creating a new digital underclass.

Williams et al (2022), from the Distributed AI Research (DAIR) Institute, confirm this heavily reliance of the AI industry on hidden labour of underpaid, precarious workers around the world. Behind the narratives of superintelligent algorithms lies an industry fuelled by millions of gig workers – data labellers, content moderators, warehouse workers, and delivery drivers – performing repetitive, low-wage tasks under surveillance-heavy and often harmful conditions. From Amazon’s warehouses to content moderation firms in Kenya, the authors show how AI development perpetuates labour exploitation, especially of workers in the Global South and marginalised populations. Despite their central role in building AI, these workers are excluded from most ethical AI debates, which remain focused on fairness, bias, and transparency in the *models* (rather than on the treatment of the *workers* that build them).

An anecdotal illustration of the activities and working conditions of workers at the bottom of the AI production chain can be found in an in-depth article in New York Magazine (Dzieza, 2023). It follows Joe, a Kenyan data annotator who rose from low-paid labelling tasks for self-driving cars to training hundreds of others in annotation boot camps. Workers label everything from clothing and emotions in TikTok to chatbot responses and medical data, often under bizarre instructions and constantly shifting rules. Despite its centrality, annotation work is underpaid and unstable. As companies move operations to cheaper regions and automate parts of the pipeline, taskers are forced into digital nomadism – using VPNs and fake IDs to access better-paid gigs abroad. Meanwhile, U.S.-based annotators doing more skilled chatbot training fare better but remain isolated from the systems they’re helping to build.

One case study details this **increasing automation in the data annotation pipeline** and shows how even annotation jobs can be impacted by AI tools (Bell, 2023). Conducting interviews with data annotators in sub-Saharan Africa, Bell (2023) documents the meticulous, repetitive tasks requiring high levels of attention and manual effort. In this case, annotators were responsible for precisely outlining every contour of objects in images, and for video data, editing these outlines frame by frame. This labour-intensive work demanded a discerning eye and was described by some as a kind of craft. Despite the repetitive nature of the work, the challenge it provided was a valued feature, giving workers a degree of discretion and skill application.

The introduction of ML assistance software in these jobs significantly altered the nature of data annotation work. The new tools automated the most repetitive aspects of image and video annotation, shifting the worker's role from creating full annotations to guiding and correcting the software's outputs. Many workers welcomed the reduced physical and mental fatigue and praised the improved speed of task completion. However, the software's inaccuracy often led to inefficiencies and frustration, as correcting poor predictions felt more taxing than doing the task manually. The automation reduced the mental challenge of the work, leading to perceptions of deskilling among some workers, though others found satisfaction in testing and improving the tools. Workers reported good collaboration with their managers and developers but were rarely involved in shaping broader aspects of their work or suggesting new technologies, representing a missed opportunity to enhance job quality. Although demand for annotators remains high and some incentive structures reward accuracy and speed, the broader market context still offers little security, low pay, and limited influence for workers in low- and middle-income countries.

Summary points

- **AI adoption reshapes job content through a combination of task automation, augmentation, and creation.** Most workers report that AI helps them complete tasks more efficiently, while fewer experience task displacement or the emergence of entirely new responsibilities.

- **AI can improve or degrade intrinsic job quality, through its effects on autonomy, skill use, and collaboration, depending on how it is implemented.** Workers benefit most when AI supports, rather than replaces, human judgment. Impacts vary by skill level: high-skilled workers are more likely to report improved learning, responsibility, and teamwork, while low-skilled workers see fewer gains.

- **AI adoption often increases work intensity by shifting human effort toward cognitively and emotionally demanding tasks, though some applications do reduce workload or strain**. In contrast, AI's impact on working time quality and work-life balance remains underexplored, with only limited evidence suggesting potential opportunities for increased flexibility in working time and location.

- **AI improves physical safety by automating dangerous or repetitive tasks and enhancing OSH management with predictive tools and wearables**. However, increased work speed, reduced oversight, and rising psychosocial risks – such as cognitive overload or technostress – can undermine these benefits if not well managed.

- **Job security concerns persist despite limited evidence of job loss**. AI exposure can raise anxiety, especially among low-skilled and digitally vulnerable workers. Effects on wages and contracts remain limited, with stronger impacts observed in freelance markets. In most standard employment settings, AI-induced task changes do not directly affect pay.

- **Job quality in the AI production chain is highly polarised.** AI developers enjoy high pay but lack diversity. Data annotators face precarious, low-paid work with limited control. While automation of annotation tasks can reduce fatigue, it may also erode skill use and task meaning.

Implications for employment

The effects of AI on task-level productivity discussed in the previous chapter could potentially have implications for employment levels. Theoretically, the effect is ambiguous. Increased productivity, and even automation, at the task-level could both increase and decrease employment levels of the associated occupation, depending on consumers' **elasticity of demand** for the product or service that the occupation produces (Autor, 2015). For example, if AI makes developers much more productive, the price of software development might decrease so much, that demand for apps and website increases and even more developers are employed. On the other hand, full automation of entire jobs (i.e. the whole task bundle) will necessarily decrease employment in those occupations. For example, if live translation by AI advances above a certain threshold, it might make human translators obsolete.

The employment effect of task-level productivity gains is thus an empirical question. Measuring this effect is not straightforward, but several different approaches are explored in the literature. First, a large body of literature aims to measure the theoretical exposure of occupations to AI, gauging the *potential* employment impact, for example by occupation, sector or region. Second, those studies that aim to investigate *actual* employment effects, either study changes in hiring trends (usually using online job vacancy data) or track occupational employment levels (using survey or administrative data). Finally, a separate strand of literature investigates online labour markets for freelancers. Each of these approaches is discussed in turn.

Exposure of occupations to AI

Defining and calculating occupational exposure

Most authors **define exposure** as the potential for time savings when using an AI tool (Eloundou et al, 2023) or the overlap between AI abilities and the human abilities required in an occupation (Felten et al, 2021; Prytkova et al, 2024). By this definition, exposure includes both automation (speed or quality increases) and augmentation. Exposure of an occupation is usually assessed at the level of the tasks or abilities that make up the occupation. This means that authors assess each task or skill within an occupation and evaluate how much it could be impacted by a particular technology (see box below more methodological details).

Box 3: Comparison of methodologies for calculating occupational exposure to AI

A recent review of 12 different exposure scores (European Commission. Directorate General for Employment, Social Affairs and Inclusion et al, 2025) documents the following approaches to measuring how much occupations could be impacted by AI.

Estimates of occupational exposure to AI and related technologies typically follow a two-step methodology. First, researchers identify the content of occupations – what tasks, skills, or abilities they involve. Second, they assess the capabilities of current technologies and map these onto the occupational content to derive exposure scores.

1. Occupational content

Most studies describe occupations using data from the US O*NET database, which provides detailed task-level descriptions. Fewer studies rely on international sources such as ISCO or ESCO. Typically, scores do not account for variation within occupations across sectors or countries, assuming fixed job profiles. The dominant approach is task-based, though some studies use skills or abilities as their unit of analysis.

2. Technological capabilities

To assess what technology can do, researchers employ various methods:

- **Annotation-based**: Experts or crowd workers (Eloundou et al, 2024; Lassébie et al, 2022), or AI models (Gmyrek et al, 2023; Loaiza et al, 2024) or a combination of the two (Eloundou et al, 2024; Gmyrek et al, 2025) label tasks for their exposure to AI.
- **External indicators**: Patent databases (Autor et al, 2024; Prytkova et al, 2024; Webb, 2020) and AI performance benchmarks (Engberg et al, 2024; Felten et al, 2023a, 2021) are used to infer AI capabilities. The AI benchmarks usually measure performance in video games, vision and language (comprehension and generation).
- **Human capabilities**: one paper evaluates which human capabilities AI *cannot* yet do namely empathy, presence, opinion, creativity and hope (EPOCH) (Loaiza et al, 2024).

Mapping of technological capability to occupational content is done either manually or through text analysis techniques (e.g. semantic similarity).

3. Aggregating exposure scores

Most studies compute scores at the task level and aggregate them into occupation-level scores using weighted averages based on task importance. A few go further by accounting for task interdependencies or assessing the task bundle as a whole (see box 4).

4. Conceptual differences across studies

- Some studies estimate general exposure, others distinguish between automation and augmentation (see box 4).
- Technological scope varies: some include robotics and software, others focus on ML/DL AI or generative AI.
- Occupational granularity ranges from 3-digit ISCO to 8-digit SOC codes.

Four trends in the measurement of occupational exposure to AI are worth mentioning. Recent developments include (1) exposure measures for *newer types* of AI, (2) *dynamic* exposure measures that track exposure over time, (3) exposure measures that distinguish between *automation and augmentation*, (4) *Incorporating worker preferences into automation scores*

Types of AI

Early exposure studies either considered general automatability by computers (Frey et al, 2017) or considered the capabilities of earlier ML/DL AI (Brynjolfsson et al, 2018; Webb, 2020). As time progressed, newer studies began to include genAI capabilities as well (Felten et al, 2021) or even focused on genAI exclusively (Felten et al, 2023a; Gmyrek et al, 2023, 2025). In an effort to measure exposure of occupations to a wider range of (AI) technologies, Prytkova et al (2024) build an open source exposure database, called TechXposure. It measures exposure across 40 different technologies, including Machine Learning and Neural Networks, but also Augmented and Virtual Reality (AR/VR), Medical Imaging and Image Processing and many ‘smart’ technologies in logistics and manufacturing.

Dynamic indicators

The exposure literature has now advanced to the point where dynamic exposure indicators are constructed, meaning the indicators follow the progress in AI development year-by-year. This can be seen in the Dynamic AI Occupational Exposure (DAIOE) score that tracks a series of AI benchmarks by year (Engberg et al, 2024) building on the methodology of Felten et al (2023a, 2021). The DAIOE demonstrates an acceleration of AI progress after 2012, with staggered breakthroughs across various AI subdomains since, such as image recognition (early 2010s) and language modelling (around 2020).

Automation vs augmentation

A final recent advancement is the effort to distinguish automation from augmentation within the broader concept of ‘exposure’. Three sets of studies take noteworthy different approaches, which are summarised in the methodological box below.

Box 4: Distinguishing automation from augmentation – three methods

Method 1: statistical distribution of task-level exposure scores

Gmyrek et al (2023, 2025) distinguish automation from augmentation at the occupational level based on the mean and standard deviation of the exposure of tasks within that occupation. Occupations with high mean exposure and low standard deviation are considered at risk of automation, while occupations with low mean exposure but high standard deviation are expected to be augmented. Occupations thus either fall in the automatable or the augmentable category. Chen et al (2025) take a similar approach: they consider occupations to be automatable if they consist of many exposed tasks, and to be augmentable if they consist of both exposed and non-exposed tasks.

Method 2: considering task interdependence and complementarity

Loaiza and Rigobon (2024) first model task interdependence through a network of task clusters, reflecting how frequently pairs of task clusters appear together across occupations. The assumption is that tasks which frequently co-occur are more likely to be functionally interdependent, and thus less amenable to isolated automation. Next, they compute automation and augmentation scores using non-linear aggregation functions. For augmentation, they apply a *convex* function, reflecting gains from diversity: an occupation is more augmentable if even one pair of task clusters is highly complementary in their human-centric attributes (EPOCH, see box 3 above). For automation, they use a *concave* function, reflecting compounding risk: if multiple clusters within a job are independently automatable, the occupation is considered more exposed – even if no single cluster dominates.

Method 3: occupational input-output mapping

Yet, another conceptual approach is taken by Autor et al (Autor et al, 2024), although they focus on broader technologies than just AI. These authors conceptualise automation risk as the overlap between patents and job descriptions (or occupational task *inputs*) and augmentation risk as the overlap between those patents and occupational *outputs*. The intuition is that if an innovation (such as more efficient solar power conversion) targets an occupation's output (such as photovoltaic cells), it makes electricians' work more valuable and generates new demand for their expertise, rather than automating their work.

Incorporating worker preferences into automation scores

Shao et al (2025) present a novel framework for assessing not only the potential for AI-automation from a technical perspective, but also the desirability of automating these tasks from a worker perspective. They construct a database combining task-level preferences from 1,500 workers across 104 occupations with capability assessments by 52 AI experts. The study reveals that while workers are generally supportive of automating repetitive, stressful, or low-value tasks, they prefer maintaining agency in creative, interpersonal, and decision-making tasks. These worker preferences, however, are not always aligned with current AI capabilities or industry investments which often focus on automating tasks with low worker preference for automation.

Findings on occupational exposure

The comparison of the 12 different AI exposure scores at level of 4-digit ISCO occupations (European Commission. Directorate General for Employment, Social Affairs and Inclusion et al, 2025) are visualised in (at the 1-digit level) in **Figure 3** and discussed in the paragraphs below.

In the late 2010's several studies focussed on ML-based AI, with an early consensus emerging that practically all occupations would be exposed to this technology (Brynjolfsson et al, 2018; Webb, 2020). Brynjolfsson et al (2018), for example, found that the suitability to machine learning was fairly similar across occupations, ranging between 2.8 and 3.9 out of 5. Webb (2020) even found highest exposure to AI among agricultural workers, especially agriculture technicians.

However, from the early 2020's newer studies converged on the finding that exposure to **overall AI** including, by then, all three types – ML, DL and genAI – is highest in high-skilled occupations, namely managers, professionals, technicians and clerical support workers (Engberg et al, 2024; Felten et al, 2021; Tolan et al, 2021). This exposure of high-skilled occupations to AI reflects the overlap between these newer AI capabilities and the knowledge-intensive, information-processing tasks common in these high-skilled occupations.

This pattern is repeated for the **genAI-**specific studies, though clerical support workers, in particular, are even more highly exposed (Eloundou et al, 2024; Felten et al, 2023a; Gmyrek et al, 2023). These roles often involve tasks such as document drafting, data entry, and report writing – functions well-suited to GenAI tools like large language models.

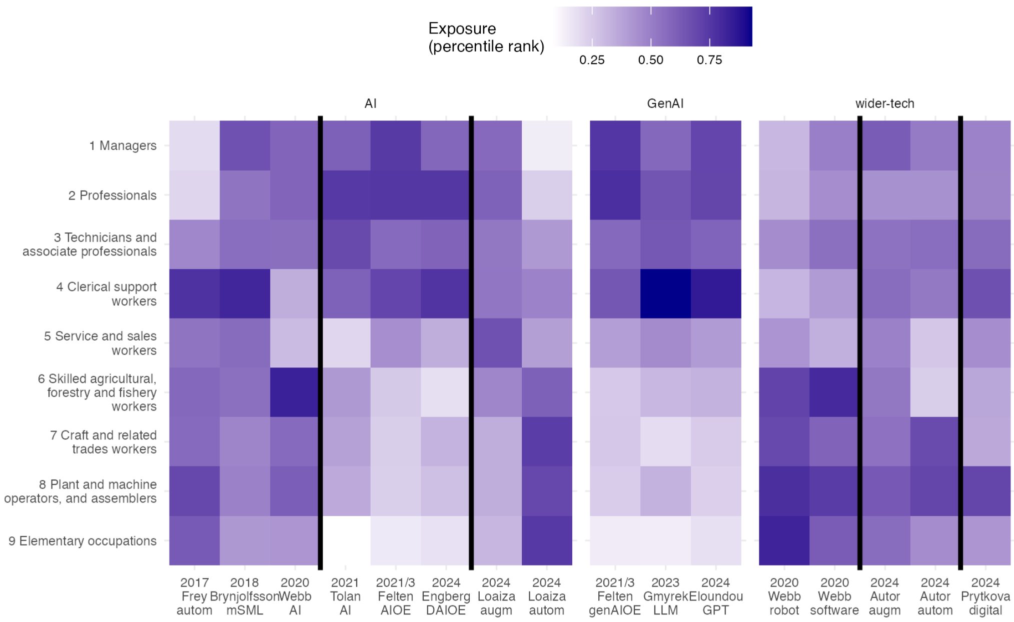
Two recent studies – not included in the review of the 12 exposure scores – again confirm this consensus. Gmyrek et al (2025) find that clerical occupations remain among the most exposed to GenAI. The study also identifies rising gen-AI exposure in certain highly digitised roles, for example, among web and media developers, data and statistics specialists, and finance or software-related occupations. Chen (2025) – combining the Gmyrek et al (2023; 2025) and Eloundou et al (2024) methodologies – finds highest exposure among correspondence clerks, interpreters and translators as well as legal and medical clerks.

A notable exception to the consensus on occupational AI exposure is Loaiza and Rigobon (2024). Using their contrasting methodology – evaluating human capabilities instead of AI capabilities – they find that uniquely human EPOCH tasks are most present in management, business and service occupations, and have been increasing in prevalence between 2016 and 2024. While their augmentation score does tend to rise across the ISCO ladder, their automation score in contrast sees its highest levels in the lower half of the ISCO taxonomy (ISCO 6-9).

Finally, Prytkova et al (2024) who again include a **wider variety** of automation technologies in their TechXposure database, identify highest exposure (averaged across the 40 types of technology) among both clerical support workers and machine operators – reflecting the dual trend of cognitive and manual routine task automation.

While the literature has thus more or less converged on the occupational exposure to recent AI developments, there is less agreement on whether automation and augmentation potential overlap. As mentioned above, Loaiza and Rigobon (2024) find a negative correlation between AI's automation and augmentation risk, suggesting that occupations at high risk of AI-driven automation are not the same as those with high augmentation potential. Autor et al (2024), however, find a positive correlation, suggesting that occupations might be both automatable and augmentable at the same time. These contrasting conclusions reflect deeper methodological differences (see box 4 above), highlighting the importance of how automation and augmentation are conceptualised, and requiring further research.

Figure 3 AI exposure by ISCO 1-digit occupation



Source: European Commission. Directorate General for Employment, Social Affairs and Inclusion et al (2025)

Note: Note: Exposure scores have been normalised as percentile ranks within each study's original distribution to ensure comparability. Darker shades indicate occupations with relatively higher exposure or risk; lighter shades indicate lower relative exposure.

Due to gendered occupational segregation – women holding different occupations than men – these occupational patterns have implications for demographic exposure as well. Applying the 12 scores to the EU-LFS reveals the following (European Commission. Directorate General for Employment, Social Affairs and Inclusion et al, 2025). Exposure to GenAI is higher among women (Felten et al, 2023b; Gmyrek et al, 2023), while men are more exposed to broader automation technologies like smart robotics and computer vision, due to occupational clustering in construction, manufacturing, and transport (Prytkova et al, 2024; Webb, 2020).

Beyond gendered exposure patterns, there is also a gender gap in the actual use of GenAI tools, which is only partially explained by differences in occupational exposure. Preliminary findings from the 7th EWCS (Eurofound, 2025) confirm that women are less likely to use GenAI tools than men, even when working in similar jobs. GenAI exposure tends to rise with educational attainment a pattern also observed in preliminary findings from the 7th EWCS (Eurofound, 2025), indicating a shift from traditional automation concerns focused on low-skilled manual jobs toward mid- and high-skilled cognitive roles.

Humlum and Vestergaard (2024) find that women are about 20 percentage points less likely than men to use ChatGPT within the same occupation, with the gap persisting even after accounting for workplace and task characteristics. Carvajal et al (Carvajal et al, 2025) report similar findings among students, showing that top-performing women are less likely to adopt GenAI tools than their male peers, despite performing equally well or better in prompting tasks. In both studies, the gender gap in use appears to be driven not by differences in skills or optimism about AI, but by differences in confidence, perceived legitimacy, and intrinsic motivation.

While Humlum and Vestergaard (2024) and Carvajal et al (2025) emphasise confidence, perceived legitimacy, and intrinsic motivation as drivers of lower adoption rates among women, another study by Acar et al (2025) point to an external factor: the social penalties attached to AI use. Their study demonstrates that female (and older) engineers are evaluated as significantly less competent when their work is labelled "AI-assisted," even when output quality is identical. Taken together, these studies highlight that adoption gaps are shaped less by ability than by workplace and cultural biases that differentially penalise underrepresented groups.

Finally, both AI and GenAI exposure is most prevalent in urban, high-income regions with a strong focus on services, while exposure to a broader set of technologies is more common in manufacturing-oriented regions, particularly in parts of central and eastern Europe (Nurski et al, 2025).

Changing hiring trends

AI's most visible impact on the labour market so far, is the clear **rise of AI-related job postings over time** (Squicciarini et al, 2021). Between 2012 and 2018, the total number of AI vacancies – identified as vacancies mentioning at least two AI skills[19] – steadily increased. For example, AI-related job postings increased in the UK from 5.7 million to 8.1 million and in the US from 14 million to 29 million. While their share is highest among (associate) professionals in the ICT, finance and professional services sectors, an increase was detected across almost all occupational groups. Moreover, AI-related roles increasingly demand both specialised, technical AI skills as well as more generic, complementary soft skills such as creativity, communication, problem-solving and teamwork, reflecting the complex integration of AI into job tasks.

This **demand for AI-complementary skills** – such as digital literacy, teamwork, and adaptability – has grown significantly, not only within those AI jobs, but also across non-AI roles in AI-intensive regions, occupations, and industries (Mäkelä et al, 2024). In contrast, skills that are **substitutable** by AI, like summarisation and customer service, are declining in value and prevalence. These authors also find similar results at the levels of **roles** (instead of skills): growth in AI roles – at the regional, sectoral and occupational level – is associated with more demand for roles that complement AI and a less demand for roles that are substitutable by AI. Notably, at the role level, these complementarity effects outweigh the substitution effects, suggesting a net positive shift in labour demand.

AI-related job postings are also **higher in 'AI exposed' occupations**, as measured by the Felten et al (2021) exposure metric. However, this evidence is only correlational and doesn't distinguish between automation and augmentation. To find causal effects, Chen et al (2025) leverage the introduction of ChatGPT in November 2023 as an exogenous shock. They find that both the number of job postings as well as the skill requirements in automatable occupations decline after the introduction of ChatGPT, while they increase for augmentable ones.

Moving to the firm-level, the aggregate growth of demand for AI-roles observed in the market is mainly **driven by establishments with high AI exposure**, i.e. whose workers engage in tasks compatible with AI's current capabilities (Acemoglu et al, 2022). AI-exposed establishments not only increase job postings for AI roles but also adjust skill requirements for non-AI roles – reducing demand for some previously required skills and introducing new ones. They also reduce overall non-AI hiring, suggesting a displacement effect outweighing potential productivity or complementarities at this stage of adoption.

While AI-exposed firms adjust their hiring patterns, Acemoglu et al (2022) detect no significant employment or wage effects from their firm-level AI exposure when aggregated at the broader occupation or industry level. The authors attribute this lack of aggregate employment effects to the small and localised impact of AI at the time of writing – as their data only goes up to 2018. Another explanation, however, is the existence of countervailing forces within firms: labour demand contraction because of substitution at the task-level, but also labour demand expansion because of growing consumer demand at the firm level (as discussed in the introduction to this chapter). Some evidence for these countervailing forces is discussed in the firm-level evidence of the next section.

[19] [19] AI-related skills in this study are identified using four broad categories of keywords: (1) general terms such as "artificial intelligence" and "machine learning"; (2) AI methods and techniques, including "deep learning", "neural networks", and "random forest"; (3) application areas like "computer vision", "natural language processing", and "robotics"; and (4) specific software tools and libraries, such as TensorFlow, Spark, and Keras.

Occupational employment trends

While skill mentions in job postings could be indicative of underlying task content (Daly et al, 2025), they vary in their coverage across occupations (Sostero et al, 2021), and they are not measures of changes in employment levels. So far, two distinct approaches have been used to estimate the effect of AI on employment: (1) by comparing employment changes between exposed and non-exposed *occupations* or *firms*, and (2) by investigating employment changes in *AI-adopting firms*.

Employment changes in exposed occupations

The first group of studies builds on some of the occupational exposure measures discussed in the section on Exposure of occupations to and examines changes in employment among exposed occupations, using official labour statistics.

Early evidence from Georgieff and Milanez (2021), based on the OECD's automation risk measure across 21 countries from 2012 to 2019[20], found **no indication of net job destruction**, as employment rose in all countries. However, occupations with higher automation risk saw significantly slower employment growth (6%) compared to low-risk occupations (18%). This slowdown was concentrated in manual and routine jobs, often held by low-educated workers, who became increasingly concentrated in roles at high risk of automation.

More recent exposure studies find that **employment trends in exposed occupations differ across skill levels**. Using register data from Denmark, Portugal and Sweden and progress in AI benchmarks (video games, vision and language) over the period 2010-2023, Engberg et al (2024) calculate AI exposure at the firm level, based on the firms' initial workforce composition. They find that AI-exposed firms increase their employment in white collar work, but decrease it in blue collar work, especially for the AI subdomains of vision and language. This leads to an overall higher level of high-skilled employment in those firms. The authors propose two possible explanations: AI may be complementing or supporting the work of highly educated workers because they hold the non-automated tasks (the ones that remain after automation), or it may be generating entirely new tasks at the higher end of the skill spectrum (the innovation effect).

Similarly, but at the *regional level*, Prytkova et al (2024) TechXposure database finds differential employment effects of exposure across skill groups and technologies. On average, across their 40 technologies, technology-exposed regions tend to polarize – increasing high- and low-skilled employment by 5%-6%, while decreasing middle-skilled (-2%). Exposure to machine learning specifically negatively impacts employment for low and middle skilled (-1.5% to -2%), while positively impacting high-skilled (+1.5%). These two studies thus suggest that AI-exposure means augmentation in high-skilled work, but automation in low-skilled work, potentially confirming the job vacancy evidence of Chen et al (2025) above. However, these two studies do not conceptually define augmentation and automation at the occupational level.

Among the studies that do conceptually distinguish between automation and augmentation, Autor et al (2024) find that their augmentation score predicts employment increases, while

[20] This OECD exposure measure was developed in Arntz et al (2016) and built on the methodology of Frey & Osborne (2017).

their automation score depresses it. Though they do not focus on AI exclusively, their study does suggest that technologies that are designed to complement the outputs of human work generate more employment, while technologies designed to automate human tasks destroy it.

Finally, even more nuance comes from Loaiza and Rigobon (2024) who find that both their automation and augmentation scores correlate negatively with employment growth. This suggest that even in augmented roles the productivity-driven substitution effect is greater than the consumer demand-driven expansion effect[21]. On the other hand, their EPOCH score – which captures tasks that AI cannot do yet – is positively correlated with employment growth: a 0.083 increase in the EPOCH score is linked to a one-unit rise in employment between 2016 and 2023. This study suggests that employment opportunities do not arise in AI-augmented roles, but in those roles that really leverage the unique human capabilities.[22]

Employment changes in AI-adopting firms

AI exposure metrics are far proxies for actual AI adoption – even though job vacancies show that AI exposed firms tend to post more vacancies with AI skills (Acemoglu et al, 2022). Several studies attempt to measure AI adoption at the firm-level more directly to analyse changes in firm-level employment.

Babina et al (2024) build a measure of firms' investment in AI-skilled human capital as a proxy for AI adoption. Such AI-investing firms experience higher growth in sales and employment through increased product innovation (more trademarks, product patents, and updates to their product portfolios). In a follow-up study[23] (Babina et al, 2023) document that as firms make these AI investments, they transition to **more educated and technically-specialised workforces** (as well as flatter organisational structures, which was discussed in the previous chapter). A rise in a firm's share of AI workers of 0.25 percentage points (i.e. a quarter of an AI worker) is associated with a 7.2% drop in workers without a college degree, alongside increases of 3.7% for those with a bachelor's, 2.9% with a master's, and 0.6% with a doctorate.

Hampole et al (2025) further document two **offsetting mechanisms on firm-level employment within AI-adopting firms**. They hypothesize that, on the one hand, AI substitutes for tasks in highly exposed occupations, depressing labour demand. On the other hand, AI-induced productivity increases at the firm-level and the ability of workers to reallocate effort across less-automated tasks within jobs, offset these substitution effects. In fact, when the exposure to AI is uneven across tasks within jobs (i.e. high dispersion of task-level exposure), which in the literature is often a measure for augmentation, they find that occupations experience increased employment within firms. As those workers shift to non-automated complementary tasks, firms become more productive and increase their overall employment. Thus, the net employment effects of AI are limited due to these offsetting dynamics: labour demand declines relatively in highly exposed occupations, but firms increase their overall employment as they become more productive. The substitution effect

[21] See introductory paragraph at the beginning of this chapter.

[22] Some occupations with high EPOCH scores include Emergency Management Directors, Human Resource Managers, Sociologists, Clinical and Counselling Psychologists, Environmental Economists and Human Factors Engineers and Ergonomists.

[23] This is a follow-up study, even though it is dated earlier. That is because the 2024 paper is already published, while the 2023 paper is still a working paper version.

leads to a contraction in employment of about 7%-9% over 5 years, while the expansion effect is about the same size, leading to a net average effect of close to zero.

All studies in this section so far have dealt with broad and indirect measures of AI adoption (including broad exposure measures or adoption induced from AI skills demand). One study captured a direct indicator of adoption through a survey of workers, but focussing on a limited and specific – though highly prominent – case of AI, namely AI chatbots (Humlum et al, 2025). The survey covers the use of both online off-the-shelf chatbots such as ChatGPT as well as in-house developed chatbots across a list of 11 occupations that are exposed to such chatbots, namely: accountants, customer support specialists, financial advisors, HR professionals, IT support specialists, journalists, legal professionals, marketing professionals, office clerks, software developers, and teachers. Using matched employer-employee data in Denmark, they find that while chatbot adoption is widespread and supported by firm-led initiatives, it has had **no measurable effect on employment, earnings or working hours**. Even among workers who report productivity benefits through time savings, the estimated pass-through to earnings is negligible. These results highlight that, despite rapid uptake of chatbots and visible changes in task content, labour market effects remain small to non-existent.

In sum, evidence on employment effects of AI remains mixed and context dependent. Occupation- and firm-level studies suggest that employment in high-skilled *AI-exposed* (both ML, DL and genAI) occupations is expanding, while low-skilled exposed occupations are contracting, especially for machine learning, but this differs across technology types. Firm-level evidence on AI adoption that includes both ML, DL and genAI points to internal reorganisation and productivity-driven growth, yet direct studies of prominent genAI tools like chatbots reveal negligible impacts on employment and earnings. In any case, there is no strong evidence on widespread job losses caused by AI adoption at the moment.

Evidence from freelance markets

If any job destruction due to AI would be going on, it would likely be detected first in online freelancing platforms. These markets are characterised by short-term, remote, and task-specific work, making them particularly responsive to technological change. In addition, their digital infrastructure allows researchers to observe rapid, granular shifts in labour demand, supply, and transactions (Demirci et al, 2025; Hui et al, 2024). These platforms provide a natural setting to study the labour market impacts of AI, given their flexibility and the close alignment between freelance tasks and the capabilities of generative AI.

Freelance occupations affected by genAI

Several recent studies have used online labour market (OLM) platforms to explore how text- and image-based genAI affect freelance markets (Demirci et al, 2025; Hui et al, 2024; J. Liu et al, 2024; Qiao et al, 2024; Teutloff et al, 2025). Exploiting the sudden and unanticipated introduction of ChatGPT in November 2022 (a text-based genAI chatbot), these authors compare a group of affected occupations (the ‘treatment group’) with a group of unaffected occupations (the ‘control group’) before and after this introduction.

The selection of the ‘treatment group’, expected to be affected by the introduction of ChatGPT, is fairly similar across the studies. Most studies consider **writing** jobs to be affected by the introduction of ChatGPT, including content writing, editing and proofreading, translation and localisation (Demirci et al, 2025; Hui et al, 2024; Qiao et al, 2024), or a wide range of writing-related activities that additionally include fiction writing, marketing, business analysis and customer service (J. Liu et al, 2024; Teutloff et al, 2025).

As text-based LLM's can also generate code, some studies additionally focus on **programming**-related categories, either a narrow focus on software, app and web development (Demirci et al, 2025; Qiao et al, 2024) or a broader focus that additionally includes database programming, design and management, data entry and processing, and statistical programming (J. Liu et al, 2024; Teutloff et al, 2025). Qiao et al (2024) and Teutloff et al (2025) explicitly label the programming-cluster as complementary to ChatGPT (or susceptible to productivity gains), while they consider the writing-cluster to be substitutable by ChatGPT (or susceptible to displacement).

Some papers additionally study the introduction of DALL·E and Midjourney in April 2022. In this case, **image**-related occupations are expected to be affected, including graphic design, image editing and art/photography services (Demirci et al, 2025; Hui et al, 2024; J. Liu et al, 2024).

Effects on labour demand, supply and matches on freelance platforms

Studies either focus on *freelance demand*, measured by the number of posted assignments by firms on the platforms; on *freelance supply*, measured by the number of bids by freelancers; or on the *matches*, measured by transaction volume or value.

Freelance demand is a primary focus for several studies, as AI is expected to either automate some tasks that tend to be outsourced to freelancers or to make internal employees more productive at those tasks, also reducing the need for freelance labour. A general consensus emerges for the *writing*-related OLM's as several studies find negative effects on the total number of job postings in the double digits, ranging from 24% (J. Liu et al, 2024; Teutloff et al, 2025) to 30% (Demirci et al, 2025). For very specific skill clusters such as "Writing 'about us' pages", the decline was as large as 59%.

No consensus is found for image- and programming related OLMs. For the *image*-related OLM's findings vary between a reduction of 17% (Demirci et al, 2025) and no effect (J. Liu et al, 2024). For *programming*-related OLM's some studies find similar declines in job postings as for writing (J. Liu et al, 2024), smaller but still significant decreases (Demirci et al, 2025) or even no decline at all (Teutloff et al, 2025). These differential effects could be due to the different nature of impact or to the different state of AI capabilities in image and programming at the time of data collection (typically 2022-2023 in these studies).

On the **freelance supply** side, AI is expected to make freelancers more productive or even enable more freelancers to enter the market, thus theoretically potentially increasing the labour supply. However, the only paper studying effects on the labour supply, finds a reduction of 14% in the number of bids made by freelancers and a 9% decrease in the number of active freelancers on the specific platform investigated (J. Liu et al, 2024). The authors argue that this is likely a supply-side response to the above-mentioned contraction in demand, leading to increased competition and reduced revenue.

In terms of **matches**, successful matches and transaction volumes (i.e. revenue for the freelancers) go down in writing- and image-related OLM's (Hui et al, 2024; J. Liu et al, 2024; Qiao et al, 2024). Again there is less consensus on programming-jobs, as some studies find increasing transaction volumes (Qiao et al, 2024), while others find similar decreases for programming as for writing (J. Liu et al, 2024). In most papers, competition (as measured by the number of bids per job) went up (Demirci et al, 2025; J. Liu et al, 2024)

Job complexity and freelancer experience

Several studies suggest that the contraction in demand mostly involves **lower-complexity** freelance assignments. For example, Teutloff et al (2025) find the highest demand reduction in short-term projects (lasting three weeks or less) and project requesting less experience. Similarly, Demirci et al (2025) find that remaining jobs – after the introduction of ChatGPT – are more complex (2% more skills requested) and offer larger budgets (+6%). This is also confirmed by Liu et al (2024), who find that average budgets go up by 15%.

Surprisingly, while offered projects become more complex after the introduction of ChatGPT, this does not seem to mean that more **experienced** freelancers fare better in terms of number of jobs or earnings. For example, Hui et al (2024) find no mitigating effect of experience on the adverse effects of genAI on freelancer employment. Neither do Qiao et al (2024) for programming jobs – and they even find a larger decrease in the number of jobs and earnings for experienced translation and localisation freelancers.

Summary points

- **High-skilled occupations are more exposed to AI, but exposure can mean either automation or augmentation.** Recent studies converge on high exposure in managerial, professional, technical, and especially clerical roles due to their cognitive and language-intensive tasks. Yet exposure does not equate to job loss: some occupations are at risk of automation, others more likely to be augmented.
- **AI reshapes hiring trends by increasing demand for AI-related roles and complementary soft skills.** AI-intensive firms post more vacancies with new skill requirements while reducing hiring in non-AI roles. Skills such as problem-solving and adaptability gain value, while tasks like summarisation or standard customer service lose relevance. Early causal evidence suggests ChatGPT's arrival depressed job postings in automatable occupations but increased them in augmentable ones.
- **Employment trends in AI-exposed occupations and firms reflect a mix of substitution and expansion effects.** High-skilled employment grows in AI-exposed firms and regions, while low- and middle-skilled roles decline. Some studies find augmentation-linked employment increases, others show even augmented roles face displacement. At the firm level, productivity gains and task reallocation offset substitution effects, often leading to net-neutral employment impacts.
- **Freelance platforms offer early evidence of displacement in writing jobs and mixed effects elsewhere.** Writing-related gigs saw steep drops in postings, matches, and revenue after genAI's introduction, especially for short-term, low-budget tasks. Programming and design jobs showed more resilience or even gains, depending on task complexity. Remaining jobs tend to require more skills and higher budgets, but even experienced freelancers are not shielded from disruption.

Implications for social dialogue and industrial relations

Social dialogue can play an important role in managing and even shaping technology adoption and implementation in workplaces but its effectiveness is challenged by declining union representation and the rise of new business models that bypass traditional labour relations (Krämer et al, 2022). The increasing use of AI slowly shifts union concerns beyond job loss and working conditions. Some governments, unions and employer organisations have started introducing initiatives to address the impact of AI at work.

The role of worker voice in technology adoption

There are several rationales for involving workers in the adoption of workplace technologies, ranging from improving implementation outcomes to ensuring fairness and accountability (Vereycken et al, 2021)[24]. While the **techno-optimist** view sees worker participation as a natural by-product of technological change – assuming technology will naturally enhance human work and align with managerial goals – both the socio-technical and critical perspectives see active employee participation as a prerequisite for successful and sustainable implementation of new technologies.

From a **socio-technical perspective**, employee participation is seen as a necessary precondition to jointly optimise both the technical and social systems within organisations to fully realise the benefits of new technologies (Vereycken et al, 2021). Technology adoption often necessitates changes in work processes and organisation, an argument that was developed in the chapter on Implications for tasks and work organisation . These changes are rarely plug-and-play: integrating AI effectively requires rethinking task allocation, workflows, and human-AI interaction. Identifying risks and opportunities during this transition requires tacit knowledge about how work is done – knowledge that is often held by workers. Participation also enhances acceptance of technology among users, thus reducing resistance to change. Even before implementation, early involvement through participatory design methods is encouraged.

Several of the above arguments can be found in empirical research as well. Unionization and collective bargaining coverage have been shown to increase productivity gains from organisational change (Black et al, 2001) and mitigate negative impacts on job quality from robotisation (Berg et al, 2022). Direct employee voice (proxied by the percentage of workers who regularly meet to discuss workplace issues) has a larger positive effect on productivity when it is done in the context of unionised establishments (Black et al, 2004).

The **critical perspective** shares the above call for participation but frames it as a necessary counterforce to growing technology-enabled managerial control (Vereycken et al, 2021). It emphasises that without collective representation workers risk being excluded from the benefits of technological change, while participation can ensure a fairer distribution of innovation gains. Although management may involve employees for functional reasons (e.g., to access tacit knowledge and resolve technical issues), the critical view warns that such

[24] This review of 58 studies on worker participation in Industry 4.0 was discussed in the opening chapter when introducing the framing perspectives on AI and work as well (Vereycken et al, 2021).

involvement often serves employer interests and highlights the need for independent, employee-led participation structures. Even limited forms of participation (e.g. problem solving on operational issues) are considered better than none, but they fall short of securing meaningful influence over the trajectory of technological change.

While Vereycken et al (2021) discussed the three perspectives in the context of Industry 4.0, they can also be found in recent fieldwork by Kochan et al (2024) who conducted over 50 interviews on generative AI with developers, business leaders, and labour leaders across a wide range of industries. They find that *business leaders* view generative AI through the lens of productivity, decision support, and creativity. *Developers*, on the other hand, are split in their views between a productivity-maximising, labour-displacing approach, sometimes referenced as the 'Turing Trap' (Brynjolfsson, 2022) and a more participatory, human-centred approach that seeks to augment rather than replace labour. *Labour leaders*, meanwhile, seek meaningful influence over its deployment, calling for greater transparency, early-stage consultation, training, and protections.

Firm-level worker voice

Firm-level worker voice in AI adoption is important, as AI induces fear of job losses and undermines workers' sense of of job security. As such, AI adoption can undermine the psychological contract, the unspoken expectations and mutual obligations between workers and employers, by weakening worker engagement and employee trust (Braganza et al, 2021).

At the same time, AI awareness among employees – beyond concerns of job losses – can also extend to understanding how AI-enabled tools can be used to convey their voice to management (Lin et al, 2024). A three-wave survey across 319 Chinese hospitality workers found a positive association between AI awareness and employee voice behaviour (defined as the inclination to speak positively about change by proactively articulating challenges and offering constructive recommendations). Both workers' orientation to learning, as well as how they perceived organisational support, strengthened the link between AI awareness and employee voice behaviour.

The qualitative study by Kochan et al (2024) highlights the absence of worker voice as a critical gap in current AI governance. Yet, employers recognise key decision points where direct worker input is essential: in identifying use cases, shaping internal governance, and redesigning work processes affected by genAI. Based on these findings, the authors propose to incorporate direct worker voice throughout the technology adoption cycle: (1) defining problems and opportunities, (2) designing work processes and technical features, (3) educating and training the workforce, and (4) ensuring fair transitions for those affected.

Firm-level worker voice played a key role in the implementation of AI technologies documented in firm-level case studies in manufacturing and finance conducted by the OECD[25] (Milanez, 2023). *Direct consultation* was common in all countries studied, often initiated by firms to gain worker buy-in and build trust. Workers were frequently involved in the development and implementation stages, providing input on use cases, as well as testing and feedback to improve user interfaces and functionality. These participatory processes not only contributed to the effectiveness of the AI technologies but also served to alleviate

[25] For more information on the OECD case studies and surveys, see 2.3 Implications for job quality.

worker concerns and support smoother transitions. *Representative consultation* – through works councils or unions – was less prevalent in the firms investigated, but more evident in Austria and Germany, where institutions, such as collective bargaining frameworks and worker representation structures, are robust and well-established. In several cases, works councils were involved from the beginning of AI projects, guiding training programmes and flagging privacy concerns. While GDPR and co-determination rights offered safeguards, concerns remained about weak oversight, information asymmetries, and pressure to approve systems. Unions often lacked the technical expertise to assess AI impacts fully, underscoring the need to strengthen social partner capacity and access to external expertise.

The accompanying OECD surveys confirm that consulting workers – directly or via representation – improves AI innovation efforts (Lane et al, 2023). Almost half of AI-adopting employers consulted workers or their representatives, often resulting in concrete outcomes such as AI guidelines and strategies, or collective agreements, and were generally linked to better performance and working conditions. Consultations mainly focussed on skills and training, with sector-specific topics like data use in finance and working conditions in manufacturing also commonly addressed. Job loss and wage impacts were least discussed.

Collective bargaining

While direct worker voice at the firm level is critical for shaping AI implementation, collective bargaining (CB) remains an essential mechanism for codifying rights, setting safeguards, and ensuring accountability – especially where regulatory frameworks are limited or vague. According to UNI Europa, the European trade union federation for the services sector, the EU's strategy (e.g. the AI Continent Action Plan)[26] fails to sufficiently include social dialogue, collective bargaining, and worker participation in shaping how AI is introduced and governed in the workplace (Roethig, 2025). The union argues that worker protections and collective bargaining are essential and more agile tools than legislation alone, since laws such as the EU's AI Act are slow to adapt, whereas collective agreements can respond more quickly to risks like job displacement and the erosion of workplace autonomy.

The OECD Employment Outlook 2023 on AI and the labour market emphasizes the relevance of CB in shaping AI adoption. Social partners can improve outcomes by negotiating training needs, data protections, and ethical safeguards. However, declining union coverage, weak representation in platform work, and significant gaps in AI-related expertise risk widening power imbalances and limiting social partners' influence over AI governance (OECD, 2023).

A global survey of union CB on digitalisation in 2020-2021 compiled over 140 exemplary clauses from collective bargaining agreements (CBA's) concerning digitalisation in public and private services from 11 countries (Voss et al, 2022). The authors note that while some unions have begun to address digitalisation, CBA's still rarely address AI-specific issues. Most agreements continue to prioritise traditional concerns such as job security and working conditions, often focussing on re- and upskilling, with limited attention to the specific

[26] Published by the European Commission in April 2025, the AI Continent Action Plan sets out the EU's ambition to become a global leader in artificial intelligence, supported by around €200 billion in public-private investment. The plan includes €20 billion for five AI "gigafactories" and the creation of a single market for data across the Union.

implications of algorithmic systems. The authors advocate for the inclusion of clauses on algorithmic management, data privacy, and the ethical use of AI.

Two years later, in 2023, a similar survey of CBA's was conducted among affiliates of UNI Europa across 43 countries in the EU and beyond, primarily targeting the service sector as well (Brunnerová et al, 2024). This survey confirmed that CB on AI is an emerging phenomenon and not yet as widespread as bargaining on other working conditions. Only 20% of the 90 surveyed trade unions reported having an AI-related CBA at the firm or sector level, while 69% did not, and 11% were unaware. A detailed analysis of 31 CBAs that did contain AI-related provisions (15 Spanish, 8 German and 3 Italian ones) showed that unions are increasingly engaging with these issues over time, particularly in areas concerning data privacy, training, and the right to disconnect.

Velazquez (2024) advocates to go further than that, arguing that current regulatory approaches in the EU and US leave a "union-shaped hole" in AI governance frameworks. The author proposes a "three-legged regulatory stool" that: 1) creates an agency that reviews AI systems from a zero-trust framework, 2) empowers unions to monitor and bargain over AI governance, and 3) incentives workers and unions to report unsafe AI practices through whistleblower bounties. This would entail expanding the scope of CB to AI deployment, governance and monitoring, and empowering unions to participate in audits, red-teaming, and industry standard setting. Such a model could also reduce the enforcement burden on regulators by distributing oversight responsibilities. While politically ambitious, this approach frames CB not just as a workplace mechanism but as a pillar of democratic AI governance.

National developments

The previous section examined collective bargaining as a general mechanism for shaping AI adoption, but countries vary in how they incorporate AI in collective worker voice, reflecting differences in industrial relations systems, legal frameworks, and union capacities. Several reviews examine the extent to which AI is addressed in collective bargaining across the EU, highlighting the diverse approaches adopted by different Member States (Ponce Del Castillo, 2024; Eurofound, 2025b).

National developments are being shaped by **EU-level initiatives** that provide direction and impetus for national social dialogue on AI. One key driver is the European Social Partners' Framework Agreement on Digitalisation, which encourages national-level dialogue and bargaining on emerging technologies, including AI. In addition, joint declarations by social partners in sectors such as banking and insurance have contributed to setting shared expectations for responsible AI adoption. A third important channel is the role of European Works Councils in multinational companies, which are initiating workplace-level agreements on AI. For instance, the IBM Germany Group Works Council negotiated a formal agreement on AI use (Krzywdzinski et al, 2023; Seibold et al, 2022), while the 'Manifesto for the Use of AI' signed at Deutsche Telekom affirms that AI must not compromise employee safety, health, or fundamental rights (Deutsche Telekom, 2023).

In **Belgium**, collective bargaining negotiations on AI have commenced in the banking and insurance sectors, with a focus on employee training funded through sectoral training schemes (Eurofound, 2025b). These draw on existing agreements, such as Collective Agreement No. 39, and joint declarations from European Social Partners in the insurance

(2021) and banking (2024) sectors. The emphasis is on ensuring that employees are informed and consulted on the introduction of AI, and that their skills and knowledge are developed to adapt to the changing work environment.

An analysis conducted by the French Centre for Employment and Work Studies (CEET) examined collective bargaining on AI in **France** across various sectors, including information and communication, finance and insurance, and manufacturing industries (Greenan et al, 2024). The study found that AI was mentioned in 331 paragraphs of 242 company agreements between 2018 and 2023, with the proportion of agreements mentioning AI doubling during this period. The IT sector accounted for a significant portion of these agreements, with around 25% focusing on employee training and competition. In contrast, the banking and insurance sector is increasingly discussing AI, with a focus on worker substitution and automation due to perceived job threats. However, the manufacturing industry is taking a different approach, using AI in innovative ways that shift the focus from replacing workers to supporting their needs.

Furthermore, experiments in France explore how social dialogue can serve as a collaborative, bottom-up mechanism for governing AI adoption in the workplace, and a complement to top-down European initiatives (such as hard regulation, standards, and soft law) (Chagny et al, 2024). Current EU initiatives risk leaving gaps in workplace settings, as developers are only required to self-assess compliance and deployers (e.g. employers) face few obligations. In contrast, bottom-up company-level negotiation is better positioned to address the complex, context-specific risks of AI systems while promoting acceptance and ethical deployment. This requires more operational forms of social dialogue, supported by tools such as AI registers, review clauses, and corporate ethics committees that include worker representation. In France, such mechanisms are being tested through initiatives like the SeCoIA Deal project and have been endorsed in national policy roadmaps.

AI adoption in **Italy** remains limited, particularly among small firms, and modest in scope (e.g. chatbots and virtual assistants), which has led to a limited number of collective agreements addressing AI (Guaglianone, 2024). Italy's industrial relations more conflictual and primarily information-based, with weak participatory rights, but digital transformation has prompted some expansion of bargaining agendas. The Italian cross industry agreement of 15 April 2024 updated the national trade collective agreement (CCNL) to address issues related to artificial intelligence (AI). This agreement expands the scope of the CCNL to include companies dealing with AI and introduces new roles to manage and coordinate AI implementation. It also emphasizes the importance of information, education, and training to ensure a responsible and constructive introduction of AI systems (Eurofound, 2025b).

Recent collective bargaining agreements between Italian telecommunications companies (Wind, TIM, and ENEL) and trade unions have included specific provisions to govern the use of an AI system that pairs customers with call centre agents. These agreements prohibit covert monitoring of agents, for example, by requiring anonymized agent codes and limiting monitoring to purposes related to organizational needs, safety, and asset protection, explicitly excluding performance surveillance. They also grant unions the right to propose improvements, which companies are obligated to assess, and allow unions to halt or suspend the deployment of the system if concerns are not adequately addressed Guaglianone, 2024). These developments indicate that unions in Italy are becoming increasingly involved in regulating the effects of AI on working conditions. Nevertheless, they still face challenges in their ability to shape the development and deployment of AI in a way that protects workers' interests.

Germany's strong co-determination framework and active trade unions – particularly IG Metall – enable a proactive approach to shaping AI in the workplace. Earlier initiatives such as Arbeit 2020 in North Rhine- Westphalia showed how structured worker involvement in digitisation can increase transparency, foster trust, and lead to agreements that benefit both employees and employers (Bosch et al, 2020; Haipeter, 2020). Although AI adoption remains limited to applications like predictive maintenance, HR analytics, and cognitive assistance systems, unions have positioned themselves to influence its trajectory early on, emphasizing human-centred AI, transparency, and worker autonomy (Krzywdzinski et al, 2023). At the national level, unions contribute to political debates, standardisation efforts, and AI ethics initiatives. At the workplace level, they develop tools to support works councils in engaging with digitalisation strategically. Agreements at firms like IBM, Airbus, and Merck demonstrate how co-determination can guide AI implementation - via oversight bodies, ethical guidelines, and participatory processes. Recent legal reforms, such as the Works Council Modernisation Act, have bolstered co-determination rights by enhancing employee representation in digital and algorithmic decision-making processes, granting works councils greater access to information, consultation, and access to technical expertise when evaluating AI systems used in the workplace. However, in a narrower context, the Hamburg Labour Court ruled (on January 16, 2024) that co-determination rights under Section 87(1) nos. 1, 6, or 7 of the German Works Constitution Act do not apply when employees use generative AI tools like ChatGPT through their own private accounts and browsers, even if the employer issues an internal usage policy (Schulke et al, 2024). Nonetheless, the court affirmed that information and consultation rights under §90 remain intact, requiring employers to engage with works councils before implementing AI systems, even if the councils cannot unilaterally block such policies.

A central development in **Spain** is the "Riders Law", originally targeting digital platform couriers by presuming an employment relationship, and was accompanied by a broader provision requiring all companies to inform worker representatives about the logic, parameters, and variables underlying AI systems that affect working conditions, hiring, or termination (Rodríguez Fernández, 2024). The complementary, but non-binding principles in the 2021 Charter of Digital Rights – such as transparency, auditability, human oversight, and non-discrimination – strengthen the normative foundation for AI regulation in the labour context. Building on these state-driven initiatives, collective bargaining has played a significant role in shaping the regulation of AI in the workplace, with the Spanish cross-industry collective agreement emphasizing human oversight, transparency, and fairness. As of 2023, 110 collective agreements in Spain regulated the implementation of new technologies, covering 505,747 employees, although the number of specific clauses regulating AI may be lower. Sectoral collective bargaining has in some cases provided even more protection than the law requires, for example in the 2021 Banking Sector Agreement which requires impact assessments of AI-driven decision-making to prevent possible bias. Similarly, a company-level agreement between Just Eat and CCOO/UGT created an "algorithm committee" composed of union and company representatives, with rights to information and oversight. Company-level agreements, such as those with El Norte de Castilla, Air Nostrum, Acciona Mobility, and AXA, have introduced AI-related clauses that prioritise worker protection, transparency, and job security, including safeguards against biased algorithm use, transparent AI-driven decision-making, and provisions for training and job security to support workers in adapting to AI technologies.

Sweden's industrial relations system is built on strong unions, high collective bargaining coverage, and limited state intervention, allowing unions and employers to shape the AI-transition through local-level agreements (Bender, 2024). Within this context, Sweden has a long-standing tradition of treating technology as a sociotechnical issue – its impact on work depends on *how* it is used, not just *what* it does. In the mining company Boliden, unions influenced the deployment of location tracking and semi-automated vehicles by negotiating how systems affect job roles, data privacy, and working time – rather than focusing on technical specifications. Unions secured rules to anonymise worker location data, prohibit its use for performance monitoring and guided the implementation of semi-automated night work. This sociotechnical bargaining strategy enables unions to assert influence even when they do not directly regulate or understand the technical workings of AI systems.

These national developments on collective bargaining suggest that existing industrial relations systems shape social partners' responses to AI in the workplace, which is confirmed in a separate comparative analysis of Denmark, Germany, Hungary and Spain (Molina et al, 2023). Across these countries, existing institutions largely determine the mix of protective mechanisms (e.g. statutory regulation, collective agreements setting minimum standards) and participatory mechanisms (e.g. consultation, co-determination) used to address the challenges of AI and algorithmic management. **Denmark** and **Germany**, where workplace-level participation rights are strongly institutionalised, rely primarily on participatory approaches. In Denmark, health and safety committees and collaboration bodies are central, while Germany relies on its tried and tested Works Councils. **Spain** relies more on protective mechanisms to regulate AI, such as statutory law and sectoral bargaining. In **Hungary**, by contrast, both protective and participatory mechanisms are weak. Regulation is limited to general GDPR provisions, and trade unions have little capacity to influence AI governance through collective bargaining. The country differences are summarised in **Table 3**, including the industrial relations context as well as the approach to AI and social dialogue.

Table 3: Country differences in AI and social dialogue

Country	Industrial relations context	Approach to AI and social dialogue	Sources
Belgium	High UD and CB coverage; Strong social partner organisations; Longstanding tradition of bipartite and tripartite consultation; Multi-level bargaining with strong sectoral agreements.	Sectoral-level AI negotiations emerging in banking and insurance. Focus on training and consultation rights, building on existing frameworks like CAO 39 and EU-level joint declarations.	Eurofound (2025b)
Denmark	High UD and CB coverage; Autonomous social partners with limited state intervention; Strong tradition of sectoral and company-level agreements.	Primarily participatory via established collaboration bodies. Health and safety committees and cooperation bodies play a central role.	Molina et al (2023)
France	Low UD but high CB coverage; State plays a central role; Fragmented union landscape; Decentralisation of bargaining and workplace representation.	Bottom-up workplace-level negotiation complements EU-level regulation. AI registers, review clauses, ethics committees (e.g. SeCoIA Deal). National policy endorsement.	Chagny and Blanc (2024)
Germany	Moderate UD but high coverage in large firms; Dual system with sectoral CB and strong works councils; Extensive co-determination rights at workplace level.	Strategic co-governance through works councils and national level. Works Council rights to technical expertise. AI agreements at IBM, Airbus, Merck. national standardisation and ethics debates.	Krzywdzinski et al (2023) and Molina et al (2023)
Hungary	Very low UD and limited CB coverage; Company-level bargaining dominates; Weak co-determination rights and fragmented social dialogue institutions.	Limited protection and participation. Reliance on general data protection rules, no targeted AI rules. Minimal influence of unions or collective bargaining.	Molina et al (2023)
Italy	High UD and near-universal CB coverage; Two-tier bargaining structure with strong national agreements; Workplace representation and sector-specific bodies.	Limited engagement but some emerging digital bargaining. 2024 cross-industry agreement extends CCNL to AI. Agreements on AI use in telecoms; limited union rights to suspend or amend implementation.	Guaglianone (2024)
Sweden	High UD and very high CB coverage; Strong sectoral and firm-level bargaining without works councils;	Sociotechnical bargaining focused on usage and work impact. Local agreements on data privacy, working time, and role changes (e.g. Boliden).	Bender (2024)
Spain	Low UD but high CB coverage; Sectoral bargaining dominates; Workplace representation via elected works councils linked to unions.	Legal mandates combined with some advanced sectoral and firm-level agreements. Riders Law; Banking Sector Agreement; Just Eat algorithm committee with union representation.	Rodríguez Fernández (2024) and Molina et al (2023)

Source: Sources mentioned in the last column. Additionally, country profiles on industrial relations context were consulted on the ETUI website.
Note: UD = Union Density; CB = Collective Bargaining

AI changing social dialogue itself

The introduction of AI into the workplace is not only reshaping job tasks and employment relationships – it also alters the conditions under which social dialogue operates as AI introduces new layers of complexity that challenge its effectiveness. Notably, the opacity, adaptability, and decentralised deployment of AI systems raise questions about the ability of existing labour institutions to represent workers' interests effectively. In response, trade unions, works councils, and supportive institutions have begun to explore new tools, legal frameworks, and organising strategies to reclaim a voice in AI governance.

Obstacles to social dialogue on AI

A first major challenge lies in the **limited organisational capacity and resources** of trade unions and works councils. Declining union presence in many workplaces, especially those adopting new business models or operating within the platform economy, weakens participatory mechanisms (Molina et al, 2023). Even where representation is present, under-resourced councils often struggle to engage with AI issues (Krzywdzinski et al, 2023). Competing priorities, such as wage negotiations during periods of inflation, further limit their bandwidth to engage meaningfully with AI-related issues – even where collective agreements had been initiated (Rodríguez Fernández, 2024).

A second critical barrier is the **lack of AI-related expertise** among social partners (Krämer et al, 2022). As algorithmic systems grow in complexity, interpreting the design, functioning and potential risks of these tools becomes more difficult. Even in countries with strong institutional capacity, like Germany and Denmark, unions lack the technical know-how to evaluate the use of AI systems, especially those developed and supplied by third-party vendors (Molina et al, 2023). The rapid evolution of AI systems exacerbates this expertise gap. In response to these challenges, the Works Council Modernisation Act, introduced in Germany on 18 June 2021, not only extends the co-determination rights of works councils regarding the deployment of AI systems in the workplace, but also explicitly grants representatives the right to consult external technical experts when needed (Eurofound, 2023).

The use of AI systems itself also **deepens information asymmetries between employers and workers** (Dencik et al, 2024). This is not only due to the opacity of AI models but also because of the extensive data collection these systems enable. Employers gain real-time insights into worker behaviour and productivity, while employees and their representatives often lack access to the same datasets or understanding of how they are used. These asymmetries make it difficult for unions to identify when algorithmic management is in place, let alone assess its effects.

Finally, despite strong industrial relations frameworks in some countries, **consultation rights are not always upheld** in practice. In some cases, ensuring compliance requires legal action, underscoring the gap between formal rights and workplace realities. The discussion of France earlier in this chapter (Chagny et al, 2024), for instance, showed that worker representatives are frequently excluded from critical phases of AI deployment such as system design, algorithmic parameter setting, and data selection. A court ruling by the Pontoise Court of Justice on a dispute between a European IT service provider and its *comité social et économique* (CSE) declared that consultation is required even when no immediate impact on working conditions is evident, and that worker committees have the right to use an expert when AI is introduced (Pontoise Judicial Court, 15 April 2022, n°22/00134). However, adherence remained weak and on 14 February 2025, the Nanterre

Judicial Court had to confirm the previous ruling again[27] (Nanterre Judicial Court, 14 February 2025, n° 24/01457). The court determined that, even in a pilot phase, the deployment of AI applications required prior consultation with the works council, leading to the suspension of the project and a fine for the company[28].

Solutions and tools for overcoming obstacles

Taken together, the above obstacles underscore the need for both institutional and legal adaptation as well as capacity building in social partners.

Institutional adaptation to AI in the workplace is currently unfolding through national institutions – legislation, collective bargaining and social dialogue – rather than EU-level channels, due to the lack of a coherent regulatory framework on AI in the workplace (Molina et al, 2023). As the comparative analysis above has illustrated, each country relies on its existing institutional strengths: Denmark and Germany build on strong participatory frameworks, such as collaboration committees and updated works council legislation; Spain has introduced statutory reforms targeting algorithmic transparency; and Hungary shows little institutional adaptation, reflecting weak social partners and a deregulatory state stance.

Trade unions across Europe are increasingly advocating for **workers' data rights** as a way to challenge growing asymmetries of power in datafied workplaces. These rights typically aim to give workers access to and control over how data about them is collected and used. Dencik et al (2024) documents how in the UK, unions such as Prospect, Community, CWU and TUC have developed detailed interpretations of data rights (including rights to transparency, access, and involvement in data-driven decisions) and another union, Community, specifically calling for workers to be informed about what data employers collect, how, and for what purpose. However, these authors also warn that without strong collective frameworks, such rights risk becoming superficial fixes that legitimise surveillance. For data rights to meaningfully empower workers, they must be embedded within broader strategies that promote workplace democracy and collective control over digital systems.

Workplace-level governance structures are emerging as important mechanisms for negotiating the implementation and oversight of AI systems. In France, the SeCoIA project has proposed internal AI ethics committees with union representation and formal AI registers to document and track workplace AI applications (Chagny and Blanc, 2024). In Spain, the Just Eat collective agreement established an "algorithm committee" composed of management and union representatives, tasked with overseeing algorithmic decision-making and ensuring fairness (Rodríguez Fernández, 2024). In Germany, workplace agreements created ethical AI committees to guide responsible use (Krzywdzinski et al, 2023).

Capacity building to support meaningful worker participation in AI governance is advancing on two fronts: equipping social partners with the knowledge and tools to engage with digital systems, and strategically using AI technologies themselves to enhance union capabilities.

Several initiatives focus on improving **digital literacy and AI readiness of social partners**. Targeting employers, the UK Institute for the Future of Work has launched a *Good Work Algorithmic Impact*

[27] https://workwiseavocats.com/en/the-sec-may-obtain-the-suspension-of-the-introduction-of-ai-tools-in-the-company-if-it-has-not-been-consulted-in-due-time

[28] https://ogletree.com/insights-resources/blog-posts/nanterre-court-of-justice-issues-first-decision-about-introduction-of-ai-in-the-workplace-in-france/

Assessment, a participatory process that supports employers in anticipating, assessing and mitigating the risks of algorithmic systems, involving workers from design to deployment and ongoing monitoring (Institute for the Future of Work, 2023). In Denmark – but targeting unions internationally – the Why Not Lab[29] has developed practical tools to empower unions, including a *Co-Governance Guide*—a structured set of 27 questions workers or their representatives can pose about workplace technologies—alongside a *Collective Data Rights Guide* and a *Digital Readiness Framework* to assess organisational capacity for both influencing and managing digitalisation.

In Germany, trade unions and works councils have actively developed **tools** to support worker involvement in digital transformation and AI adoption. IG Metall's *Transformation Atlas* introduces works councils to the challenges of digitalisation and AI, fostering internal reflection and preparedness (Krzywdzinski et al, 2023). Building on this, IG Metall developed the *Company Map*, a participatory tool where employees and works councils jointly visualise anticipated technological changes. The *Digitalisation Compass* enables councils to assess a company's digitalisation strategy and evaluate its implications for employees.

Finally, **AI systems** themselves are being appropriated as **tools for union empowerment**. One example is an AI-enabled chatbot initially developed by IBM and later repurposed by a US alt-labour network and an Australian union. When reoriented from a service model to an organising model, the chatbot provided workers – particularly in fragmented or precarious jobs – with direct access to union information, enabled real-time workplace mapping, and supported grassroots organising efforts. Far from replacing human organisers, the chatbot enhanced union resources and made visible internal debates about knowledge and power in digital infrastructure (Flanagan et al, 2021).

These initiatives illustrate that capacity building is not only about technical upskilling, but also about union's digital infrastructures and strategic orientations to make worker participation in AI governance more effective.

Summary points

- **Worker voice is essential for responsible and effective AI adoption.** Participation helps align AI deployment with real work practices, drawing on workers' tacit knowledge and improving acceptance. Socio-technical and critical perspectives stress that meaningful involvement is needed to realise benefits and prevent harm. Evidence shows workers, developers, and managers have differing goals and priorities in AI deployment, highlighting the need for inclusive governance to reconcile these perspectives.
- **Firm-level worker voice shapes how AI is designed and deployed.** Consulting workers improves AI implementation, from identifying use cases to improving functionality. While direct consultation is more common, representative participation is less widespread and often hampered by limited technical and legal expertise to assess AI systems and their impacts on job quality. Building capacity and ensuring early engagement of workers are key to equitable outcomes.
- **Collective bargaining is a growing, but still limited, tool for shaping AI at work.** Many agreements address training and data privacy, but few cover AI governance. Some scholars argue for expanding bargaining rights to include AI oversight and audits, making unions

[29] https://www.thewhynotlab.com/services/tools-and-guides

enforcement partners. This would reduce regulatory gaps and strengthen democratic governance of AI.

- **National approaches to AI and social dialogue vary widely.** Countries with strong participatory institutions, like Germany and Denmark, rely on co-determination mechanisms and formal worker-employer collaboration bodies, such as works councils and joint committees. Others, like Spain and France, focus more on legal mandates and sectoral agreements. In weaker systems, such as Hungary's, union influence remains minimal.
- **AI challenges traditional social dialogue but also opens space for innovation.** Unions struggle with shrinking presence, knowledge gaps, and data asymmetries. New tools like algorithm committees, co-governance guides, and digital readiness frameworks are emerging in response. Some unions even deploy AI to support organising, showing how dialogue can adapt to digital realities.

Conclusions

This review **defines** artificial intelligence (AI) as any system that autonomously performs cognitive tasks – such as predictions, decisions, or content generation – regardless of the underlying technique. AI is distinct from algorithmic management (AM), which refers specifically to the use of such systems in organisational governance functions like scheduling, monitoring, and allocating work. In contrast, AI applications within the production function include, for example, validating insurance claims or detecting product defects. The review mostly focuses on machine learning (ML), deep learning (DL), and generative AI (genAI), as these are the most studied in the recent literature on workplace applications. Occasionally, older optimisation algorithms have been included when they perform autonomous operational decisions. Across all these cases, the focus is on systems that emulate human perception, interpretation, or communication and thereby impact how tasks are executed.

Evidence from **task-level** studies demonstrates that AI's productivity effects vary by task type. ML/DL systems often outperform humans in structured decision tasks such as medical diagnostics, particularly when operating independently from humans. In contrast, genAI proves most effective in open-ended creation tasks, such as writing, communication, and idea generation, especially when augmenting less-experienced users. Across domains like software development, legal analysis, and design, genAI accelerates task completion and shifts human effort toward higher-value editing and judgment. These findings highlight the importance of developing triage systems that allocate tasks dynamically between humans and AI, rather than defaulting to joint decision-making.

AI adoption requires complementary changes in **work organisation** to be effective. Productivity gains from earlier waves of digital technology, such as ICT, only materialised when firms adapted workflows, hierarchies, and coordination mechanisms. This remains true for AI. ML/DL decision technologies work best in modular work systems or when enhanced coordination supports integration across roles. GenAI may also shift task boundaries, redistributing responsibilities across roles or skill levels. Whether this leads to deskilling or empowerment depends on how organisations redesign jobs, structure internal career ladders, and support human-AI collaboration. Without adjustments in organisational design, AI's full benefits may remain unrealised.

The effects of AI on **job quality** are mixed and context dependent. Most workers report task augmentation from AI, but fewer experience task loss or new task creation. Depending on how it is designed, implemented, and used in the workplace, AI can increase autonomy, collaboration, and skill use – but may also raise work intensity. Physical working conditions often improve, but emotional demands such as managing interpersonal interactions and handling customer frustrations – can increase, especially as AI takes over routine tasks and leaves humans to perform roles that require soft skills and social interaction. Cognitive load may also rise due to the need to oversee and coordinate with AI systems. At the same time, there is a risk of cognitive underload, where job complexity is reduced below optimal levels. This can lead to lower attention and engagement, which may negatively affect physical safety and even increase the likelihood of workplace injuries. Meanwhile, the AI production chain itself is marked by polarisation: AI developers are well-paid and high-status, whereas data annotators often face low pay, precarious contracts, and limited agency, despite being integral to system performance.

AI's impact on **employment** is shaped by the interplay between substitution and augmentation. High AI exposure is found in cognitive, mid- and high-skilled occupations, including managerial, professional, and clerical roles, but exposure does not automatically imply job loss. Firms' adoption of AI increases their demand for technical and soft skills, while reducing demand in less AI-intensive roles. Firm-level studies show that employment gains thanks to productivity increases may indeed offset losses due to automation, potentially leading to net-neutral outcomes overall. However, evidence from freelance markets does show disruption in routine writing tasks, with more resilience in complex or high-budget work, as well as programming and design work.

Finally, **social dialogue** plays a key role in shaping how AI affects work, though practices remain uneven across countries. Worker voice, whether direct or representative, can improve AI implementation by surfacing tacit knowledge needed for AI implementation and supporting AI acceptance. Collective bargaining increasingly covers workers' training and data protection, but AI governance and oversight are rarely addressed. National approaches differ: Germany and Denmark rely on participatory mechanisms like works councils; Spain and France emphasise legal mandates and sectoral agreements; Sweden adopts a sociotechnical bargaining approach; Italy and Belgium show early signs of digital bargaining within traditional multi-level systems; while Hungary offers only limited protection and participation due to weaker institutions. New tools, such as algorithm committees, co-governance guides, and digital readiness frameworks, are emerging to strengthen social partner engagement and build capacity to adapt industrial relations to AI's growing presence in the workplace.

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