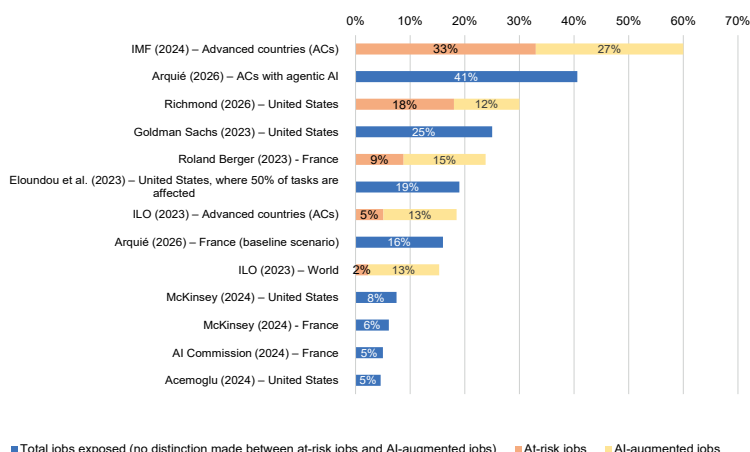


Artificial Intelligence and Its Effects on Employment

Martin Chopard, Elisa Cotet, Tristan Gantois and Eloïse Villani

- Artificial intelligence (AI) capabilities have rapidly advanced with the rise of large language models (LLMs) and generative AI, offering new opportunities for automation in every industry of the economy.
- As with previous technological revolutions, AI has provoked unease: according to the *Baromètre du numérique* 2025, a survey on the use of digital technologies, 62% of French people think it puts jobs at risk.
- AI may affect the volume of employment through two opposing channels: (i) it could replace some workers whose tasks can be automated, and (ii) it could increase worker productivity and stimulate labour demand.
- Empirical studies cannot determine the total effect of AI on employment, due to a lack of temporal perspective and the fact that AI adoption by firms remains modest. However, certain trends could be linked to the emergence of AI. The first rounds of redundancies attributable to AI are mainly in the most exposed industries (finance and IT), although AI adoption is sometimes used as a cover for other reasons for redundancies. Furthermore, there appears to be a slowdown in the employment of young workers.
- During previous technological revolutions, the jobs created by new technologies offset those lost, and the nature of work was deeply transformed. In light of this, public policy measures must provide support, particularly in the area of training, to workers so they can retrain when their jobs are put at risk by AI, and foster AI's diffusion across the economy.
- In a globally competitive environment, investing in AI is necessary to support competitiveness – and therefore employment – as remaining competitive will be increasingly tied to the adoption of AI.

**Estimated percentage of jobs exposed to AI
(as a % of total employment)**



Source: L. Baquero (2025), "*Emploi et IA générative : panorama des travaux économiques existants*" (in French only), the National Union for Employment in Industry and Commerce (Unédic) and DG Trésor.

The most recent papers are cited herein.

How to read this Chart: Between 5% and 60% of jobs are estimated to be exposed to AI. At-risk jobs refer to those with a significant share of tasks that can be performed by AI, without necessarily implying that these jobs will disappear. AI-augmented jobs are those with some tasks that can be carried out by AI, thereby freeing up workers' time to accomplish new higher value-added tasks.

1. Artificial intelligence could affect the total volume of employment through several channels, but the effect remains relatively small for now

1.1 As a general-purpose technology, artificial intelligence will gradually change work processes across entire segments of the economy

In this paper, artificial intelligence (AI) refers to a set of techniques that allow machines to simulate certain human cognitive functions,¹ based on a broad definition encompassing several tools (e.g. text generators, image recognition applications, text mining and machine learning). Large language models (LLMs), the adoption of which has increased significantly with the development of generative AI,² have seen exponential advancement and currently represent the main channel for generative AI's diffusion.³

As demonstrated by previous general-purpose technologies, such as the steam engine and electricity, their diffusion and related productivity gains across the economy tend to occur gradually. Clearly, AI differs in its mass availability and easy-to-use conversational interfaces, enabling the acceleration of its adoption. However, as in previous waves of innovation, AI forces firms to reorganise, reconfigure working methods and skills, and make additional investments, which could delay the onset of its associated productivity gains.⁴ At macroeconomic level, the effects of AI could therefore follow a J-curve, with adaptation costs having a negative impact on productivity at first, followed by a more pronounced acceleration of gains over the longer term.⁵

1.2 Two opposing channels are having an impact on employment through individual productivity gains

The economic literature has already shown that AI adoption results in significant individual-level productivity gains. Available experimental studies find substantial gains when AI is used in certain target areas in occupations of different skill levels, as it increased productivity by 14% for customer service agents⁶ and by 26% for software developers.⁷ These findings may nevertheless be too conservative, as the majority of them are based on AI models that have since been surpassed in performance by more recent iterations.

Economists agree that AI has the potential to deliver productivity gains in the future, but the exact scale of these gains in aggregate terms remains uncertain. Their estimates ultimately depend on the pace and scale of AI's diffusion in the economy, the performance expectations for various AI tools, the development of the infrastructure required for the roll-out of AI, and the gradual adaptation process involving workers and firms (e.g. additional investments, digital training and reorganisation of processes).

At macroeconomic level, AI's effects on employment are based on opposing mechanisms.⁸ The automation of certain tasks can reduce labour demand and lead to job losses: this is known as the displacement effect. AI-induced productivity gains can also stimulate demand by lowering costs, improving the quality and diversity

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- (1) L. Besson, A. Dozias, C. Faivre, C. Gallezot, J. Gouy-Waz, B. Vidalenc (2024), "[The Economic Implications of Artificial Intelligence](#)", *Trésor-Economics*, No. 341. S. Chardon-Boucaud, A. Dozias, C. Gallezot (2024), "[The Artificial Intelligence Value Chain: What Economic Stakes and Role for France?](#)", *Trésor-Economics*, No. 354.
 - (2) Generative foundation models can, for instance, create text, images and audio in response to a prompt.
 - (3) Future developments in AI, such as agentic AI (systems that can perform a series of tasks independently) and physical AI (robotics with AI capabilities that enable them to operate autonomously in the physical world) could substantially alter the economic implications and the effects on employment examined in this paper.
 - (4) F. Venturini (2022), "[Intelligent technologies and productivity spillovers: Evidence from the Fourth Industrial Revolution](#)", *Journal of Economic Behavior and Organization*.
 - (5) E. Brynjolfsson, D. Rock, C. Syverson (2021), "[The Productivity J-Curve: How Intangibles Complement General Purpose Technologies](#)", *American Economic Journal: Macroeconomics*, American Economic Association.
 - (6) E. Brynjolfsson, D. Li, L. Raymond (2025), "[Generative AI at Work](#)", *The Quarterly Journal of Economics*, 140(2), pp. 889-942.
 - (7) K. Z. Cui et al. (2025), "[The Effects of Generative AI on High-Skilled Work: Evidence from Three Field Experiments with Software Developers](#)", *Management Science*.
 - (8) D. Acemoglu, P. Restrepo (2019), "[Automation and New Tasks: How Technology Displaces and Reinstates Labor](#)", *Journal of Economic Perspectives*, 2019, 33 (2), pp. 3-30.

of products and services, and accelerating production. Due to these improvements, productivity gains boost employment in AI-adjacent occupations, and even in those directly exposed to AI. In fact, workers in these occupations can become comparatively less expensive to employ thanks to the productivity gains enabled by AI, and therefore be more in demand, in line with the Jevons paradox. For example, this can be illustrated by bank clerks after the introduction of ATMs and by accountants following the adoption of office software.

1.3 At present, empirical literature on AI does not find a clear impact on aggregate employment

The latest empirical studies on AI, which have only limited hindsight, do not show that it has a significant aggregate effect on employment (see Box 1, Table 1). Previous research shows rather contrasting findings.⁹ While these studies have a slightly longer temporal perspective, they cover AI technologies that are

outdated in comparison to more recent models, which reduces their pertinence.

This lack of a measurable effect is due to two main factors. First, AI's diffusion is still incomplete: according to the Global AI Adoption Index, enterprise adoption of AI in the European Union was around 20% in 2025 and frictions inherent to its roll-out are delaying the attendant macroeconomic effects. Second, even when AI is adopted, substitution and productivity mechanisms tend to offset each other. In a given industry, firms adopting AI experience an increase in sales and create more jobs than they eliminate (Babina et al., 2024; Lebastard et al., 2026). AI adoption can, however, bring about negative reallocation effects for competitors not adopting it; at aggregate level, productivity gains can also spread through general equilibrium effects (price decreases, increased purchasing power and redirection of demand towards other industries), which offset substitution-related job losses.

Box 1: Methodological implications of the empirical literature on AI's effect on employment

Empirical research measuring AI's effects on aggregate employment generally uses a two-part strategy: (i) measuring occupational exposure to AI, and then (ii) establishing the relationship between this exposure and observed changes in employment, at aggregate level, as well as by occupation, population group (low- or high-skilled workers, youth/seniors) and industry.

To measure occupational exposure to AI, researchers assess to what degree the various tasks of a given occupation can be automated or heavily augmented by AI tools, generating significant time savings while maintaining satisfactory quality. They determine an exposure score for each task and then aggregate them at occupation level, factoring in the relative importance of the various tasks carried out. This assessment can be conducted using expert input, patent analytics or AI tools, and thus involves a degree of uncertainty. Various studies use such methods to quantify different AI exposure measures within a given occupation,^a while others employ survey data on firm-level AI adoption.

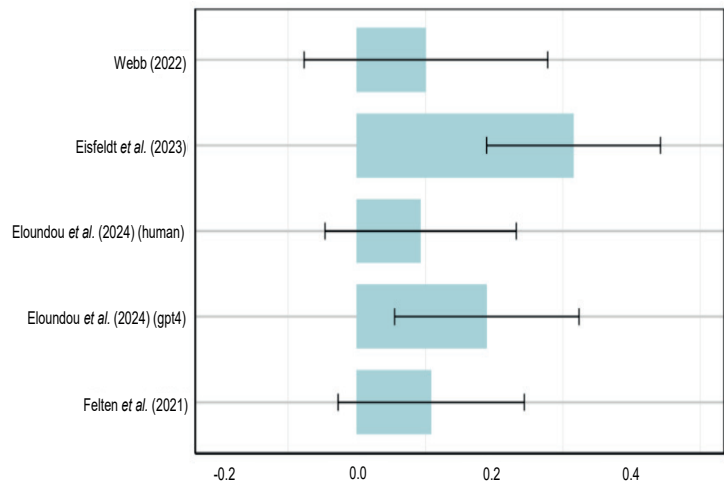
In a second phase, researchers statistically estimate the effect of this exposure on employment. The most frequently used method involves comparing changes in employment, hiring or job postings among occupations and firms relatively exposed to AI, by running econometric regressions (e.g. the difference-in-differences method). The most recent studies can use the release of ChatGPT in November 2022 as a tipping point: if the trajectory of the most exposed categories splits off after that time from that of the least exposed categories, part of this divergence can be attributed to AI's diffusion. Nevertheless, these studies can produce very different results depending on the method used: this is illustrated by an analysis by Eckhardt et al. (2025), which found that unemployment trends for AI-exposed workers can vary considerably based on the AI exposure measure used (see Chart 1).

a. M. Del Rio-Chanona, E. Ernst, R. Merola, D. Samaan, O. Teutloff (2025), "AI and Jobs. A review of theory, estimates and evidence", *arXiv preprint*.

(9) To mention just a few studies, Humlum and Vestergaard (2025) did not find AI to have a significant impact on aggregate employment, whereas Babina et al. (2024) found it to have a positive impact and Bonfiglioli et al. (2025) a negative impact. A. Humlum, E. Vestergaard (2025), "Large Language Models, Small Labor Market Effects", *NBER Working Paper*, 33777. T. Babina, A. Fedyk, A. He, J. Hodson (2024), "Artificial intelligence, firm growth, and product innovation", *Journal of Financial Economics*, 151, 103745. A. Bonfiglioli, R. Crino, G. Gancia, I. Papadakis (2025), "Artificial intelligence and jobs: evidence from US commuting zones", *Economic Policy*, 40(121), pp. 145-194.

Findings from the empirical literature should be interpreted with caution. First, these studies mainly cover AI's current capabilities, despite the fact that its future impact could be greater. Surveys, however, attempt to break past this limitation by gauging what economic stakeholders anticipate in coming years, but bias is still a problem: for example, the most productive or innovative firms are usually early adopters of AI tools, which makes it difficult to establish a causal relationship and limits the ability to extrapolate the findings. In addition, job postings data often overrepresents skilled workers and major companies, to the detriment of other labour market segments. Lastly, statistical reporting lags limit the scope of the most recent studies. Despite these drawbacks, papers such as Yotzov et al. (2026, which surveyed nearly 6,000 firms, serve to measure market sentiment and, for some economic theorists, this is a relevant indicator.^b

Chart 1: Change in the unemployment rate for the most AI-exposed workers relative to all other workers, between the periods 2022-2023 and 2024-2025 (in pp), by AI exposure measure



Source: S. Eckhardt, N. Goldschlag (2025), "AI and Jobs: The Final Word (Until the Next One)", Economic Innovation Group.

How to read this Chart: The blue-grey bars represent, for each AI exposure measure used, the change in unemployment for the occupations most exposed to AI relative to all other occupations, for the periods 2022-2023 and 2024-2025; the corresponding confidence intervals indicate the statistical uncertainty surrounding these estimates. Only the exposure measures proposed by Eisefeldt et al. (2023) and Eloundou et al. (2024) show a statistically significant relative increase – of between 0.2 and 0.3 pp – in unemployment for the most exposed workers.

b. Yotzov et al. (2026), op. cit.

Table 1: Overview of data estimates of the effects of AI on the aggregate level of employment

Papers	Response of employment	Geographical scope
Hartley et al. (2025) ^a	0	United States 2010-2023
Teeselink (2025) ^b	–	United Kingdom 2021-2025
Lebastard et al. (2026) ^c	0/+	Europe 2025
Baslandze et al. (2026) ^d	0	United States 2025
Yotzov et al. (2026) ^e	0	United States, United Kingdom, Germany and Australia 2022-2025

a. J. Hartley, F. Jolevski, V. Melo, B. Moore (2025), "The Labor Market Effects of Generative Artificial Intelligence", SSRN Working Paper.

b. B. Teeselink (2025), "Generative AI and Labor Market Outcomes: Evidence from the United Kingdom", SSRN Working Paper.

c. L. Lebastard, D. Sondermann (2026), "Artificial intelligence: friend or foe for hiring in Europe today?", ECB Blog, 4 March.

d. Baslandze et al. (2026), "Artificial Intelligence, Productivity, and the Workforce: Evidence from Corporate Executives", NBER Working Paper, 34984.

e. Yotzov et al. (2026), "Firm Data on AI", NBER Working Paper, 34836.

The lack of an aggregate effect of AI on employment does not mean that there are no localised job losses: since 2025, announcements of AI-related job cuts have been climbing, both in the United States and France.

These announcements increasingly fuel a perception of AI as a direct threat to employment. Accordingly, the *Baromètre du numérique 2025*, a survey covering digital devices and infrastructure, found that 62% of French people think that artificial intelligence puts jobs at risk.¹⁰

(10) The 2025 edition of the survey was published jointly by the Electronic Communications, Postal and Print Media Distribution Regulatory Authority (ARCEP), the Regulatory Authority for Audiovisual and Digital Communications (ARCOM), the General Council for the Economy (CGE) and the National Agency for Regional Cohesion (ANCT).

However, these findings need to be put into the appropriate context. In 2025, AI-related job losses accounted for between 4.5% and 6.2% of the redundancies announced in the United States and are dwarfed by more dramatic gross flows of job creation and destruction.¹¹ In a similar vein, reflecting the previous redundancy figures, a report from LinkedIn also shows no effect of AI on hiring in roles with varying AI exposure.¹² Lastly, according to the OECD,¹³ the changes in the number of job vacancies in the industries identified as being most exposed to AI are not markedly higher or lower than in the industries

less exposed to AI, with the United States being the exception in this regard.

Some of the redundancy announcements could also be a case of “mislabelling”, meaning that AI may be used to justify decisions that are actually being made due to reorganisation/restructuring, post-pandemic staff adjustments or financial constraints. Accordingly, 59% of US companies have admitted to using AI to explain hiring freezes¹⁴ and, in several redundancy announcements, AI appears to have been used as a pretext for job cuts.¹⁵

2. There are heterogeneous effects on employment across different occupations, workers and industries, but no consensus has emerged

2.1 AI exposure varies by task (and therefore by occupation), and for those exposed to AI, the effects differ primarily depending on their degree of substitutability and complementarity

To understand AI's potential impact on a given occupation, the task-based framework¹⁶ breaks down the relevant occupation into a set of tasks in order to measure the degree of AI exposure (see Box 1).

Cognitive tasks, such as information processing and analytical reasoning, are most exposed to generative AI, and to LLMs in particular. Conversely, the most physical tasks, targeted by robotics, are considered to be less exposed for the time being. Social tasks fall somewhere in the middle.¹⁷

However, AI exposure levels alone do not determine the final impact on employment. For the tasks exposed

to AI, we must differentiate between those in which AI primarily complements workers and those in which it can substitute for them.¹⁸

When AI complements workers, it automates lower value-added tasks, thereby enabling workers to focus on the tasks in which they retain a comparative advantage: judgment and evaluation, social interactions, and interpreting context.¹⁹ In this instance, the resulting higher productivity could boost employment: at constant wages, given that workers become more productive, their relative cost falls for firms, which can encourage them to hire more workers.²⁰ Productivity gains can also lower prices and stimulate demand, when the latter is sufficiently sensitive to changes in prices (see Chart 2).

(11) In aggregate, all types of redundancies combined account for only a fraction of employment contract terminations in the United States (37% on average), with such terminations also including resignations, retirements, the expiry of fixed-term contracts, etc.

(12) LinkedIn (2026), “[The EU Labor Market: Unlocking Competitiveness in the Age of AI](#)”.

(13) OECD (2026), “[OECD Economic Outlook](#)”.

(14) According to a report from ResumeTemplates.com which surveyed 1,000 US business leaders about their hiring and workforce plans for 2025 and beyond (April 2026).

(15) Outside observers provide nuance to the idea that these redundancies are mainly driven by AI. One such observer is Josh Bersin, who provides the example of a FinTech startup which announced in 2026 that it would dismiss 40% of its employees. In his opinion, the decision was taken more so to correct for overexpansion following the COVID-19 pandemic, a phenomenon more likely to affect US Big Tech companies.

(16) D. Acemoglu, P. Restrepo (2019), op. cit.

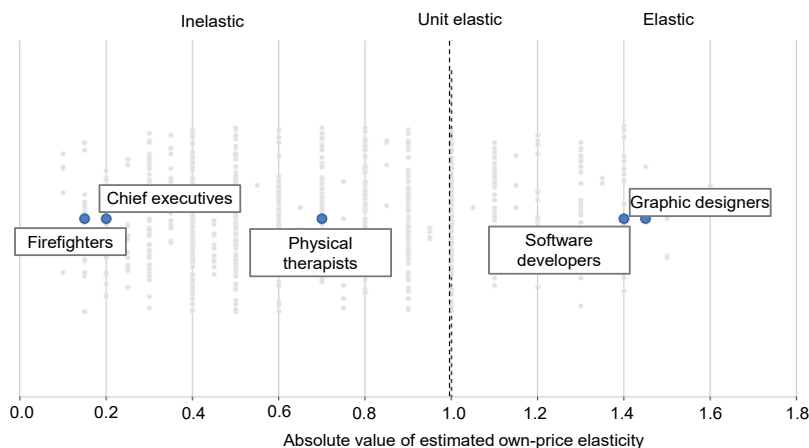
(17) P. Casas, E. Fernández-Macías, F. Martínez-Plumed, E. Gómez, I. González-Vázquez, S. Salotti (2026), “[Revisiting the occupational impact of AI in the generative AI era](#)”, JRC Working Papers Series on Labour, Education and Technology, 2026/02.

(18) Autor et al. are among the first to have studied this topic, in 2003 (D. Autor, F. Levy, R. J. Murnane (2003), “[The Skill Content of Recent Technological Change: An Empirical Exploration](#)”, *The Quarterly Journal of Economics*, 118(4), 1279-1333). This approach has been adopted in many more recent papers mentioned in this section.

(19) D. Acemoglu, D. Autor, S. Johnson (2026), “[Building Pro-Worker Artificial Intelligence](#)”, *NBER Working Paper*, 34854.

(20) D. Acemoglu, P. Restrepo (2019), op. cit.

Chart 2: Estimated own-price elasticity of demand for goods and services produced by different occupations



Source: A. M. Richmond (2026), *“The AI jobs transition framework: Mapping AI’s near-term impact on jobs”*, OpenAI.

How to read this Chart: Own-price elasticity measures the relative percent change in quantity demanded for a 1% opposite change in price. For firefighters and chief executives, own-price elasticity is close to 0: demand for their services is virtually price-insensitive. Conversely, graphic designers and software developers have an own-price elasticity above 1, meaning lower prices induced by AI would lead to a sharp increase in demand for their output.

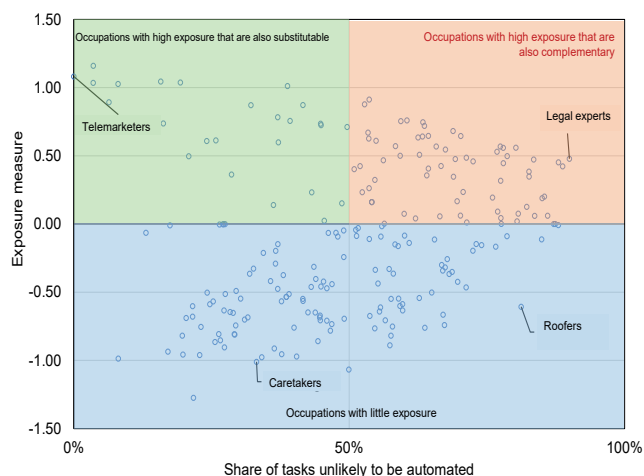
When AI substitutes for workers, for example in occupations heavy in codifiable or repetitive tasks (secretaries, accountants and telemarketers), AI adoption and the resulting productivity gains could reduce employment. But AI can also support continued employment in occupations where some tasks can be substituted with AI, particularly when it is used to improve cybersecurity or a firm’s overall production processes.²¹

A French study ranks occupational families based on their degree of AI exposure and whether they are associated with complementarity or substitutability (see Chart 3).

At aggregate level, the available estimates, while speculative, show that between 5% and 60% of jobs are potentially exposed to AI in the short- to medium-term (see Chart on cover page). Within this broad category, only some of these jobs would be potentially substitutable by AI. The other jobs exposed to AI would undergo changes in their tasks, without disappearing entirely. By way of illustration, in a report from OpenAI, Richmond (2026) finds that an estimated 18% of US jobs are at a higher automation risk, 24% will see a marked shift in their task composition, 12% will grow because of AI and 46% will be less affected in the short term.²² Lastly, in France, Arquíe et al. (2026) suggest that 3.8% of task content is currently at risk of automation by generative AI, with the figure rising to

16.3% in two to five years, as AI’s capabilities continue to advance.²³

Chart 3: Ranking of each occupational family by AI exposure and relative substitutability/complementarity



Source: A. Bergeaud (2024), *“Exposition à l’intelligence artificielle générative et emploi : une application à la classification socio-professionnelle française”* (in French only).

How to read this Chart: The chart ranks the different occupational families based on their AI exposure measure and their degree of substitutability with AI. The exposure measure is obtained by multiplying the average score of an occupation’s task substitutability by AI by an aggregate measure based on the general characteristics of the occupation rather than on its detailed task composition. A value of 0 indicates average exposure; a negative value means below-average exposure and a positive value above-average exposure. Telemarketers are found to be the most exposed and most substitutable (green area), while legal experts, architects and doctors, although exposed, hold occupations that are more complementary to AI (orange area).

(21) P. Aghion, S. Bunel, X. Jaravel, T. Mikaelson, A. Roulet, J. Søgaard (2025), *“How Different Uses of AI Shape Labor Demand: Evidence from France”*, *AEA Papers and Proceedings*, 115, pp. 62-67.

(22) A. M. Richmond (2026), *op. cit.*

(23) A. Arquíe, A. Duthoit, G. Sublieau (2026), *“The Next Automation Frontier: A Scenario Map of AI Labour Exposure”*, Coface Economic Publications, Focus. The indicator refers to the share of tasks performed by workers that are at risk of automation, weighted by each occupation’s share of total employment, rather than the share of jobs at risk of elimination.

2.2 At individual level, biased technological change could disadvantage certain labour market segments, with particular concerns for young people

Technological revolutions tend to generate a phenomenon called “biased technological change”, with some workers affected more than others. The arrival of robotics, for example, had a more negative impact on manual workers while giving an edge to their non-manual counterparts. The current situation is more complex to judge *ex ante* given that AI also concerns high-skilled occupations.

However, high-skilled workers are exactly those who possess the most transferable skills, putting them in a better position to take advantage of AI’s benefits and to adapt to shifts in the labour market.

Accordingly, occupational skill level cannot reliably predict the impact AI will have on a given worker. The most recent empirical studies (see Table 2) have not revealed any particular trend of AI-induced labour market segmentation by occupational skill level.

Likewise, AI presents a mixed picture depending on workers’ ages. For young workers, who are less experienced and more inclined to adopt the technology, AI can accelerate skills acquisition and reduce the productivity deficit early on in their careers. But AI also automates codified tasks – those based on explicit, reproducible rules – that often form the basis of much junior-level work.²⁴ This has led to concerns about young workers’ entry into the labour market and, over the longer term, a shortage of workers able to fill senior roles.

Table 2: Summary of ex post evaluations of AI’s effects on the level of employment by occupational skill level

Papers	Response of employment			Geographical scope and time period
	Low-skill/ low-income occupations	Mid-skill occupations	High-skill/ high-income occupations	
Hosseini et al. (2025) ^a	–	–	–	United States 2015-2025
Teeselink (2025) ^b	0		–	United Kingdom 2021-2025
Felten et al. (2019) ^c	0		+	United States 2010-2016
Bonfiglioli et al. (2025) ^d	–		+/0	United States 2000-2020
Albanesi et al. (2023) ^e	0	0	+	16 European countries 2011-2019
Georgieff et al. (2022) ^f	0		+	23 OECD countries 2012-2019
Huang (2024) ^g	0	–	0	United States 2010-2021

a. S. M. Hosseini, G. Lichtinger (2025), “Generative AI as Seniority-Biased Technological Change: Evidence from U.S. Résumé and Job Posting Data”, *Working Paper*.

b. B. Teeselink (2025), *op. cit.*

c. E. Felten, M. Raj, R. Seamans (2019), “The Occupational Impact of Artificial Intelligence: Labor, Skills, and Polarization”, NYU Stern School of Business.

d. A. Bonfiglioli, R. Crino, G. Gancia, I. Papadakis (2025), *op. cit.*

e. S. Albanesi, A. Dias da Silva, J. Jimeno, A. Lamo, A. Wabitsch (2023), “New Technologies and Jobs in Europe”, *IZA Discussion Paper*, 16227.

f. A. Georgieff, R. Hyee (2022), “Artificial intelligence and employment: New cross-country evidence”, OECD Social, *Employment and Migration Working Paper*, 265.

g. Y. Huang (2024), “Labor Market Impact of Artificial Intelligence: Evidence from US Regions”, *IMF Working Papers*, 199, International Monetary Fund.

Note: Only the papers shown in blue include data collected after generative AI was developed. Studies prior to its development cover the impact of technologies such as machine learning, natural language processing, image recognition and predictive analytics. Empty cells denote aspects not examined by the papers concerned.

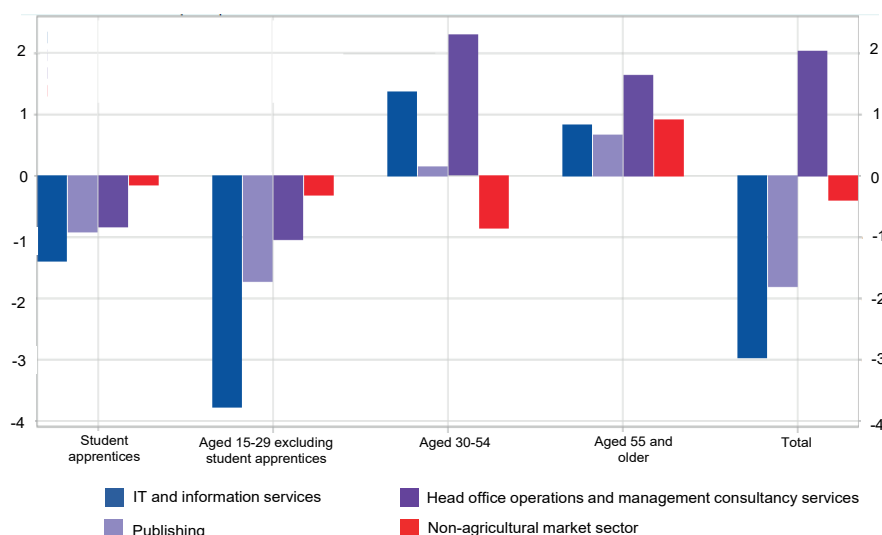
(24) S. M. Hosseini, G. Lichtinger (2025), *op. cit.*

A small number of preliminary foreign studies tend to confirm some of these concerns (see Table 3): Brynjolfsson et al. (2025) show that employment for workers aged 22 to 25 in the most AI-exposed occupations declined by 16% relative to other workers between November 2022 and July 2025 in the United States.²⁵ This finding is supported by Massenkoff and McCrory (2026) from Anthropic,²⁶ as well as by Hosseini et al. (2025).²⁷ This potential decline in young workers' employability could risk producing negative externalities throughout their careers due to the loss of accumulated experience.²⁸

In France, the National Institute of Statistics and Economic Studies (INSEE) has also highlighted a

pronounced adjustment in young workers' employment in several industries highly exposed to AI,²⁹ although no causal relationship was found (see Chart 4). In addition, unemployment in the 15-24 age group rose two points, from 19.1% to 21.1%, between Q1 2025 and Q1 2026. Nevertheless, other factors such as the deteriorating economic environment may also play a role in the situation facing young workers. Their employment is generally more sensitive to current economic conditions than that of older workers, especially owing to the fact that they are overrepresented in fixed-term contracts and industries exposed to changes in economic conditions.³⁰

Chart 4: Contributions to changes in employment by age group between Q4 2023 and Q4 2025 in France (total change expressed as a % and contributions by age group expressed in pp)



Source: INSEE (2026), *"Inflation rekindled and growth weakened"*, *Economic Outlook*.

How to read this Chart: In IT and information services, the 3.8 pp contraction in employment for workers aged 15-29 has more than offset the slight rise in employment for workers from other age groups, resulting in an overall 3.0 pp decrease.

(25) E. Brynjolfsson, B. Chandar, R. Chen (2025), *"Canaries in the Coal Mine? Six Facts about the Recent Employment Effects of Artificial Intelligence"*, *Working Paper*.

(26) M. Massenkoff, P. McCrory (2026), *"Labor market impacts of AI: A new measure and early evidence"*, *Working Paper*, Anthropic.

(27) S. M. Hosseini, G. Lichtinger (2025), *op. cit.*

(28) L. Garicano, L. Rayo (2025), *"Training in the Age of AI: A Theory of Apprenticeship Viability"*, *Working Paper*, LSE.

(29) INSEE (2026), *op. cit.*

(30) A. Ghoshray, J. Ordóñez, H. Sala (2016), *"Euro, crisis and unemployment: Youth patterns, youth policies?"*, *Economic Modelling*, 58(C), pp. 442-453.

Table 3: Summary of ex post evaluations of AI's effects on the level of employment by worker experience

Papers	Response of employment		Geographical scope and time period
	Juniors	Seniors	
Bonfiglioli et al. (2025) ^a	Exposed to AI that automates work	–	United States 2015-2025
	Exposed to AI that “augments” work	+/-0	
	Other occupations	0	
Hosseini et al. (2025) ^b	Firms with high AI adoption rates	–	United States 2015-2025
Humlum and Vestergaard (2025) ^c		0	Denmark 2023-2024
Teeselink (2025) ^d		–	United Kingdom 2021-2025
Massenkoff et al. (2026) ^e		–	United States 2022-2026

a. E. Brynjolfsson, B. Chandar, R. Chen (2025), op. cit.

b. S. M. Hosseini, G. Lichtinger (2025), op. cit.

c. A. Humlum, E. Vestergaard (2025), op. cit.

d. B. Teeselink (2025), op. cit.

e. M. Massenkoff, P. McCrory (2026), op. cit.

Note: All the papers listed cover, at least in part, the post-ChatGPT period. Empty cells denote aspects not examined by the papers concerned. The “seniors” category is defined differently depending on the paper: Brynjolfsson et al. (2025) define it by age (50 and over), while Teeselink (2025) and Hosseini and Lichtinger (2025) define it by position level, with senior roles beginning at manager level for the former, and at associate level for the latter.

2.3 In the short term, the main industries exposed to AI include finance, IT and business services

AI exposure varies by industry: finance and insurance, IT services, publishing and professional and technical services are, at first glance, said to be more exposed to generative AI. On the other hand, agriculture, construction and part of the manufacturing industry, which involve more physical tasks, are thought to be much less exposed.

For example, in France, the information and communications technology industry and the scientific and technical services industry account for the majority of firms that have adopted AI, with adoption rates of 59% and 33% respectively in these industries in 2025, whereas adoption is much lower in the construction and

hospitality and food service industries (9% and 12% respectively).³¹

The first announcements of AI-related job cuts primarily concern the IT industry, which the literature identifies as highly exposed and for which it provides empirical data confirming advanced adoption. Certain statements made by business executives, for example, suggest that AI-generated code could quickly become a dominant practice, leading to job losses.³² Various observers also draw a link between job cuts in the IT industry and a massive investment spree focused on expanding AI, with firms seeking to free up additional financial resources to fund such projects.³³ This strategy is more common among Big Tech companies investing in AI, such as Meta and Google, than among AI developers: OpenAI, for instance, has plans to double its workforce in 2026.³⁴

(31) Eurostat (2025), “Survey on the Use of Information and Communication Technologies in Enterprises”.

(32) For instance, the chief executive of Microsoft, Satya Nadella, estimated in July 2025 that 20% to 30% of the company's code was written by AI, and that 95% of it would be AI-generated by 2030. During that same month, Microsoft confirmed a new round of job redundancies, with approximately 9,000 roles expected to be eliminated.

(33) *Fortune* (2026), “Big Tech will spend nearly \$700 billion on AI this year. No one knows where the buildout ends”.

(34) *Financial Times* (2026), “OpenAI to double workforce as business push intensifies”.

3. In the longer term, the net effect of artificial intelligence on employment remains uncertain

3.1 Several scenarios are possible and vary depending on technological change and the extent of job creation and loss

The AI technologies currently in use, particularly the LLMs employed on an ad-hoc basis to assist with certain tasks, have limited effects on aggregate employment at this stage. In the longer term, however, it is difficult to predict which of the possible scenarios will prevail.

A scenario in which capital is substituted for (primarily skilled) labour on a massive scale remains a possibility, especially if the most advanced AI technologies, such as agentic AI and physical AI,³⁵ end up being widely adopted. Arquié et al. (2026) estimate that if agentic AI becomes broadly adopted, over 40% of occupations will have more than 30% of their tasks become potentially automatable.³⁶

However, an examination of previous technological revolutions suggests that caution is warranted and that a scenario of “creative destruction” is more likely. In support of this, a literature review of the past four decades concludes that past technological innovations created more jobs than they destroyed.³⁷ For example, the expansion of the internet in the 2000s and the advent of electricity in the 20th century transformed jobs without reducing the level of employment. More recently, predictions made in the early 2010s about automation causing large-scale job destruction did not come to pass.³⁸ This illustrates how difficult it is to draw conclusions about a given technology’s actual impact on employment based on its technical capabilities,

since a task’s exposure to the technology does not necessarily mean that workers will be replaced and new needs arise as technologies free up the workforce. These findings are corroborated by Autor et al. (2022), who show that innovation continuously creates new jobs: 60% of today’s workers have jobs that did not exist in 1940.³⁹

Historically, productivity gains from technological progress have therefore helped to increase production and real income without durably reducing aggregate employment;⁴⁰ on the other hand, they have gone hand in hand with a major sectoral reconfiguration of employment and a reduction in hours worked.⁴¹

3.2 The adoption of artificial intelligence will incur transition costs and thus require support measures

The technological shock of AI will profoundly transform the labour market. This transition could negatively affect certain workers or regions, owing to barriers to occupational and geographical mobility, and to the obsolescence of certain skills. According to simulations from Bocquet (2026), the costs associated with the slow pace of workforce reallocations (corresponding to the difference between the theoretical economic gains from an immediate reallocation and the actual economic gains from a gradual adjustment) following the widespread adoption of robots in France would reduce the benefits of such technology by 40%.⁴² In any case, labour market adjustment should be eased through training policies and occupational support measures, which would focus on identifying the workers

(35) Agentic AI refers to systems that can perform a series of tasks independently, whereas physical AI involves AI-powered robots that interact autonomously with the physical world.

(36) A. Arquié, A. Duthoit, G. Sublieu (2026), op. cit.

(37) K. Hötte, M. Somers, A. Theodorakopoulos (2022), “Technology and jobs: A systematic literature review”, *Technological Forecasting and Social Change*, 194.

(38) C. B. Frey, M. Osborne (2013), “The Future of Employment: How susceptible are jobs to computerisation?”, *Working Paper*, Oxford Martin School. For example, the paper estimates that 47% of total US employment is at risk of being automated over the following decade or so, with certain occupations projected to all but disappear.

(39) D. Autor et al. (2022), “New Frontiers: The Origins and Content of New Work, 1940-2018”, *NBER Working Paper*, 30389.

(40) D. Autor (2015), “Why Are There Still So Many Jobs? The History and Future of Workplace Automation”, *Journal of Economic Perspectives*, 29(3), pp. 3-30. New occupations, such as AI prompt specialists, are already emerging.

(41) A. Bick, N. Fuchs-Schündeln and D. Lagakos (2018), “How Do Hours Worked Vary with Income? Cross-Country Evidence and Implications”, *American Economic Review*, 108(1), pp. 170-99. G. Cetté, S. Drapala and J. Lopez (2023), “The Circular Relationship Between Productivity and Hours Worked: A Long-Term Analysis”, *Comparative Economic Studies*, 65(4), pp. 650-664.

(42) L. Bocquet (2026), “Reconversions professionnelles après un choc technologique : le rôle des métiers-ponts”, *French Council of Economic Analysis, Focus* no. 134 (in French only).

with the most difficult retraining needs and the key skills for workers to develop through occupational training to benefit from the use of AI in the workplace. The “Future Skills and Jobs” scheme under the France 2030 Investment Plan has, in particular, introduced changes to the training offering so as to address the needs of the tech industry.

3.3 At economy level, the risk of falling behind as a result of not adopting AI relative to competing economies is real and requires decisive public policy measures

Varied impacts are expected for firms and countries alike: as was the case for robotics,⁴³ the stakeholders who adopt AI earlier and more intensively in industries exposed to global competition will have a competitive advantage that could eventually lead to market share gains and the creation of additional jobs. Conversely, countries where AI adoption by firms remains modest will risk lagging behind in competitiveness.

Based on available data, France falls in the middle range in Europe. The country’s firm-level AI adoption rate (18% according to the OECD in 2025) is close to the European average (20%), but lower than rates in the Nordics, particularly in industries where the expected productivity gains are highest. AI adoption between 2024 and 2025 advanced more rapidly in France (up by 8 pp) compared to the European average (up by 6 pp), suggesting that the country is starting to catch up.

Since AI is as much a driver of productivity as it is a factor reshaping jobs and skills, France has undertaken several initiatives, including the *Osez l’IA* (“Dare to Try AI”) programme launched in 2025, which aims to fast-track the technology’s uptake across the entire economy and train 15 million professionals by 2030. To accomplish this, it draws on awareness-raising initiatives, business support measures and training opportunities, in particular those through an AI academy.

(43) P. Aghion, C. Antonin, S. Bunel and X. Jaravel (2023), “[Capital industriel moderne, demande de travail et dynamique des marchés de produits : le cas de la France](#)”, *Working Paper*, INSEE (in French only).

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