

**DIRECTORATE FOR SCIENCE, TECHNOLOGY AND INNOVATION
DIGITAL POLICY COMMITTEE**

Thriving with AI: harnessing AI's potential for the economy

Revised draft

This document is a revised draft of one of the two reports summarising key insights of the 2025-26 horizontal project, “Thriving with AI: Empowering Economies, Societies and Citizens”, focusing on harnessing AI’s potential for the economy. The outline of this report [DSTI/DPC(2025)21] and the first draft [DSTI/DPC(2025)21/REV1] were shared for feedback with participating OECD bodies in the Fall of 2025 and Spring 2026 respectively. This revised draft incorporates input from delegations.

The horizontal project on “Thriving with AI” concludes at the end of 2026. This report will incorporate the most recent OECD work and data available at the time of publication. Work referenced as “forthcoming” in the current draft is planned for publication by the end of 2026. In particular, additional evidence relevant to sections “AI Adoption: Impacts on productivity and economic growth” and “AI and work” is expected to become available and will be incorporated in a final version ahead of approval and declassification by the Digital Policy Committee envisioned at its December 2026 meeting. The accompanying report “Harnessing AI’s potential across key sectors” is put forward for approval and declassification.

Action requested: The Digital Policy Committee is invited to review and comment on this report by 19 October 2026. This document is also shared with OECD bodies contributing to the Horizontal Project for information.

digitalpolicycommittee@oecd.org
OECD.AIHP@oecd.org

JT03593548

Table of contents

Abstract	3
Executive summary	4
Harnessing AI for the economy	6
UNDERSTANDING THE ECONOMIC IMPACTS OF ARTIFICIAL INTELLIGENCE TO HARNESS ITS BENEFITS	6
WHAT IS ARTIFICIAL INTELLIGENCE?	6
AI IS RESHAPING ECONOMIC ACTIVITY	8
AI AND COMPETITION: IMPACTS ON COMPETITION POLICY AND ENFORCEMENT	14
AI AND WORK	21
Annex: AI key terms and topics informing this analysis	30
References	33
NOTES	39
 Figures	
Figure 1. AI's macroeconomic gains will vary widely across countries	12
Figure 2. Open-weight generative AI models now outnumber closed-weight models	17
Figure 3. Generative AI model quality has improved steadily in recent years	18
Figure 4. AI model prices have been falling on average by 90% since June 2023	19
Figure 5. Most SMEs report generative AI has had no effect on overall staff need (yet)	23
Figure 6. The use of algorithmic management tools is already the norm in many countries	24
Figure 7. Regions with a low risk of automation are now highly exposed to generative AI, and vice-versa	26
Figure 8. Labour market exposure to generative AI could range from 16% to 77% across regions	26
 Boxes	
Box 1. Types of tasks performed by AI systems	7
Box 2. Measuring competition among firms in the age of AI: initial evidence from microdata	20

Abstract

The development and adoption of Artificial intelligence (AI) are reshaping economies – with the potential to lift productivity, boost competition and transform labour markets. This report draws on OECD evidence on AI’s expected economic impacts, examining how AI adoption and diffusion unfold across firms, sectors and countries. It assesses the role of complementary assets such as skills, data and digital infrastructure in enabling productivity gains and analyses implications for competition and market power, drawing on new indicators to assess AI-related barriers to entry and market concentration. Finally, the report highlights evidence on the evolving impacts of AI in the labour market. Together, this evidence provides insights to help governments develop policies that build trust in AI and harness its potential for economic progress.

Executive summary

1. ***The development and adoption of artificial intelligence (AI) are reshaping economies, with the potential to lift productivity, boost competition, and transform the labour market.*** Capturing and distributing AI's economic benefits will not happen automatically. This report brings together OECD analysis and evidence on: AI adoption across firms, regions and countries; implications for competition and market power; and emerging labour market impacts. Together, these insights aim to support policymakers harness the potential of AI for economic growth. The OECD Recommendation on Artificial Intelligence underpins the analysis, as the first intergovernmental standard that aims to foster innovation and trust in AI based on shared values.

AI adoption, productivity and economic growth

2. ***AI adoption is accelerating, but with significant differences across firms, sectors and regions.*** In 2025, one in five firms on average across OECD countries reported using AI, up from 14% in 2024, with adoption concentrated in ICT and professional services and traditional sectors lagging.

3. ***AI adoption depends heavily on complementary assets and enablers.*** These include digital infrastructure and digital technologies, AI-enabling inputs (data, algorithms and compute), skills, and finance. They are complemented by broader enabling conditions such as reliable and affordable energy to power and cool AI data centres, as well as the cybersecurity and cyber resilience of digital infrastructure. Firm-level evidence shows that AI-adopting firms tend to be more productive than non-adopters, but much of this productivity advantage reflects these complementarities, in line with a productivity “J-curve” hypothesis in which gains materialise gradually following sustained investment and work processes adaptation, after which gains can be significant.

4. ***Generative AI is demonstrating productivity gains and could boost long-term economic growth as adoption spreads.*** Experimental evidence shows sizeable task-level productivity gains, particularly when AI complements human capabilities: 40% in professional writing tasks, and 30% in software coding. OECD modelling aggregates these gains to obtain macroeconomic estimates on productivity, suggesting substantial positive effects on long-term growth in most scenarios, with important variation across countries.

5. ***SMEs still lag behind large firms in the uptake of AI tools, and remote regions risk falling behind.*** Adoption gaps persist across firm sizes and geographies, reflecting challenges in accessing data, digital infrastructure and skills. Targeted policies are needed to accelerate adoption among small firms and in remote regions to ensure AI supports broad-based productivity growth rather than reinforcing existing divides.

6. ***Uncertainty about technical, legal and organisational risks vary across sectors and can deter firm-level investment, particularly for smaller firms.*** This is especially true in high-stakes sectors like healthcare and finance. OECD voluntary frameworks and enterprise guidance support AI innovation and adoption by providing firms resources for risk management reporting and demonstrating trust and accountability.

AI and competition: market dynamics and enforcement challenges

7. ***AI is reshaping competitive dynamics across the economy, both within the AI value chain and across downstream markets.*** While AI can lower entry barriers and spur innovation, risks related to

market concentration, gatekeeping and dependence on critical inputs such as compute, data and skills also need to be considered.

8. ***Measures of AI market dynamics show increasing AI model choice and falling per usage prices, but potential bottlenecks in compute, data and skills.*** OECD estimates that between 2023 and 2026 quality-adjusted per usage prices for cloud-based AI models fell by 90%. However, the direction of overall costs is unclear, especially as usage is becoming more intensive with agentic AI systems. Foundation AI models have also been changing; about a third of models at the technological frontier have been replaced every month by cheaper and higher performing models, including open-weight models. However, these favourable competition dynamics coexist with risks around access to compute, data and skills, including the possibility that concentration in AI infrastructure may create operational, cybersecurity and supply-chain dependencies.

9. ***In downstream markets, AI is altering competitive dynamics in ways that can both strengthen and weaken competition, reducing costs and minimum scale but also favouring data-rich incumbent firms, enabling algorithmic pricing and reinforcing lock-in.*** These dynamics underscore the need to apply competition tools with precision and monitor AI-driven market changes and the effectiveness of competition tools across jurisdictions

AI and work

10. ***AI is changing the nature of work – the skills required, tasks performed and management approaches.*** Workers and employers tend to view AI's impact on worker performance positively, although with some reservations. Recent evidence suggests AI has resulted in task-level changes within jobs rather than full automation of occupations. For example, four in five workers in manufacturing and finance report that AI has increased their performance, and most employers in those sectors do not yet report significant impacts on overall employment levels. New OECD evidence also suggests that AI-adopting firms are no more likely than other firms to have reduced headcount, and only a small share of workforce reductions are attributed mainly to AI. Given the rapid rate of innovation and adoption, the impact of AI on overall employment needs to be continuously monitored.

11. ***Workers, firms, sectors and regions differ in their exposure to AI, while AI itself can help expand labour market opportunities for some groups.*** Exposure to generative AI varies sharply across regions within OECD economies, ranging from 16% to 77%, and workers do not benefit from AI adoption to the same extent: low-skilled, older and female workers often face greater risks of being left behind. AI could also expand labour market opportunities, for example by helping people with disabilities overcome labour market barriers, or by reducing productivity gaps between workers. Countries are already responding to these changes with a range of policy measures, from skills development programmes and social dialogue frameworks to place-based approaches that tailor policy to local exposure and readiness.

Harnessing AI for the economy

Understanding the economic impacts of artificial intelligence to harness its benefits

12. Harnessing AI for the economy requires moving beyond headline adoption figures to understand where, how and for whom AI generates economic value. AI is rapidly transforming the functioning of economies: reshaping innovation and productivity pathways, potentially altering competitive dynamics and influencing financial systems. To capture these gains while managing trade-offs, policymakers need a clearer and deeper understanding of AI's opportunities, impacts and risks.

13. This report draws on data, trends and policy insights from across the OECD as part of its Horizontal Project on AI "*Thriving with AI: harnessing AI's potential for the economy*". It builds and draws on the **OECD AI Principles** which, adopted in 2019 and updated in 2024, establish the foundational framework for the responsible stewardship of trustworthy AI (OECD, 2024^[1]). They are comprised of five values-based principles (inclusive growth, human-centred values, transparency, robustness and accountability) and five actionable recommendations for policymakers on research and development, the AI-enabling ecosystem, governance and policy environment, human capacity and labour market transformation, and international co-operation.

14. The first section of this report maps AI **adoption and diffusion** at economy-wide and firm levels, examining implications for innovation, productivity and economic growth. The second section explores AI impacts on **competition policy and enforcement**, examining barriers to entry and market concentration. The third section **on AI and work** examines how AI is reshaping labour markets, exploring impacts on job quantity, quality and the participation and protection of workers. A companion report covers AI impacts across key sectors (OECD, Forthcoming^[2]).

What is artificial intelligence?

15. The OECD Recommendation on AI (OECD, 2024^[1]) provides a widely adopted definition of an AI system that underpins analysis of economic impacts and provides a common reference point: "*an AI system is a machine-based system 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. Different AI systems vary in their levels of autonomy and adaptiveness after deployment*". The OECD definition is deliberately flexible to reflect a broad understanding of AI. AI is a general-purpose digital technology with transformative potential across sectors, encompassing a broad range of methods, from early logic-based or symbolic systems to statistical AI approaches, including generative AI such as large language models (LLMs). These have more recently helped enable agentic AI uses whereby AI systems plan, execute tasks and adapt with increasing autonomy.

16. Topics typically encompassed by the term "AI" and in the definition of an AI system include categories of techniques such as machine learning and knowledge-based approaches, and application areas such as computer vision, natural language processing notably in the form of large language models,

speech recognition, intelligent decision support systems, intelligent robotic systems, as well as the novel application of these tools to various domains (OECD, 2024^[3]) (Box 1). AI technologies are developing at a rapid pace and additional techniques and applications are constantly emerging. For example, “AI agents” and “agentic AI” are increasingly embedded in organisational workflows, with potential implications for productivity and giving rise to distinct policy considerations (OECD, 2026^[4]; OECD, 2026^[5]). An explanation of key terms used in this report can be found in the Annex.

Box 1. Types of tasks performed by AI systems

Outputs generally reflect different tasks or functions performed by AI systems¹. They include, but are not limited to:

- **Recognition** (identifying and categorising data, e.g., image, video, audio and text, into specific classifications as well as image segmentation and object detection),
- **Event detection** (connecting data points to detect patterns, as well as outliers or, anomalies or imputing missing data),
- **Forecasting** (using past and existing behaviours to predict future outcomes),
- **Personalisation** (developing a profile of an individual and learning and adapting its output to that individual over time),
- **Interaction support** (interpreting and creating content to power conversational and other interactions between machines and humans, possibly involving multiple media such as voice text and images),
- **Goal-driven optimisation** (finding the optimal solution to a problem for a cost function or predefined goal) and reasoning with knowledge structures (inferring new outcomes that are possible even if they are not present in existing data, through modelling and simulation).

AI systems frequently perform several tasks, such as event detection, forecasting and personalisation, before producing an outcome that influences the environment. Notable examples include:

- **Generative AI or content generation:** which includes generating new images, video, text, assessment and audio. This task combines forecasting and recognition tasks. However, the output often combines several existing elements such as images, text and audio to generate an object that was never seen before. This task tends to use structured learning. Examples of content generation include machine translation, generative art, news stories – including fake news - and “deep fake” videos.
- **Autonomous systems:** Robots and robotic systems increasingly embed different tasks (e.g. recognition, goal-driven optimisation) to perform real world actions. Similarly, autonomous systems can perform recognition tasks to try to find an optimal solution path and then act accordingly. In an autonomous vehicle, this could be a recommendation to turn to minimise travel time, followed by the execution of the action. This system is autonomous in the sense that it does not require human supervision to act on its environment, but the way in which it performs its task (recognition) is not autonomous, as it relies on supervised learning.
- **Monitoring and control systems:** These systems manage, command, direct or regulate the behaviour of other devices or systems using control loops. Control systems generally assess environments through recognition, event detection or forecasting and propose a goal-driven action. They range from domestic heating controllers to large industrial control systems that use reinforcement learning to manage processes or machines. Control systems are common in the context of robotics or factories. One example of a control system is a fraud detection system with an event detection task combined with an action (e.g. freezing a bank account).

Source: OECD (2024), "Explanatory memorandum on the updated OECD definition of an AI system", <https://doi.org/10.1787/623da898-en>.

AI is reshaping economic activity

17. AI's economic potential - with significant opportunities for productivity and growth - is real but not automatic. This report draws on a breath of recent OECD research, data and analysis. It shows how the potential of AI can only be realised through broad-based AI adoption and its effective integration in business processes and work practices. It examines the necessary investment, environment and complementary assets - skills, data, compute and related technologies - required for broad adoption. And it breaks down AI diffusion across firms and individuals. Finally, the report examines evidence on productivity gains from AI at micro and macro levels to date and considers the implications for market power and competition. The OECD AI Principles underscore AI's potential in driving economic growth, as well as the role of all actors and stakeholders in the AI ecosystem.

18. The first section of the report examines drivers of AI diffusion across firms, sectors and geographies and how far adoption has progressed and where barriers persist. It focuses on SMEs and the role of local context in shaping adoption patterns. It then turns to the evidence on productivity gains from AI at micro and macro levels to date, which have implications for market power and competition covered in the following section.

AI adoption is accelerating but with significant differences across sectors and firms

19. AI diffusion across firms and sectors is growing and accelerating. In 2025, 20.2% of firms reported using AI, up from 14.2% in 2024 and 8.7% in 2023. Yet AI adoption rates differ across industries and firms. ICT firms reported the highest adoption (57.3%), followed by professional and scientific services (36.8%) (OECD, 2026^[6]).

20. From 2023 to 2025, AI use more than doubled from 7% to 17.5% among small firms and from 13.6% to 29.5% among medium-sized firms on average across OECD countries (OECD, 2026^[7]). However, persistent gaps remain in adoption between SMEs and large firms, among which the average AI adoption rate reached 52.08% in 2025. Closing them requires support to be tailored to the needs of different types of SMEs (OECD, 2025^[8]) (OECD, 2026^[9]).

21. AI use also differs by application, reflecting business priorities and sector needs. For example, customer chatbots and virtual assistants are more common in telecommunications and travel; robotic process automation in pharmaceuticals and electricity supply; AI-embedded autonomous vehicles in the automotive industry; and AI-powered data analytics in professional scientific and technical services. In 2025, it was estimated that 75% of the 30 agentic AI systems² covered in the 2025 AI Agent Index, had been used to assist with coding, software engineering, or computer interfaces (Casper et al., 2025^[10]).

22. Gaps in AI adoption by firm size underline why diffusion requires active policy attention. The concentration of AI use among large, digitally mature and high-capacity firms raises concerns about widening productivity and capability gaps, underscoring the need for tailored, coordinated policy responses if countries want to capture the potential benefits of AI across their economies (OECD, 2024^[11]). To guide policy responses, the OECD categorises SME AI adopter profiles - Novices, Optimisers, Explorers, and Champions - with four corresponding ecosystem-level enablers - connectivity, AI-enabling inputs (data, compute, algorithms), skills, and finance - (OECD, 2025^[8]).

Firm-level enablers and complementary assets are key for AI adoption by firms

23. Digital transformation builds on enabling, or complementary, technologies and assets. Firms' use of AI often builds on enablers such as cloud computing, customer relationship management (CRM) and enterprise resource planning (ERP) software, and fast broadband connectivity, reflecting considerable interdependencies among different digital technologies. Analysis of cross-country microdata underlines the importance of skills and digital capital, for adoption. Over 2017-2023 across firms in 15 OECD Member countries, AI use is significantly linked to complementary assets in two domains: technological capital (digital infrastructure and other digital technologies) and workers' human capital (ICT skills, training, tertiary education, and technical occupations, as well as socio-emotional and foundational skills) (Calvino, Costa and Haerle, 2026^[12]). These factors are also likely to determine the depth and quality of AI adoption, with different implications for productivity.

Technological capital and capacity

24. The complexity of AI tools and their intended use or application also influences AI adoption by firms. Adoption pathways differ across types of AI systems, particularly between generative AI, whose models create new outputs, such as text, code, audio, images and video, often in response to prompts, and non-generative AI. They also depend on how these systems are combined and adapted to business needs and local market conditions.

25. Firms already using predictive or automation AI were often better placed to adopt generative AI, reflecting differences in knowledge, investment, data, software, equipment and organisational culture. At the same time, the growing availability of AI-as-a-Service, including generative AI tools based on pre-trained models, has significantly lowered barriers to adoption, enabling firms to leverage and experiment with AI without requiring advanced technical skills. While advanced customisation, integration, and deployment can still require significant expertise, these tools can be adapted to a wide range of business contexts across many domains and sectors, facilitating adoption by smaller, less-resourced actors. In contrast, developing and deploying predictive AI models can still require substantial computing resources and deep technical expertise.

Human capital and skills

26. Across countries, AI adoption is positively associated with ICT skills (5 of 6 countries analysed); ICT training (2 of 5); and technological capital (9 of 9). Tertiary education and technical occupations also appear critical. For example, in Denmark, the Netherlands and Portugal, a one percentage point increase in the share of tertiary-educated workers is associated with a higher likelihood of AI adoption of 0.53, 0.24 and 0.15 percentage points, respectively.

27. These complementary assets also drive productivity outcomes. Cross-country firm-level evidence prior to the rapid rise of generative AI shows a productivity advantage for AI adopters, ranging from 7.7% in France to 31% in Belgium. However, these productivity differences are largely driven by existing advantages of adopting firms in human and technological capital. When controlling for these complementary assets, the productivity advantage of AI adoption disappears in most countries. This finding suggests that firm-level returns from AI adoption may still be materialising, and that a wide range of complementary assets are necessary to boost both AI adoption and productivity (Calvino, Costa and Haerle, 2026^[12]).

The hidden cost of adopting AI

The availability of reliable, affordable energy and effective cooling solutions is an increasingly important enabling condition for AI infrastructure

28. Beyond firm-level enablers of AI adoption, the availability and cost of AI services also depend on the physical infrastructure that underpins its development and deployment. Data centres provide the compute capacity needed to train and run AI models, and AI services can draw on compute located remotely from users. Proximity may nevertheless matter for latency-sensitive applications requiring real-time responses, as well as for economic, security and governance considerations (Lehdonvirta et al., 2025^[13]). Reliable electricity supply and effective cooling are important upstream conditions for this infrastructure. Data centre electricity demand is rising rapidly, driven largely by AI-optimised facilities (IEA, 2025^[14]; IEA, 2025^[15]; IEA, 2026^[16]), and power supply can be constrained by local grid capacity, competing uses and price dynamics. In addition to higher baseline demand, large AI workloads can create sharp swings in electricity use (e.g. synchronised training and inference patterns), raising grid management challenges and operating costs. This strengthens the case for energy-efficient compute and more flexible, modular data-centre design, including software-hardware co-design and AI-specific chip architectures to reduce resource intensity (Beals, 2025^[17]; Kübler et al., 2026^[18]; OECD, Forthcoming^[19]).

29. Cooling adds a further constraint on AI infrastructure development as high-density AI compute increases thermal loads and reliance on energy- and water-intensive cooling systems. Solutions such as liquid/immersion cooling and waste-heat recovery can reduce cooling burdens and improve overall efficiency, while differences in domestic energy endowments (notably access to competitive, low-carbon power) may shape comparative advantages in hosting AI infrastructure. These infrastructure constraints point to the importance of aligning AI infrastructure planning with local grid capacity and water availability (OECD, 2022^[20]).

Geographic patterns and place-based factors also shape AI adoption trajectories

30. Gaps in AI uptake have widened between cities and regions within countries since generative AI became widely available. The fastest EU regions on uptake are also the innovation leaders in Europe (Kergroach and Héritier, 2025^[21]). In particular:

- Capital regions lead: Brussels, reported twice as many business adopters in 2024 (32%) as in 2023; (16%). Oslo, Norway, reached 26% (up from 12%). In Korea, Seoul (39%, 2023) led among service-oriented metropolitan regions.
- Non-capital regions show strong uptake where industrial specialisation is high. In Denmark, Central Jutland and Region Zealand (35% and 28%), and Southern Denmark (21%), stand out as hubs for green and health tech, robotics and advanced manufacturing; Gwangju (Korea) (60%, 2023) for next-generation vehicle, smart energy and biomedical industries; and Gangwon-do (52%) hosts an international logistics and business complex (KFEZ, 2025).
- By contrast, less innovative regions lag and are widening the territorial divide. Great Plain and North Hungary, Romania and Innlandet, Norway all rank the lowest in the EU for AI adoption, reflecting a slower acceleration between 2023 and 2024.

31. In-depth OECD work on Korea illustrates uneven adoption of AI within countries (OECD, 2025^[22]). Korea is a global AI frontrunner with high rates of adoption among firms, and an ambition to become a top three global AI powerhouse (AI “G3”) by 2030. The adoption gap between SMEs and large firms is also comparatively small at the national level (1.3, compared with 3.3 across OECD countries). Nevertheless, important regional differences persist. The gap between SMEs and large firms is particularly pronounced in Jeju (6.3) and Ulsan (4.0), followed by Gangwon-do and Gyeongsangnamdo (3.0) and Jeollabuk-do (2.3).

Yet even within the same country and sector, firms show large differences in AI uptake, suggesting local factors beyond specialisation and skills

32. Local sector specialisation shapes both the types of AI applications likely to emerge and the capacity of firms and workers to adapt. However, even in the same country and sector, firms in different regions differ in AI uptake, suggesting that other factors matter (Kergroach and H  ritier, 2025^[21]). Within-country gaps are largest in the most AI advanced sectors, such as information and communication services. In ICT, Spain shows a significant gap between top-performing region Extremadura (91% adoption rate) and bottom La Rioja (11%). Extremadura benefits from high-speed fibre connectivity, proximity to submarine cables, low-cost renewable energy, two large-scale carbon-neutral data centres, and supercomputing facilities (Edged US, 2025^[23]; Tracxn, 2025^[24]; Computaex, 2025^[25]).

33. A few key approaches emerge from AI deployment in regions and cities that can support policy development targeted at boosting local and regional AI adoption (OECD, 2025^[26]). First, implementing AI projects requires an incremental approach. Sequencing allows a city to build maturity gradually while maintaining public trust. Second, scaling AI requires investment in democratic processes, new capabilities, and structured city-to-city collaboration. A critical limitation is governance readiness and public legitimacy. Third, systemic scaling of AI is most feasible when national regulation, multi-city deployment, and experimentation instruments are co-ordinated under a unified architecture.

34. Finally, policy co-ordination across areas and levels of government, as well as multi-level governance frameworks, are key for aligning action, standards, and investments, facilitating data sharing and system interoperability, and overcoming fragmentation and scalability gaps in regions.

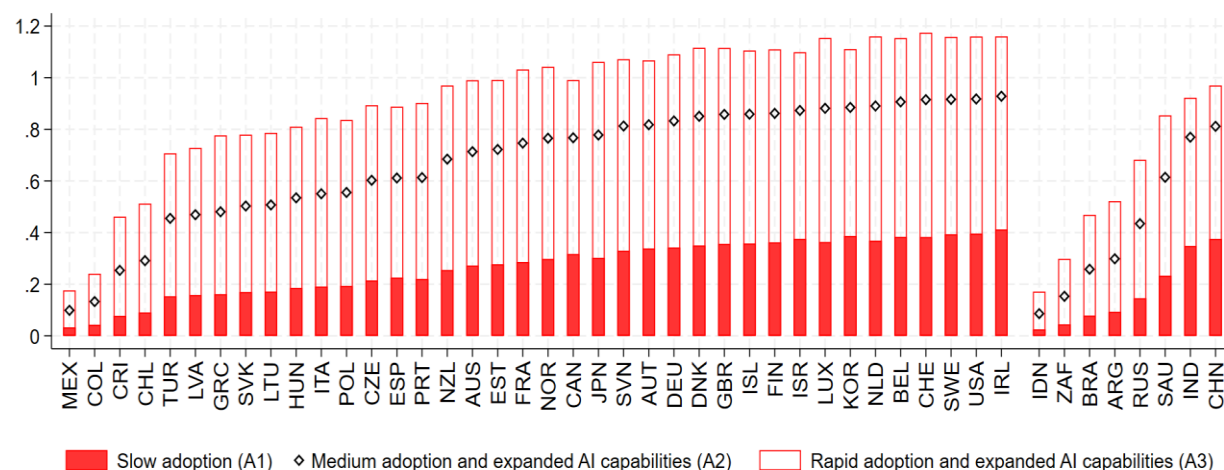
AI, notably generative AI, is projected to boost macro-level productivity over the next decade, but gains will vary widely by country and adoption pace

35. Large productivity gains have been observed from AI use at the microeconomic level, notably from generative AI use, while gains at the macroeconomic level are harder to quantify and tend to rely on modelling assumptions and scenarios. Recent analytical work relies on such approaches to estimate the expected long-term productivity gains from AI (Filippucci et al., 2026^[27]) extending and updating previous analysis focusing on the United States and G7 economies (Filippucci, Gal and Schief, 2024^[28]; Filippucci et al., 2025^[29]).

36. Recent analysis reveals large cross-country differences across the OECD in terms of the expected gains from AI (Figure 1). In the medium-paced AI diffusion scenario – where AI adoption follows a similar pace as previous digital technologies – AI-driven productivity gains over the next ten years are expected to contribute to aggregate labour productivity and per capita real income growth by between 0.1 and 0.95 percentage points annually, depending on the country³ (Filippucci et al., 2026^[27]).

Figure 1. AI's macroeconomic gains will vary widely across countries

Predicted per capita real income gains due to AI over the next 10 years, percentage points (annualised)



Note: The three scenarios capture three sets of assumptions regarding AI adoption (slow, medium and fast, in Scenarios A1, A2 and A3, following previous GPTs such as electricity, computers and internet, and mobile phones, respectively) and AI exposure (baseline capabilities in Scenario A1 and expanded capabilities in Scenarios A2 and A3, from (Eloundou, 2024^[30]), where more details can be found).

Source: Filippucci et al (2026), "AI meets trade: Global linkages and the cross-country distribution of the gains from AI", <https://doi.org/10.1787/13081644-en>.

37. The most advanced adopters, particularly the most knowledge-intensive and service-intensive economies, such as, Ireland, Israel, Switzerland and the United States, are at the high end of this range, given that current generative AI mostly impacts cognitive tasks.⁴ In the more rapid adoption scenario, the productivity gains amount to nearly 1.2 percentage points per year for these countries. This is substantial and comparable to the previous productivity boom associated with computers and the internet in the mid-1990s, which was most strongly detectable in the United States. Given AI's potential to accelerate the pace of innovation – which is outside the scope of these OECD studies – several analyses view much larger gains as also plausible (Nordhaus, 2021^[31]; Aghion, Jones and Jones, 2017^[32]; Trammell and Korinek, 2023^[33]). On the other hand, especially in the short run, during the transition to an AI based economy, negative risks can emerge through labour markets, something that is difficult to model and quantify for the time being given the evidence is only starting to appear and still unclear.⁵

When examining lower- and middle-income countries, income per capita gaps vis-a-vis advanced economies remain due to structural differences in terms of lower levels of education and less developed digital and, especially, energy infrastructure (Chaar et al., 2025^[34]). To benefit from a stronger catching up effect due to AI, policy reforms that improve these and related areas will be crucial. International co-operation can complement these domestic efforts, including through peer learning and the exchange of best practices, support for technology adoption and capacity building, and international collaboration to foster knowledge spillovers.

Human-AI collaboration is key to turning productivity gains into economic growth

38. Analysis leveraging recent empirical research shows that the benefits of generative AI are large but vary by task and user expertise, with human-AI collaboration being key to unlocking benefits (Calvino, Reijerink and Samek, 2025^[35]). For instance, carefully designed experimental studies among call centre agents show a 14% increase in their productivity from using generative AI, more than 40% in professional

writing, and around 30% when writing software code with AI tools (Brynjolfsson, Li and Lindsey, 2025^[36]; Noy and Zhang, 2023^[37]; Cui et al., 2026^[38]). Significant gains from the use of generative AI are observed through the automation of tasks and the optimisation of business operations. This is particularly pronounced for scenarios where generative AI complements human capabilities. More specifically, greater relative benefits are often experienced by less-skilled individuals in well-defined tasks, while for more experienced workers, gains are dependent upon the integration of deep domain knowledge to manage complex outputs effectively.

However, risk and uncertainty can deter adoption and raise costs for firms

39. AI risks, hazards and harms can create additional barriers to adoption, heightening uncertainty and exposing adopters to economic, legal and reputational risks. Technical risks can arise from poor-quality, poisoned or sabotaged data, algorithmic failures and opacity, deficient infrastructure, and network disruptions (e.g., power, broadband or Internet of Things (IoT)), as well as human error or misuse during training, deployment or oversight. Potential consequences span workplace safety risks from malfunctions; privacy, data and intellectual property protection infringements arising from data leaks, copyright theft or abusive inference; market distortions from algorithmic collusion; and corporate liability from predatory or dark commercial practices or environmental harm (Kergroach and H  ritier, 2025^[21]).

40. AI can also heighten cybersecurity and information integrity risks and undermine trust in digital content and AI systems. While many of these harms are already well documented, new ones are gradually emerging, including at systemic scale (Bengio et al., 2026^[39]). Rapid advances in AI capabilities can further alter risk profiles, threat vectors and the balance between attack and defence in cyberspace, making it difficult for organisations to anticipate emerging risks, assess their implications and implement appropriate safeguards in a timely manner.

41. Risk management needs to reflect global, national, and local perspectives. AI systems, data flows and digital services often operate across jurisdictions, making cross-border co-ordination essential where risks cannot be fully addressed through national frameworks alone. At the same time, local conditions – including infrastructure quality, data governance practices, skills, cultural norms and subnational regulations – shape how risks arise, their impacts, and appropriate mitigation measures. Accounting for these factors can strengthen public trust and legitimacy by aligning AI systems with local needs and expectations.

42. A sectoral perspective is also essential, as AI risk profiles differ across sectors in type, incidence and severity, as do the regulatory obligations firms face. In healthcare, risks mainly relate to patient safety, diagnostic and treatment accuracy, and privacy. In professional, scientific and technical services, AI may affect expert judgement, confidentiality, research integrity and legal, engineering or auditing responsibilities. OECD work on common guideposts for interoperable AI risk management (OECD, 2023^[40]), AI accountability (OECD, 2023^[41]), and due diligence for responsible AI in enterprises (OECD, 2026^[42]) offers voluntary principles to help businesses navigate these challenges. The Hiroshima AI Process (HAIP) Reporting Framework (OECD, 2026^[43]) provides a widely recognised and used tool demonstrating how voluntary reporting mechanisms can support transparency and help build public trust in AI, with reports made publicly available on the OECD.AI Policy Observatory. However, sector-specific guardrails remain necessary where safety requirements, compliance obligations and liability risks are particularly high.

Key policy considerations for AI adoption, impacts on productivity and economic growth

43. AI's growth potential depends less on the technology itself than on the conditions under which it is adopted and used. Policy design is therefore critical to realising AI-driven productivity gains broadly across firms, sectors and regions rather than remaining concentrated among early adopters.

44. **Strengthening diffusion rather than frontier innovation alone.** While frontier AI capabilities continue to advance rapidly, aggregate productivity gains depend on widespread adoption by firms outside the technological frontier. Policies that support diffusion – including advisory services, upgrading skills, enabling experimentation through flexible labour and capital markets and other support measures as well as sector-specific implementation tools – can help close adoption gaps, particularly for SMEs and firms in traditional sectors where productivity gains remain largely untapped.
45. **Investment in complementary assets is essential for adoption and in translating AI adoption into productivity gains.** Evidence suggests that AI delivers measurable productivity and adoption improvements only when combined with adequate skills, digital infrastructure and organisational change. This suggests a need for policy focus on workforce upskilling and reskilling, managerial capabilities and investment in digital infrastructure alongside incentives for AI uptake.
46. **Targeted support is needed to ensure widespread adoption across firm size and geography.** Persistent gaps in AI adoption between large and small firms, as well as between innovation hubs and lagging regions, risk exacerbating productivity gaps and territorial inequalities. Place-based policies are needed to strengthen digital infrastructure, local innovation ecosystems and AI-related skills in lagging regions, alongside SME-focused digital programmes and improved access to finance and infrastructure to help broaden adoption and prevent AI from reinforcing existing economic divides.
47. **Generative AI creates new opportunities but does not eliminate structural adoption barriers.** While foundation and pre-trained models reduce the costs of experimentation and lower technical entry thresholds, firms' capacity to integrate these tools effectively still depends on absorptive capacity, data availability and organisational readiness. To enable *effective* use – not just access – policy action will need to provide guidance, foster skills development and support integration into core business processes.
48. **Reducing uncertainty and addressing perceived risk can accelerate effective adoption.** Lack of clarity about the potential legal consequences and concerns regarding violation of data protection and privacy rules tend to be among the most common reasons for enterprises deciding not to use AI (OECD, 2026^[6]). Clear, predictable and interoperable policy frameworks – combined with practical guidance on risk management and due diligence – can lower uncertainty, reduce compliance costs and support broader uptake without undermining trust.
49. **Macroeconomic policies need to anticipate gradual and uneven productivity effects.** AI adoption is associated with adjustment costs and delayed productivity gains at firm and aggregate levels. It will therefore be important for policies to account for transition dynamics, including reallocation across firms and sectors, and support labour and capital mobility to ensure that productivity improvements translate into sustained economic growth rather than temporary dispersion or disruption.
50. OECD estimates point to AI as a potentially powerful driver of productivity and economic growth, but one whose benefits are neither automatic nor broadly distributed. Policies that foster diffusion, strengthen investments in complementary assets and reduce adoption frictions will be central to converting technological progress into broad-based economic gains. How AI diffuses across firms and regions will not only determine productivity outcomes, but also shape competitive conditions across markets, which are examined in the following section.

AI and competition: impacts on competition policy and enforcement

51. AI development and deployment are reshaping business performance, cost structures and strategic advantages, with important implications for market power. While AI technologies open new avenues for firm entry and innovation, they also raise concerns about market concentration, gatekeeping and exclusionary behaviour. Effective competition promotes further innovation and ensures firms are rewarded based on merit rather than existing market positions. As a far-reaching GPT, AI could significantly

reshape rivalry across the wider economy, altering how firms compete across sectors. In response, authorities are monitoring the effectiveness of competition policy tools and enforcement practices to support the ability of firms to start, scale-up, challenge and displace incumbents, thereby enhancing innovation and long-term economic growth.

52. AI competition dynamics can be viewed in three particular ways, highlighting implications for competition policy and enforcement. First, competition dynamics are evolving between AI model developers, application developers and deployers (i.e. actors involved upstream in the AI value chain, also referred to as “AI markets” in this analysis), as fully realising the benefits of AI depends on maintaining effective competition across the AI value chain. This makes defining markets and assessing the state of competition in any given layer of the AI stack challenging. Second, there is the impact on competition in other sectors (i.e. those not involved in the AI value chain or “AI markets”) because of AI adoption itself. Lastly, questions of how to measure such dynamics are pertinent, which is a growing area of OECD empirical work.

53. Relevant provisions of the OECD AI Principles directly frame AI–competition interactions namely the policy recommendation to “foster a digital ecosystem for AI” that calls on governments to promote open, competitive markets, data access and interoperability. These are key to preventing concentration, gatekeeping and exclusionary behaviour across the AI value chain. Finally, the principles on transparency and accountability support effective competition enforcement, aligned with the ability to scrutinise AI-driven conduct and market effects. Together, these provisions position competition as a core enabler of AI-driven innovation, entry and long-term economic growth across AI markets and the wider economy.

54. Fully realising AI’s economic benefits requires effective competition throughout the AI value chain, including among providers of AI infrastructure, cloud services, foundation models, applications and deployment solutions, as well as among firms adopting and deploying AI (OECD, 2024^[44]; OECD, 2025^[45]; OECD, 2025^[46]).

55. While still evolving, there are risks to competition across the AI value chain, including control of key inputs such as compute, data and talent. OECD evidence shows increasing concentration of AI investment, notably in segments that rely heavily on such inputs. In 2025, IT infrastructure and cloud services firms attracted USD 109.3 billion in venture capital (VC) investment (42% of the global total), mega-rounds above USD 100 million accounted for roughly 73% of total AI VC funding, and US-based firms received around three-quarters of global AI VC investment (OECD, 2026^[47]). Although not evidence of market power in itself, this concentration may strengthen the position of firms and ecosystems with superior access to strategic key inputs.

56. First, firms that control critical inputs for advanced AI systems – compute, data and talent – may restrict competition through vertical integration; large incumbents already benefit from greater access to these inputs, as well as from network effects and advantages linked to their large user bases in traditional digital services. There is also the risk of market-tipping factors, such as potential feedback effects from data that favours incumbents. Second, powerful incumbents may leverage gatekeeping positions in consumer or business markets to distort choice in advanced AI model services, through practices such as vertical foreclosure or product bundling, raising risk of consumer lock-in, higher prices and slower innovation over time. Third, partnerships among key players may reinforce or extend existing market power along the value chain. While the current landscape specifically for generative AI-related products and services appears to be largely competitive, with many active models and new entrants (André et al., 2025^[48]), these competition risks require monitoring as they could crystallise in the future, and some trends appear to suggest concentration could develop among leading providers.

57. Access to AI infrastructure – also known as AI compute – is a notable competition risk. This includes both access to AI compute as a service for AI model development and use, as well as competition considerations related to the AI compute supply chain itself. AI compute relies on complex supply chains which carry competition impacts from characteristics such as high supplier concentration and limited

multi-sourcing due to substantial capital requirements, long development cycles and specialised know-how, for example in semiconductor manufacturing (OECD, 2025^[49]). Advanced accelerators (i.e. AI semiconductors or AI chips) depend on components developed by only a handful of firms worldwide, while other parts of the chip memory, fabrication and packaging supply chain are similarly concentrated. Relatedly, vertical integration, partnerships and investment linkages can generate efficiencies but also create risks of foreclosure or advantage accumulation across AI compute providers – both with regards to AI compute supply chain component providers and AI compute service providers, such as cloud providers including hyperscalers.⁶ Such partnerships may also risk reinforcing competitive advantages into adjacent layers of the AI value chain, including AI models and downstream applications.

58. Agreements determining how and when firms can obtain AI accelerators are particularly relevant. Transparency around the conditions of access to such infrastructure is an important component in maintaining sufficiently competitive market entry conditions. Ensuring AI compute interoperability and manageable switching costs is also important for competitive dynamics. Switching providers at different layers of the AI stack can be complex, e.g. due to technical constraints, when components are optimised for specific hardware, commercial factors (such as data transfer charges) and the need to reconfigure solutions to new architectures. Openness can support interoperability within and compatibility across different layers of the AI stack, including through open standards and protocols (OECD, 2026^[50]).

59. Beyond concerns in the supply of AI infrastructure, other potential competition concerns involve entrants struggling to access users and user-related data. This could occur, for example, if developing scalable platforms to access consumers, and their data, is made difficult by existing providers using their market positions to favour their own services. Data is likely to be a key input to providing AI related digital services, ongoing product improvement, greater personalisation and potentially interconnectivity between products. There could also be concerns if AI services are sold as part of a bundle or accessed through ecosystems with locked-in consumers, for example if suppliers start with open systems and then close them over time.

AI adoption could reshape downstream competition dynamics, lowering barriers in some markets while raising concentration and collusion risks in others

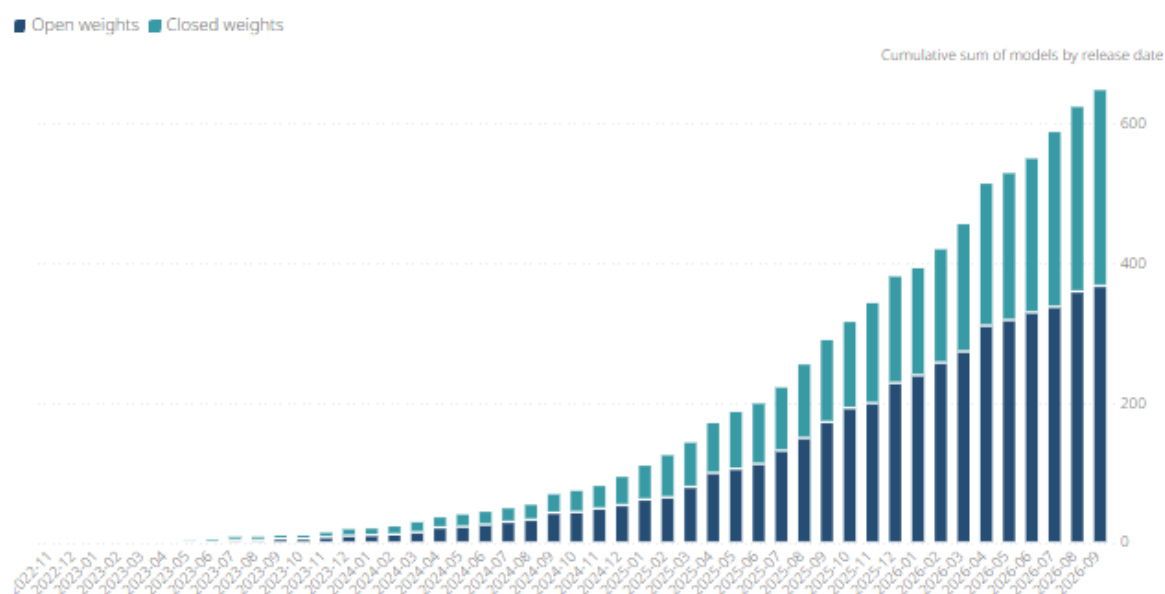
60. Beyond the competitiveness of AI markets themselves, the adoption of AI has the potential to reshape competition in downstream markets that use AI as an input into areas like production, service delivery, logistics and customer engagement. While AI is impacting nearly every sector of the economy, the effects of AI on competition downstream are mixed and it is too early to assess its overall impact (OECD, 2025^[51]). It is likely that the overall effects will vary by sector, with AI promoting competition in some markets while potentially lessening it in others. Effects may also be mixed within the same market, as differences in firms' ability to access, adopt and benefit from AI may create competitive advantages for some firms and disadvantages for others. Beyond these effects of AI adoption itself, competitive conditions in upstream AI markets, including in the supply of AI models, may also influence competition in downstream markets.

61. On the one hand, AI may actually *support* competition in downstream markets, for example by lowering barriers to entry. This includes reducing minimum efficient scale and enabling product differentiation and innovation, through its effects on augmenting productivity and reducing costs. Its ability to enhance consumer search processes, such as through the use of recommender systems or AI agents, may further enhance competition by reducing search costs and frictions (OECD, 2025^[51]) and lead to potential benefits for consumers through greater choice. Open-weight AI model and open-source AI tools may also help to foster a competitive environment and contribute to innovation by enabling greater access to experimentation, facilitating knowledge diffusion and expanding participation in AI development (OECD, 2025^[52]; OECD, 2026^[50]). Analysis of open-weight models finds that releasing weights can lower entry barriers, widen access to capabilities, support sensitive-data management, and broaden participation by

enabling collaboration and skills development, including by start-ups and SMEs. This, in turn, can spur AI applications tailored to diverse languages and contexts, strengthening competition (OECD, 2025^[52]; OECD, 2026^[50]). In the past several years, the number of available open weight generative AI models and generative AI foundation models has exceeded the number of closed weight models (Figure 2).

Figure 2. Open-weight generative AI models now outnumber closed-weight models

Cumulative number of generative AI models, November 2021 to mid-September 2026



Note: Open weights indicate that the trainable weights – the values the model adjusts during training to make more accurate predictions – are available for download for local deployments. The models included in this dataset are those available from cloud-service providers. While the list is not exhaustive, Artificial Analysis attempts to capture all models that are commonly used or interesting to AI users and practitioners. Data downloads provide a snapshot in time. Caution is advised when comparing different versions of the data. Please see the [methodological note](#) for more information.

Source: OECD.AI (2026), data from Artificial Analysis, last updated 2026-09-15, accessed on 2026-09-15, <https://oecd.ai/>

62. On the other hand, AI may also *reduce* competition in downstream markets. This can result, for example, from issues related to data access for downstream adopters, particularly in sectors where data is hard to access or replicate. Such dynamics allow existing providers to leverage valuable data (e.g. customer or proprietary data) to adapt AI systems in unique ways to reduce costs or differentiate their products. This highlights general risks that new entrants may face in their ability to leverage AI tools on a level-playing field with existing providers. Significant first-mover advantage could also affect competition dynamics if early adopters of AI are able to establish strong market positions that result in firm exit and barriers to entry create obstacles to competition being restored over the longer term.

63. There are also concerns linked to how the adoption of AI tools could lead to algorithmic collusion (OECD, 2025^[53]). In sectors like travel, entertainment, retail, and platform-based service, an increasing number of firms have transitioned to algorithmic pricing mechanisms facilitated by AI tools. This involves the use of automated price-setting to optimise pricing decisions - often in real-time - in response to evolving market conditions. This has the potential to change market dynamics, raising possible competition, consumer protection and data privacy issues, particularly regarding the legality of price discrimination and collusion practices (OECD, 2025^[53]).

Efforts to measure AI competition dynamics show increasing AI model choice and falling prices, while acknowledging potential bottlenecks in compute, data and skills

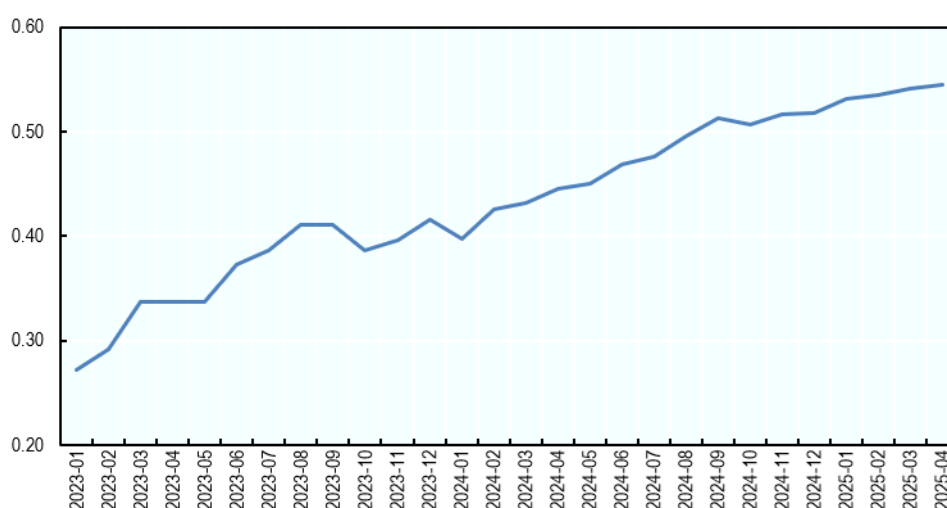
64. Measuring evolving competition dynamics across the AI value chain and in AI users is a growing area of OECD expertise to help inform decision making by relevant authorities and policymakers. Product Market Indicators and related metrics for AI can give competition authorities earlier signals of concentration, bottlenecks and exclusionary conduct, equipping them with evidence to inform policy action.

65. Recent OECD work presents a novel data collection approach using indicators based on AI foundation model characteristics, prices and providers (André et al., 2025^[48]). It identifies several trends that are indicative of current dynamism, eventually conducive to faster adoption by potential users.⁷ First, the number of available AI foundation models has risen rapidly, with such models developed by an increasing number of companies and offering several interaction modalities (e.g. text, voice, image). Second, using common industry benchmarks to evaluate AI models' performances and collecting AI-related prices from cloud providers, it constructs an *AI Economic Frontier* by identifying, each month, the best models in terms of the price-performance trade-off.

66. As illustrated by Figure 3, which shows the quality evolution of text-to-text models, the performance of generative AI models has continued to improve rapidly since 2023, with successive generations of models reaching markedly higher scores on commonly used evaluation benchmarks. In addition, the developers and models that make it to the technological frontier have been changing: about a third of models at the frontier have been replaced every month by cheaper and better-performing models.

Figure 3. Generative AI model quality has improved steadily in recent years

Average quality (performance) of text-to-text generative AI models, January 2023 to April 2025



Note: The quality index reflects how well a model performs a task, based on standard benchmarks. Please see the [methodological note](#) for more information.

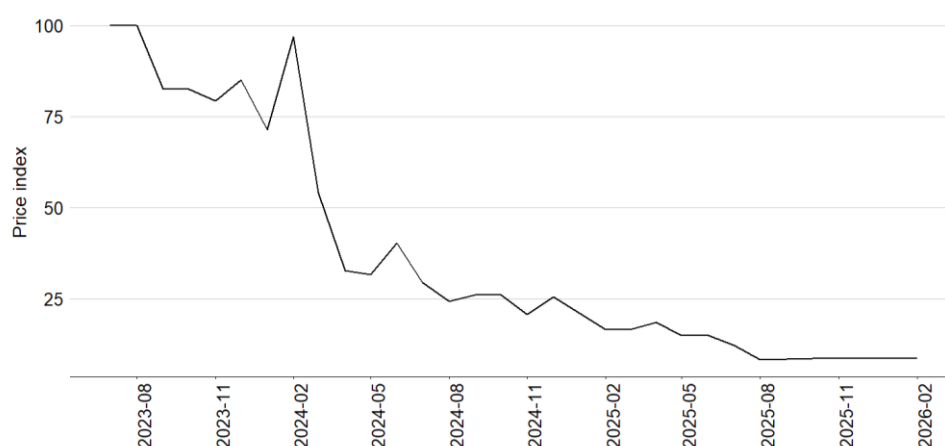
Source: OECD.AI (2026), data from AI knowledge on Demand (AIKOD) database, last updated 2025-10-31, accessed on 2026-09-15, <https://oecd.ai/>

67. Third, the quality-adjusted AI price index developed by the paper has fallen by 90% on average in between 2023 and 2026 (Figure 4.). Notwithstanding the favourable developments in terms of dynamism in model offerings, this work acknowledges several looming risks such as bottlenecks in the key inputs to

AI, notably compute, data and skills. Moreover, the overall cost of AI adoption goes beyond the price of accessing AI models, as effective integration in business processes may require organisational changes and upgrading managerial practices and skills, harvesting new data - and rising AI usage intensity. Indeed, more recent agentic systems use substantially more computing power and hence cost more to operate than chatbot type usage (OECD, 2026^[54]).

Figure 4. AI model prices have been falling on average by 90% since June 2023

The evolution of the quality-adjusted AI price index (normalised to 100 in the starting period)



Note: The index represents the evolution (starting in June 2023) of the quality-adjusted price of using AI models from the cloud. See more details in the source.

Source: Updates based on André et al. (2025), "Developments in Artificial Intelligence markets: New indicators based on model characteristics, prices and providers", <https://doi.org/10.1787/9302bf46-en>.

68. The relationship between AI and competition is complex and depends on both the type of AI technology and the firms involved in its development and use. To better understand these dynamics, recent OECD work develops a framework for analysing competition across the AI value chain and presents new cross-country evidence on AI adoption, innovation and market structure. The analysis points to both pro-competitive opportunities, particularly for innovative and younger firms, and emerging competition concerns that warrant continued monitoring. Further details are presented in Box 2.

Box 2. Measuring competition among firms in the age of AI: initial evidence from microdata

Recent OECD work proposes a conceptual framework to analyse the links between AI and competition, distinguishing among different actors in the AI value chain and among various types of AI technologies. The framework distinguishes between AI systems based on traditional statistical AI methods and newer AI systems that generate content (i.e. generative AI), and between AI users and AI developers. This is particularly relevant as competition mechanisms can differ across these dimensions. The analysis provides initial empirical evidence, drawing on microdata sources across countries and focusing on downstream actors in the AI value chain.

Users leveraging traditional statistical AI methods (non-generative) do not appear to realise greater market power, at least on average in the early period observed. However, there is an association between firms engaged in AI-related patenting activity and higher growth, particularly in the ICT sector, where AI is often a core output. When it comes to generative AI, such tools can offer opportunities for smaller and younger firms, but the benefits may be more easily unlocked by firms with higher digital capabilities (e.g. possessing advanced skills, access to data and compute). When it comes to AI start-ups, the analysis points to a relatively dynamic ecosystem, with sustained entry and venture capital (VC) investments, though intense acquisition activity by incumbents may warrant attention from competition authorities regarding potential impacts on future innovation and competition.

Note: This analysis covers both AI model developers, application developers and deployers (including AI patenting firms) in addition to firms using AI downstream in the AI value chain (i.e. actors who have adopted AI).

Source: OECD (2026), "Competition in the age of AI: Initial evidence from microdata", <https://doi.org/10.1787/6f88a1ea-en>.

Public procurement can support competitive dynamics in AI markets

69. Public procurement strategies can directly shape market access and competitive dynamics, with spillover effects on innovation, service quality and value for money for governments. Supporting competition in public tenders is therefore a multi-dimensional endeavour, underpinned by the core principles set out in the OECD Recommendation on Public Procurement (OECD, 2015^[55]; OECD, 2025^[56]).

70. Beyond ensuring efficiency and compliance, public procurement can act as a powerful demand side policy tool, allowing governments – through early market engagement, aggregation of demand and outcome-oriented specifications – to shape incentives for AI suppliers and influence market structure. The OECD highlights procurement as a critical governance mechanism for AI adoption in the public sector and highlights the need for safeguards, transparency, and accountability in AI-enabled procurement processes (OECD, 2025^[57]).

71. When procuring AI products and services, governments operate in markets characterised by rapid technological change, information asymmetries between suppliers and buyers, and the growing importance of proprietary data, models and other complementary assets. Combined with high switching costs and questions around data ownership, these factors can undermine competition. These dynamics underline the need for procurement frameworks to preserve competition throughout the lifecycle of AI systems, including through clearly specified requirements, the use of supplier frameworks or trusted vendor lists, and contractual conditions on data access and intellectual property that keep future competition viable. Such approaches can strengthen contestability in AI markets, reduce vendor lock-in, support the participation of innovative firms and SMEs, and facilitate the broader diffusion of AI technologies across the economy.

Key policy considerations for AI and competition

72. **Interoperability, clear and fair access conditions for key inputs like AI compute and enhancing transparency and portability to reduce switching costs and lock-in risks can promote effective competition across the AI value chain.** Fully realising AI's economic benefits requires effective competition across the AI value chain, particularly between upstream providers of AI infrastructure, cloud services, foundation models, applications and deployment solutions, as well as among downstream firms adopting AI. Measures that promote or enable interoperability, including at the orchestration and integration layers, alongside clear access conditions and greater transparency regarding compatibility, including through open-source solutions where appropriate, can enhance portability, lower switching costs, and reduce unnecessary technical and contractual barriers.,

73. **Adequate resources, updated tools and technical expertise can support the timely, proportionate and innovation-friendly enforcement in global AI markets.** To assist competition authorities in continued monitoring efforts, tools of competition authorities must keep pace while being mindful of fostering innovation. As technologies evolve, conventional competition indicators may not sufficiently capture all competitive dynamics in an AI age. Ensuring timely and proportionate competition enforcement that leverages lessons from previous cases is also vital, alongside the use of complementary tools such as market studies, providing data and analysis to diagnose and improve competitive conditions. Given the importance of effective competition in AI and downstream markets, it will be important for policymakers to also ensure that national competition authorities continue developing technical expertise and are sufficiently resourced to develop, attract and retain the necessary skills to monitor competition as AI evolves.

74. **Aligning competition policy and AI policy frameworks supports complementarity and avoids regulatory overlap or gaps.** Competition policy will need to seek complementarity and alignment with other AI governance efforts, such as those related to labour markets, data protection and privacy, public procurement, intellectual property rights, cybersecurity and online safety, amongst others, to avoid regulatory overlap, gaps or undue burdens that could disincentivise innovation. AI policy action, in turn, will benefit from considering competition to avoid potential negative impacts on innovation and productivity growth. AI policy can also work to promote competition, for example by facilitating an enabling environment for key AI inputs like data, compute and skills.

75. **By working together, competition authorities can facilitate international co-operation to tackle shared challenges and leverage lessons learned.** Given the global nature of AI markets, and in particular AI infrastructure and models, there are likely to be many interdependencies across jurisdictions. Cross-border co-operation and knowledge sharing can help competition authorities respond effectively to developments, allowing authorities to learn from each other and jointly tackle shared issues. This could include also considering how AI-based tools could support effective competition policy. Continued active participation in international fora, such as the OECD and International Competition Network, can aid in this regard.

AI and work

76. One of the most visible ways in which AI affects the economy is through its impact on jobs. AI is expected to have a profound impact on labour markets, by changing the tasks that workers perform, how they perform them, and the skills they require. Recent evidence suggests that AI is more likely to transform tasks within jobs rather than fully automate occupations, with effects varying across tasks and skill levels. AI is already delivering significant benefits in the workplace, such as improved productivity and higher quality and safer work. However, it can also lead to task automation, job transitions and changes in job quality, risks to occupational safety and health, and growing disparities between workers, amongst others.

77. Successful adoption of AI in the workplace requires identifying and addressing potential adverse impacts on workers throughout the AI lifecycle, including on working conditions, data protection and fairness. Outcomes for both workers and employers are likely to improve when workers or their representatives are meaningfully consulted and engaged throughout the design, implementation and use of AI systems, including with respect to their potential impacts on tasks, working conditions and job quality consistent with the OECD AI Principles (Principle 1.1). Outcomes are also likely to improve when workers have been trained and have the right skills to work with AI.

78. This section examines AI's effects on job quantity, job quality, and how these impacts vary geographically, between small and large firms, as well as between workers. It considers the specific challenges faced by Small and Medium-sized Enterprises (SMEs) across urban and non-urban contexts, and reviews recent policy responses across OECD countries, highlighting what is working to spread opportunities, protect workers and support smooth transitions. While such results point to performance gains in specific tasks, broader firm-level productivity impacts remain uneven and are still emerging.

Workers and employers tend to be positive about the impact of AI on decision-making and performance

79. Workers and employers tend to be positive about the impact of AI on performance. Four in five workers in manufacturing and finance said that AI had increased their performance either a little or a lot, and three in five employers in those sectors were positive about AI's overall impact on work (Lane, Williams and Broecke, 2023^[58]). Similarly, around two thirds of SMEs using generative AI reported that it helped increase employee performance within the company (OECD, 2025^[59]). That being said, the evidence suggests that while, so far, while AI's breadth of application is wide - i.e. it touches many occupations - its depth remains limited, with only a small share of tasks affected in most occupations. This may help explain why the impact of AI on work organisation and, therefore, on productivity at an aggregate level, have so far has been limited (OECD, Forthcoming^[60]).

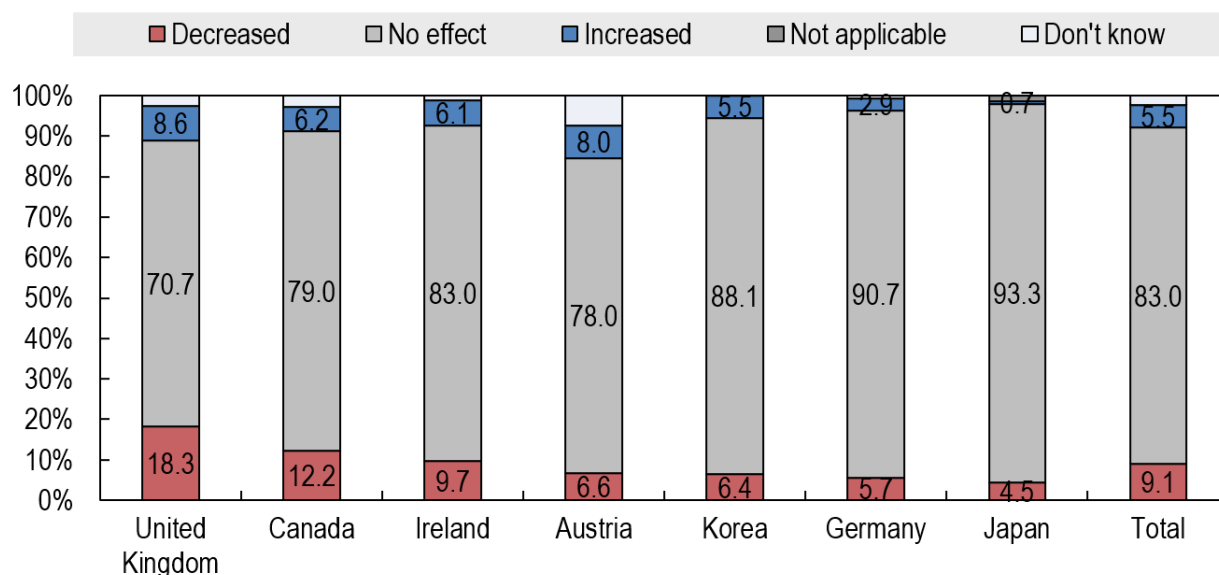
80. AI also supports, informs or speeds up decisions by workers and their managers, especially by improving access to information and analysis. 60% of mid-level managers report that algorithmic management tools (i.e. software to automate managerial tasks, such as giving instructions to workers, monitoring and evaluating them) increase the quality of managerial decisions. These benefits depend significantly on how AI tools are integrated into workflows and how workers interact with them in practice.

81. AI can also be used to address labour shortages and skill gaps. Nearly two in five SMEs report worker shortages in the past two years, while a third report a lack of skills or experience. Of these, nearly 40% say that generative AI helps compensate for the skills gap, and a quarter said it helps compensate for worker shortages (OECD, 2025^[59]).

82. While employers generally acknowledge that improving worker performance and reducing staff costs are among the primary reasons for adopting AI, more than half of employers in manufacturing and finance say that AI has not (yet) had an impact on employment (Lane, Williams and Broecke, 2023^[58]), and roughly one quarter say that AI has decreased employment, only slightly more than the share reporting an increase. Most SMEs using generative AI report that it had no effect on the overall number of staff their company needed (Figure 5). New 2026 OECD surveys suggest that 10% of AI-adopting firms have reduced headcount over the past year – a similar share to non-adopting firms – and only 10% of those attribute the headcount reduction mainly to AI (OECD, Forthcoming^[61]). These patterns reflect the fact that most AI adoption to date has focused on augmenting existing work rather than large-scale workforce restructuring.

Figure 5. Most SMEs report generative AI has had no effect on overall staff need (yet)

% of SMEs that report generative AI decreased, had no effect or increased the overall number of staff needed, by country, 2024



Note: SMEs using generative AI were asked: "Can you tell me whether the use of generative AI within your company has increased or decreased or had no effect on the overall number of staff your company needs?".

Source: OECD (2025), *Generative AI and the SME Workforce: New Survey Evidence*. <https://doi.org/10.1787/2d08b99d-en>.

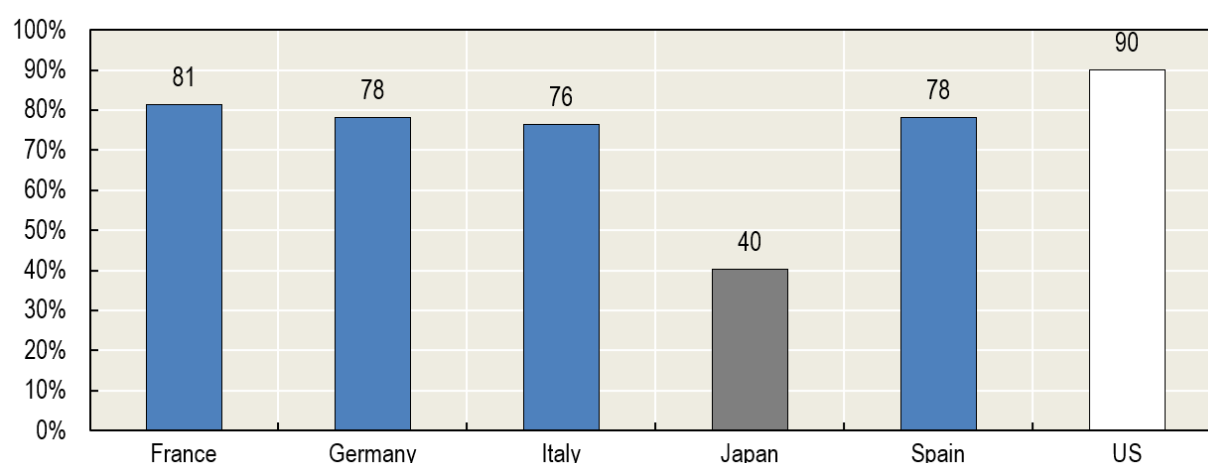
AI may not lead to massive job destruction, but it will change workers' tasks and how they are managed

83. AI continues to automate specific tasks within jobs, particularly routine activities, such as simple customer-service queries, as well as more complex but codifiable tasks such as optimising delivery routes and drafting standard e-mails and reports. Many jobs involve tasks that could be affected by AI and other advanced technologies. However, exposure to AI varies considerably both across and within occupations, reflecting differences in the tasks workers perform. Current AI capabilities are closest to occupations characterised by routine information-processing and administrative tasks (OECD, 2026^[62]). Workers continue to express concerns about how AI may affect their roles and job security. This reinforces the importance of analysing AI impacts at the task level rather than at the level of entire occupations.

84. While most jobs are unlikely to disappear entirely, they will almost certainly undergo change: AI will automate some tasks, it will create new tasks, and it will affect the distribution of tasks within jobs. The balance between automation, augmentation and new task creation varies significantly across occupations and worker groups. AI will also change how workers are managed. Recent developments point to a rapid expansion in the use of data-driven management and monitoring tools, raising new questions around transparency, worker autonomy and control. OECD evidence suggests that algorithmic management tools – i.e. tools that automate managerial tasks such as giving instructions to workers, monitoring and evaluating them – are already widely used across a number of countries (Figure 6) (Milanez, Lemmens and Ruggiu, 2025^[63]).

Figure 6. The use of algorithmic management tools is already the norm in many countries

Percentage of managers whose firms provide at least some form of algorithmic management software, 2024



Note: Managers were asked whether their firms have adopted software to partially or fully automate different tasks. Firms are identified as adopters of algorithmic management tools if respondents indicate that their firms use any of the software use cases identified. Algorithmic management is defined as the use of technological tools which may include AI, to fully or partially automate tasks traditionally carried out by human managers, such as giving instructions to workers, monitoring, and evaluating them.

Source: Milanez, Lemmens and Ruggiu (2025), *Algorithmic management in the workplace: New evidence from an OECD employer survey*, <https://10.1787/287c13c4-en>.

To make the most of the adoption of AI in the labour market, countries, employers and workers must adjust to changing skill needs

85. Foundational skills (literacy, numeracy, problem-solving) are a prerequisite for the effective uptake and use of more advanced digital technologies (OECD, 2026^[64]). Workers require a combination of digital, social and managerial skills to work effectively with AI systems, rather than only specialised AI skills (OECD, 2025^[59]; Milanez, Lemmens and Ruggiu, 2025^[63]; OECD, 2026^[64]). The demand for data literacy, ICT skills and creativity and innovation skills increases most following AI adoption (OECD, 2025^[59]; Milanez, Lemmens and Ruggiu, 2025^[63]).

AI can improve job quality, depending on AI system design and deployment

86. AI can have a positive impact on the quality of jobs. More than half of workers using AI in the manufacturing and finance sectors report that AI has improved their enjoyment of work (63%) and mental health (55%), either by a little or by a lot. This positive impact of AI on the quality of jobs could be particularly important in the context of population ageing, as it could help extend people's active working lives.

87. Well-designed AI systems can help improve performance and support more evidence-based decision-making in the workplace through the analysis of data on workers and job applicants. Nevertheless, outcomes depend on how AI systems are designed, deployed and governed. When they rely on selective, incomplete or biased datasets, or where there is limited capacity to interpret and use the information provided by AI, their use may increase risks relating to occupational safety and health, discrimination and privacy. More than a quarter of mid-level managers have concerns about the inability to follow the logic of algorithmic decisions or recommendations and inadequate protection of workers' physical and mental health. More than one in five workers do not trust their employer to only use AI that is safe and trustworthy (Lane, Williams and Broecke, 2023^[58]). Most workers in manufacturing and finance who report AI-related data collection express concerns about data collection, with around three in five

workers agreeing (strongly or somewhat) they feel increased pressure to perform at work due to data collection, and over half worrying about their privacy (Lane, Williams and Broecke, 2023^[58]). At the same time, increased data collection and monitoring enabled by AI systems may intensify performance pressures and reshape workplace dynamics. There is some evidence that AI may increase work intensity, for example by automating routine tasks and increasing the share of complex tasks in a job. However, work intensification does not necessarily result in a reduction in job quality as it may also provide greater job satisfaction (Lane, Williams and Broecke, 2023^[58]).

AI's benefits and risks at work are not evenly distributed and impacts also differ within occupations, depending on workers' skills, experience and access to AI tools

88. If implemented with appropriate safeguards in place, AI could benefit some workers traditionally underrepresented in the labour market (OECD, 2024^[65]), as well as boost the performance of the least experienced or the lowest performing workers. For instance, many AI-powered solutions have been developed that can support people with disability (Touzet, 2023^[66]). Such tools can provide workarounds for disability (such as live captioning for individuals who are deaf, or speech recognition algorithms for people with dysarthric speech) or address disabilities directly (such as gait-correction prosthetics, or mental health conversational agents). When asked about which groups would benefit from AI, nearly half of employers identified workers with disabilities (Lane, Williams and Broecke, 2023^[58]). AI tools that address skewed outcomes from AI systems have also been developed.⁸

89. At the same time, low-skilled and young workers remain at a higher risk of automation (Lassébie and Quintini, 2022^[67]; Brynjolfsson, Chandar and Chen, 2025^[68]), and employers believe that both low-skilled and older workers are most likely to be negatively impacted by AI (Lane, Williams and Broecke, 2023^[58]). AI may be contributing to the worsening unemployment rates of young graduates, with nearly half of AI-adopting firms who had experienced headcount reductions due to AI saying that entry level jobs were more affected than others. However the share of AI-adopting firms reducing headcount due to AI remains low (less than 3%) (OECD, Forthcoming^[61]) and the evidence suggests that the worsening labour market situation of young graduates is a long-term trend that predates the advent of generative AI (OECD, 2026^[69]). In addition, AI users with a university degree are more positive than those without about the impact of AI on their performance and working conditions.

90. There is a risk that those without tertiary education, female and older workers lose out due to lower access to AI-related employment opportunities and to productivity-enhancing AI tools in the workplace (Lane, 2024^[70]). Differences in AI use between men and women can be driven by occupational segregation, with men in technology roles granted a first-mover advantage. However, even within the same occupations, women are less likely to use AI than men. Other explanations include the concentrations of premium AI tool licenses among firm leaders and management roles (where women are underrepresented); and a lack of time available to part-time workers (disproportionately women), which serves to limit the experimentation and training through which AI competence develops (OECD, Forthcoming^[71]). Smaller firms (and their workers) use AI to a lesser extent than larger firms and are therefore less able to benefit from AI (OECD, 2025^[59]). Finally, AI could alter the balance of bargaining power in favour of employers as it creates information asymmetries and increases the threat of automation (OECD, 2023^[72]).

Labour market exposure to generative AI varies sharply across regions within countries

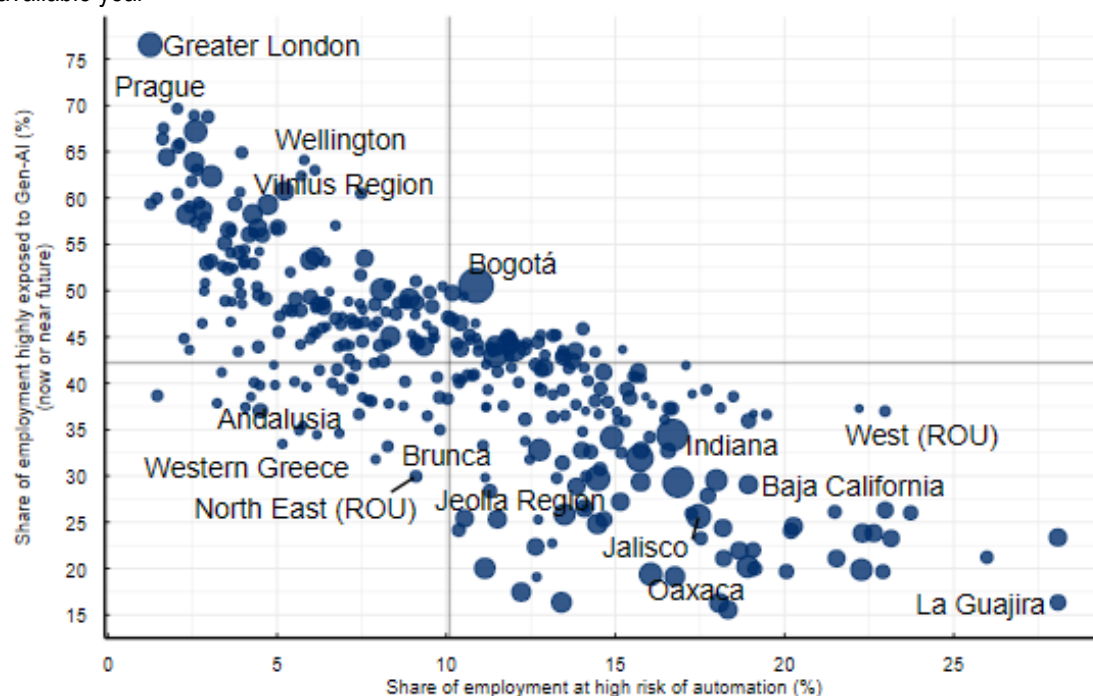
91. Beyond geographic differences in firm AI adoption, the labour-market effects of AI will also vary considerably across regions. Importantly, the geography of generative-AI exposure differs from that of previous waves of automation. For instance, regions with a higher share of workers expected to be highly exposed to generative AI tend to have a lower share of workers at high risk of automation from automating technologies more generally (Figure 7). While higher exposure to generative AI should not be equated with

a high risk of automation (as AI may complement workers and improve their productivity rather than replace them) this suggests that the nature of the risks may vary considerably across regions.

92. Gaps between regions in exposure to generative AI – i.e. the share of workers who will have to interact with generative AI and could be either automated or augmented by it - are stark: the share of workers expected to be highly exposed in the near future ranges from 16% in Guerrero (Mexico) to 77% in Greater London (United Kingdom) (Figure 7). On average, the gap between regions within countries is around 14 percentage points, with the most exposed region 1.6 times more exposed than the least exposed region. In some countries, gaps are even greater, with the most exposed regions more than three times as exposed as the least exposed. These differences imply that the scale and nature of labour-market adjustment needs will also vary substantially within countries.

Figure 7. Regions with a low risk of automation are now highly exposed to generative AI, and vice-versa

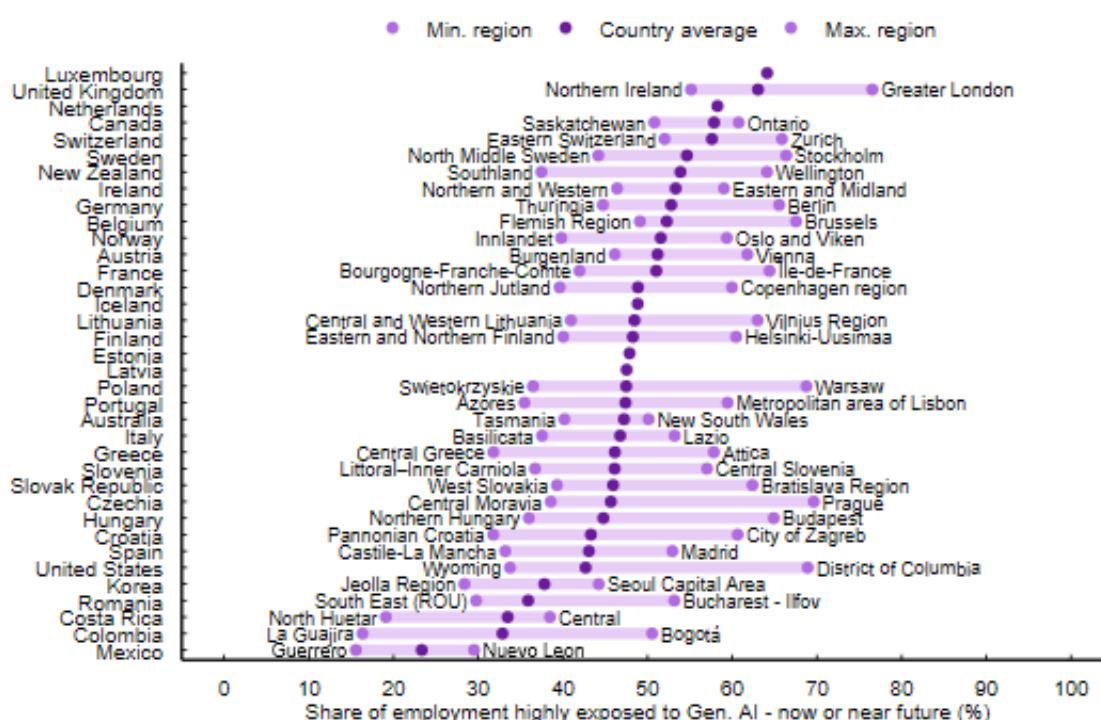
Share of employment highly exposed to generative AI now or in the near future and at high risk of automation, latest available year



Note: Horizontal and vertical lines represent unweighted regional averages. Size of bubble represents labour market size (employment). Estimates for TL-2 regions except for Slovenia which is TL-3. Last available year is 2024 for Canada and Korea, 2023 for Australia, Colombia, Costa Rica, Mexico, New Zealand, the United Kingdom, and the United States, 2022 for all others.
Source: OECD (2024), *Job Creation and Local Economic Development 2024: The Geography of Generative AI*, <https://doi.org/10.1787/83325127-en>.

Figure 8. Labour market exposure to generative AI could range from 16% to 77% across regions

Share of employment highly exposed to generative AI now or in the near future, latest available year



Note: Estimates for TL-2 regions except for Slovenia which is TL-3. Last available year: 2024 for Canada and Korea, 2023 for Australia, Colombia, Costa Rica, Mexico, New Zealand, the United Kingdom, and the United States, 2022 for all others.

Source: OECD (2024), *Job Creation and Local Economic Development 2024: The Geography of Generative AI*, <https://doi.org/10.1787/83325127-en>.

93. Regional exposure alone will not determine labour-market outcomes. The capacity of workers and local labour markets to adjust will also matter. Regions differ in their skills profiles, occupational and sectoral structures, and access to opportunities for training and reskilling. As a result, similar levels of exposure to AI may have different consequences across places: regions with stronger skills bases and adjustment capacity may be better positioned to realise the benefits of AI, while those with weaker capacity may face greater risks of workers being left behind. These differences reinforce the case for tailoring labour-market and skills policies to local conditions.

Key policy considerations for AI and work

94. AI is a transformative technology that is reshaping jobs, workplaces and the lives of workers across OECD countries. Managing this change requires future-ready and resilient labour markets, supported by skills policies, social dialogue, place-based approaches and governance frameworks that ensure all workers and their families benefit from the opportunities created by technological change. This section points to a wide range of policy measures that countries can adopt to spread AI's benefits, protect workers and support smooth labour market transitions.

95. **Skills development, training and lifelong learning policies can help workers and jobseekers adapt to AI-driven changes in labour markets, including through:** monitoring skills trends and delivering training through dedicated centres; updating certification and skills frameworks to reflect AI; financial support for AI-related training; and creating programmes to equip workers and jobseekers with the skills needed to use AI, across different age groups, educational levels and sectors. The United States, for instance, recently launched America's AI Action Plan, which includes a focus on expanding AI literacy and skills development, and rapidly retraining and helping workers thrive in an AI-driven economy.

96. **Monitoring labour market impacts and supporting worker transitions can help maximise the benefits of AI while mitigating disruption, including through:** monitoring labour market impacts across workers and regions; targeting upskilling and reskilling for jobseekers, people affected by mass lay-offs and those most exposed to AI; supporting research and experimentation to increase AI adoption; supporting SMEs in AI adoption, including AI-as-a-service models; and promoting AI adoption guidelines for the workplace aligned with international standards and human-centred principles. In Canada, the AI Assist programme – an initiative by the National Research Council of Canada Industrial Research Assistance Program – supports SMEs in developing generative AI and deep learning solutions safely and ethically.

97. **Privacy, data protection and non-discrimination safeguards can support trustworthy AI use in the workplace,** including through: establishing safeguards for data protection and privacy; implementing measures to improve data quality for reliable and responsible AI deployment; developing regular monitoring mechanisms; updating existing frameworks; and issuing practical guidance on trustworthy AI at work. In France, the *Commission Nationale de l'Informatique et des Libertés* (CNIL) – the data protection authority – is consulting stakeholders to develop sector-specific recommendations that provide greater legal certainty on privacy issues.

98. **Occupational safety and health measures can help ensure that AI is deployed in ways that protect worker well-being,** including through: supporting the development of AI and robotics tools to enhance occupational safety and health; embedding AI into labour and safety frameworks; encouraging employers to conduct risk and impact assessments to safeguard occupational safety and health in AI-enabled workplaces; and monitoring and raising awareness of AI implications for occupational safety and health. In Italy, the Istituto Italiano di Tecnologia is developing AI-based robotics, such as exoskeletons, to reduce workplace health and safety risks.

99. **Transparency, explainability, accountability and risk-management measures can support the responsible adoption of AI in workplaces,** including through: promoting transparency, human oversight and traceability measures; providing self-assessment tools to support businesses in strengthening AI governance practices; and promoting risk management frameworks to identify, assess and mitigate AI-related risks proportionate to their impact. Japan's AI Guidelines for Business (Version 1.1) emphasise transparency, explainability and accountability as do the OECD AI Principles, the HAIP Reporting Framework and relevant tools from the OECD.AI catalogue of tools and metrics. These approaches are increasingly reflected in responsible business conduct and due diligence frameworks, which support organisations in identifying, preventing and mitigating adverse impacts throughout the AI lifecycle.

100. **Social dialogue can help anticipate, manage and distribute the impacts of AI on workers and workplaces,** including through: implementing national strategies that embed social dialogue as a principle in AI adoption and use; and encouraging consultation with social partners at different levels, from national-level consultations to workplace practices. In Germany, the Works Constitution Act gives works councils rights to participate in workplace organisation and occupational health and safety, including through digitalisation committees that review the introduction or major modification of technologies.

101. **Policies tailored to local exposure, readiness and infrastructure can support more inclusive AI adoption and labour market transitions.** In regions and activities with high exposure to AI and strong readiness for uptake, policy will need to focus on enabling safe and productive adoption, for example by providing targeted advice and support to SMEs to identify and deploy appropriate AI tools, and support to reskill workers as their jobs change or guide job transitions. Policy efforts will also need to support the diffusion of AI to regions that currently lag behind in AI uptake, by tackling barriers such as limited digital connectivity, smaller skills pools, and more limited networks and support for digital entrepreneurship.

102. **Local institutions and innovation ecosystems can help firms, particularly SMEs, build the capabilities needed to adopt and benefit from AI.** While national AI agencies and strategies provide

direction, regional and local authorities are well placed to manage targeted adoption programmes, particularly for SMEs. Strong local ecosystems anchored by universities, research centres, business associations and intermediaries can help firms build the technical and organisational capabilities needed to adopt AI, through training, mentorship, pilot projects and peer learning. Such place-based networks are particularly important in extending AI benefits beyond frontier firms and leading regions.

Annex: AI key terms and topics informing this analysis

This list draws on key terms, used to inform this analysis, included in published OECD work. The descriptions and definitions included in this analysis are context dependent and may thus vary according to the context of use.

Term	Description
Artificial intelligence system	“a machine-based system 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. Different AI systems vary in their levels of autonomy and adaptiveness after deployment” (OECD, 2024 ^[11]).
AI system lifecycle	An AI system lifecycle typically involves several phases that include to: plan and design; collect and process data; build model(s) and/or adapt existing model(s) to specific tasks; test, evaluate, verify and validate; make available for use/deploy; operate and monitor; and retire/decommission. These phases often take place in an iterative manner and are not necessarily sequential. The decision to retire an AI system from operation may occur at any point during the operation and monitoring phase (OECD, 2024 ^[13]).
AI system inputs	Input is used both during development and after deployment. Input can take the form of knowledge, rules and code humans put into the system during development or data. Humans and machines can provide input. During development, input is leveraged to build AI systems, e.g., with machine learning that produces a model from training data and/or human input. Input is also used by a system in operation, for instance, to infer how to generate outputs. Input can include data relevant to the task to be performed or take the form of, for example, a user prompt or a search query” (OECD, 2022 ^[73]). Training data and inputs differ from prompts, although prompts can also be considered a form of input to AI models at the inference stage during model use.
AI system outputs	“The output(s) generated by an AI system generally reflect different functions performed by AI systems. AI system outputs generally belong to the broad categories of recommendations, predictions, and decisions. These categories correspond to different levels of human involvement, with “decisions” being the most autonomous type of output (the AI system affects its environment directly or directs another entity to do so) and “predictions” the least autonomous. For example, a driver-assist system might “predict” that a pixel region in its camera input is a pedestrian; it might “recommend” braking, or it might “decide” to apply the brake. Generative AI systems that produce “content” —including text, image, audio, and video—have gained significant momentum. Although one could, for example, view the generation of text as a sequence of decisions to output particular words (or predictions of words that would be likely to appear in a specific context), content generation systems have become such an important class of AI systems that they are included as their own output category” (OECD, 2024 ^[13]).
Algorithm	Algorithms are used to develop models (e.g., with reasoning and decision-making algorithms) based on machine and/or human inputs/data (OECD, 2024 ^[13]). There are three major categories of AI algorithms: supervised learning, unsupervised learning, and reinforcement learning. The key differences between these algorithms are in how they are trained, and how they function. More recently, self-supervised and semi-supervised learning have emerged as AI systems that vary in levels of autonomy.
Symbolic AI / Rules-based AI	“Symbolic AI uses logical representations to deduce a conclusion from a set of constraints. It requires that researchers build detailed and human-understandable decision structures to translate real world complexity and help machines arrive at human-like decisions. Symbolic AI is still in widespread use, e.g. for optimisation and planning tools” (OECD, 2019 ^[74]).
Statistical AI	“Statistical AI, whereby machines induce a trend from a set of patterns, has seen increasing uptake recently. A number of applications combine symbolic and statistical approaches. For example, natural language processing (NLP) algorithms often combine statistical approaches (that build on large amounts of data) and symbolic approaches (that consider issues such as grammar rules)” (OECD, 2019 ^[74]).
Machine learning	“[A] branch of artificial intelligence (AI) and computer science which focuses on development of systems that are able to learn and adapt without following explicit instructions imitating the way that humans learn, gradually improving its accuracy, by using algorithms and statistical models to analyse and draw inferences from patterns in data” (EU-US Trade and Technology Council, 2023 ^[75]) The “learning” process using machine-learning techniques is known as “training”. A machine-learning technique called “neural networks”, and its further subset technique

	called “deep learning”, has enabled leaps in technological AI developments (OECD, 2019 ^[74]).
AI inference	“The concept of “inference” generally refers to the step in which a system generates an output from its inputs, typically after deployment. When performed during the build phase, inference, in this sense, is often used to evaluate a version of a model, particularly in the machine learning context” (OECD, 2024 ^[3]).
AI model	AI models are actionable representations of all or part of the external context or environment of an AI system (encompassing, for example, processes, objects, ideas, people and/or interactions taking place in context). AI models use data and/or expert knowledge provided by humans and/or automated tools to represent, describe and interact with real or virtual environments (OECD, 2022 ^[73]).
Foundation model	“Foundation models, sometimes referred to as or categorised under “general-purpose” AI models, are machine learning models that can be adapted to perform a wide range of downstream tasks, such as tasks involving text synthesis, behaviour prediction, image analysis and content generation (Bommasani, 2021 ^[76] ; Jones, 2023 ^[77]). Foundation models can be standalone or integrated into a variety of downstream AI systems and models, either directly or after additional training referred to as “fine-tuning.” There are two primary types of foundation models: generative models, which learn the patterns and distribution of input data to create new, plausible outputs (such as OpenAI’s GPTs), and discriminative models, which predict data labels by distinguishing between different classes in a dataset (like Google’s BERT) (OECD, 2022 ^[73]). It is important to note that not all generative or discriminative models qualify as foundation models” (OECD, 2025 ^[52]).
Generative AI models	“Generative AI models create new outputs (e.g., text, code, audio, images, video), often in response to prompts, based on their training data” (OECD, 2023 ^[78]).
AI language model	A model that can process, analyse or generate natural language text trained on vast amounts of data, using techniques ranging from rule-based approaches to statistical models and deep learning. Chatbots, machine translation and virtual assistants that recognise speech are applications. Not all language models are generative in nature, and they can be large or small (OECD, 2023 ^[78]).
Multimodal AI	AI that combines multiple types of data – such as data from text, image or audio – such as through machine-learning models and algorithms. Multimodal AI is key for AI research and applications such as in manufacturing and robotics (The Alan Turing Institute, 2023 ^[79]).
AI openness	AI openness exists on a spectrum. It is not binary but ranges from fully closed systems with restricted access to fully open models that permit unrestricted access, modification, and use. This spectrum encompasses various system components, including data, code, and documentation. Recognising this range is essential for understanding the policy implications of different levels of openness across these components (OECD, 2025^[52]). The term “open source” in AI has limitations and tends to lead to confusion. The term “open source” originates from software development and does not accurately describe AI systems. Unlike traditional software, AI “source code” may refer to inference code, training code, or both – and each can be made publicly available independently. Furthermore, AI models can have other critical components such as model weights and training data, which can also be shared or kept private (OECD, 2025^[52]).
Open-weight AI models	Foundation models with publicly available trained weights. These models can generate content and perform a variety of tasks across different applications. While licensing is an important aspect of the discussion surrounding the availability of AI models, recent OECD analysis has focused on open weights due to their growing relevance in policy discussions about the benefits and risks associated with these models (OECD, 2025 ^[52]).
Agentic AI	“Agentic AI refers to systems composed of multiple co-ordinated AI agents that can break down tasks, collaborate, and pursue complex objectives autonomously over extended periods. These systems are designed to operate in more open-ended, less predictable physical or virtual environments and to function with minimal human supervision” (OECD, 2026 ^[51]).
Adaptiveness	Typically related to AI systems based on machine learning that can continue to evolve after initial development. The system modifies its behaviour through direct interaction with input and data before or after deployment. Examples include a speech recognition system that adapts to an individual’s voice or a personalised music recommender system. AI systems can be trained once, periodically, or continually and operate by inferring patterns and relationships in data. Through such training, some AI systems may develop the ability to perform new forms of inference not initially envisioned by their programmers (OECD, 2024 ^[3]).
AI system autonomy	“...[T]he degree to which a system can learn or act without human involvement following the delegation of autonomy and process automation by humans. Human supervision can occur at any stage of the AI system lifecycle, such as during AI system design, data collection and processing, development, verification, validation, deployment, or operation and monitoring. Some AI systems can generate outputs without these outputs being explicitly described in the AI system’s objective and without specific instructions from a human” (OECD, 2024 ^[3]).
AI incident	“An AI incident is an event, circumstance or series of events where the development, use or malfunction of one or more AI systems directly or indirectly leads to any of the following harms: (a) injury or harm to the health of a person or groups of people; (b) disruption of the management and operation of critical infrastructure; (c) violations of human rights or a breach of obligations under the applicable law intended to protect fundamental, labour and intellectual property rights; (d) harm to property, communities or the environment” (OECD, 2024 ^[80]).
AI hazard	“An AI hazard is an event, circumstance or series of events where the development, use or malfunction of one or more AI systems could plausibly lead to an AI incident, i.e., any of the following harms: (a) injury or harm to the

	health of a person or groups of people; (b) disruption of the management and operation of critical infrastructure; (c) violations to human rights or a breach of obligations under the applicable law intended to protect fundamental, labour and intellectual property rights; (d) harm to property, communities or the environment" (OECD, 2024 ^[80])
AI compute	"AI computing resources ('AI compute') include one or more stacks of hardware and software used to support specialised AI workloads and applications in an efficient manner" (OECD, 2023 ^[81]).

References

- Aghion, P., B. Jones and C. Jones (2017), *Artificial Intelligence and Economic Growth*, National Bureau of Economic Research, Cambridge, MA, <https://doi.org/10.3386/w23928>. [32]
- André, C. et al. (2025), “Developments in Artificial Intelligence markets: New indicators based on model characteristics, prices and providers: New indicators based on model characteristics, prices and providers”, *OECD Artificial Intelligence Papers*, Vol. No. 37, <https://doi.org/10.1787/9302bf46-en>. [48]
- Beals, T. (2025), *Exploring a space-based, scalable AI infrastructure system design*, <https://research.google/blog/exploring-a-space-based-scalable-ai-infrastructure-system-design/> (accessed on 18 March 2026). [17]
- Bengio, Y. et al. (2026), *International AI Safety Report 2026*, <https://internationalaisafetyreport.org/publication/international-ai-safety-report-2026>. [39]
- Bommasani, R. (2021), *On the Opportunities and Risks of Foundation Models*, <https://doi.org/arXiv:2108.07258>. [76]
- Brynjolfsson, E., B. Chandar and R. Chen (2025), *Canaries in the Coal Mine? Six Facts about the Recent Employment Effects of Artificial Intelligence*, https://digitaleconomy.stanford.edu/app/uploads/2025/11/CanariesintheCoalMine_Nov25.pdf (accessed on 4 February 2026). [68]
- Brynjolfsson, E., D. Li and R. Lindsey (2025), “Generative AI at Work”, *The Quarterly Journal of Economics* 2, pp. 889–942, <https://doi.org/10.1093/qje/qjae044>. [36]
- Calvino, F., H. Costa and D. Haerle (2026), “Digital technology diffusion in the age of AI: Cross-country evidence from microdata”, *OECD Science, Technology and Industry Working Papers*, No. 2026/01, OECD Publishing, Paris, <https://doi.org/10.1787/ebc2debe-en>. [12]
- Calvino, F., J. Reijerink and L. Samek (2025), “The Effects of Generative AI on Productivity, Innovation and Entrepreneurship”, *OECD Artificial Intelligence Papers*, Vol. No. 39, <https://doi.org/10.1787/b21df222-en>. [35]
- Casper, S. et al. (2025), *The AI Agent Index*, <https://doi.org/10.48550/arXiv.2502.01635>. [10]
- Chaar, T. et al. (2025), “AI and the global productivity divide: Fuel for the fast or a lift for the laggards?”, *OECD Artificial Intelligence Papers*, Vol. No. 51, <https://doi.org/10.1787/c315ea90-en>. [34]
- Computaex (2025), *Centro de Supercomputación de Extremadura*, <https://www.computaex.es/>. [25]

- Cui, K. et al. (2026), “The Effects of Generative AI on High-Skilled Work: Evidence from Three Field Experiments with Software Developers”, *Management Science*, <https://doi.org/10.1287/mnsc.2025.00535>. [38]
- Edged US (2025), *MERLIN Properties and Edged Energy Partner With Spanish Regional Government of Extremadura To Build Two Gigawatt-Scale AI Data Center Campuses*, <https://www.edged.us/news/merlin-properties-and-edged-energy-partner-with-spanishregional-government-of-extremadura-to-build-two-gigawatt-scale-ai-data-center-campuses> (accessed on 14 March 2025). [23]
- Eloundou, T. (2024), “GPTs are GPTs: Labor market impact potential of LLMs”, *Science*, <https://www.science.org/doi/abs/10.1126/science.adj0998>. [30]
- Eurostat (2025), “Use of artificial intelligence in enterprises”, *Statistics Explained, European Commission*, <http://Statistics Explained, European Commission>, https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Use_of_artificial_intelligence_in_enterprises. [85]
- EU-US Trade and Technology Council (2023), *Terminology and Taxonomy for Artificial Intelligence*, <https://digital-strategy.ec.europa.eu/en/library/eu-us-terminology-and-taxonomy-artificial-intelligence>. [75]
- Filippucci, F. et al. (2026), “AI meets trade: Global linkages and the cross-country distribution of the gains from AI”, *OECD Artificial Intelligence Papers*, Vol. No. 57, <https://doi.org/10.1787/13081644-en>. [27]
- Filippucci, F. et al. (2025), “Macroeconomic productivity gains from Artificial Intelligence in G7 economies”, *OECD Artificial Intelligence Papers*, Vol. No. 41, <https://doi.org/10.1787/a5319ab5-en>. [29]
- Filippucci, F., P. Gal and M. Schief (2024), “Miracle or Myth? Assessing the macroeconomic productivity gains from Artificial Intelligence”, *OECD Artificial Intelligence Papers* No. 29, <https://doi.org/10.1787/b524a072-en>. [84]
- Filippucci, F., P. Gal and M. Schief (2024), “Miracle or Myth? Assessing the macroeconomic productivity gains from Artificial Intelligence”, *OECD Artificial Intelligence Papers*, No. 29, OECD Publishing, Paris, <https://doi.org/10.1787/b524a072-en>. [28]
- IEA (2026), *Key Questions on Energy and AI*, <https://www.iea.org/reports/key-questions-on-energy-and-ai>. [16]
- IEA (2025), *AI is set to drive surging electricity demand from data centres while offering the potential to transform how the energy sector works*, <https://www.iea.org/news/ai-is-set-to-drive-surging-electricity-demand-from-data-centres-while-offering-the-potential-to-transform-how-the-energy-sector-works>. [14]
- IEA (2025), *Energy and AI*, International Energy Agency, <https://www.iea.org/reports/energy-and-ai/energy-demand-from-ai> (accessed on 29 October 2025). [15]
- Jones, E. (2023), *What is a foundation model?*, Ada Lovelace Institute, <https://www.adalovelaceinstitute.org/resource/foundation-models-explainer/>. [77]

- Kergroach, S. and J. H  ritier (2025), "Emerging divides in the transition to artificial intelligence", *OECD Regional Development Papers*, No. 147, OECD Publishing, Paris, <https://doi.org/10.1787/7376c776-en>. [21]
- K  bler, F. et al. (2026), "From Concept to Prototype: Realizing an in-orbit AI-system utilizing optical computing", *CEAS Nature Space Journal*, <https://doi.org/10.1007/s12567-025-00612-z> (accessed on 17 March 2026). [18]
- Lane, M. (2024), "Who will be the workers most affected by AI?: A closer look at the impact of AI on women, low-skilled workers and other groups", *OECD Artificial Intelligence Papers*, No. 26, OECD Publishing, Paris, <https://doi.org/10.1787/14dc6f89-en>. [70]
- Lane, M., M. Williams and S. Broecke (2023), "The impact of AI on the workplace: Main findings from the OECD AI surveys of employers and workers", *OECD Social, Employment and Migration Working Papers*, No. 288, OECD Publishing, Paris, <https://doi.org/10.1787/ea0a0fe1-en>. [58]
- Lass  bie, J. and G. Quintini (2022), "What skills and abilities can automation technologies replicate and what does it mean for workers?: New evidence", *OECD Social, Employment and Migration Working Papers*, No. 282, OECD Publishing, Paris, <https://doi.org/10.1787/646aad77-en>. [67]
- Lehdonvirta, V. et al. (2025), "Measuring domestic public cloud compute availability for artificial intelligence", *OECD Artificial Intelligence Papers*, No. 49, OECD Publishing, Paris, <https://doi.org/10.1787/8602a322-en>. [13]
- Milanez, A., A. Lemmens and C. Ruggiu (2025), "Algorithmic management in the workplace: New evidence from an OECD employer survey", *OECD Artificial Intelligence Papers*, No. 31, OECD Publishing, Paris, <https://doi.org/10.1787/287c13c4-en>. [63]
- Nordhaus, W. (2021), "Are We Approaching an Economic Singularity? Information Technology and the Future of Economic Growth", *American Economic Journal: Macroeconomics*, Vol. 13(1), pp. 299–332, <https://www.jstor.org/stable/27113840>. [31]
- Noy, S. and W. Zhang (2023), *Experimental Evidence on the Productivity Effects of Generative Artificial Intelligence*, Elsevier BV, <https://doi.org/10.2139/ssrn.4375283>. [37]
- OECD (2026), "The agentic AI landscape and its conceptual foundations", <https://doi.org/10.1787/396cf758-en>. [5]
- OECD (2026), "Agentic AI in organisations: Early insights from practitioner interviews", *OECD Artificial Intelligence Papers*, No. 65, OECD Publishing, Paris, <https://doi.org/10.1787/1257a26f-en>. [4]
- OECD (2026), *Artificial Intelligence markets: Recent developments and competition issues*, OECD Publishing, Paris, <https://doi.org/10.1787/d531d73f-en>. [54]
- OECD (2026), *Benefits of AI openness: OECD discussion paper for the G7*, OECD Publishing, Paris, <https://doi.org/10.1787/746e8c9a-en>. [50]
- OECD (2026), *Businesses using artificial intelligence (AI)*, <https://data-explorer.oecd.org/s/589> (accessed on 1 June 2026). [7]

- OECD (2026), "Empowering SMEs in the age of AI: The 2026 OECD D4SME Survey", *OECD SME and Entrepreneurship Papers*, No. 78, OECD Publishing, Paris, <https://doi.org/10.1787/bf5a9816-en>. [9]
- OECD (2026), *Hiroshima AI Process (HAIP) Reporting Framework*, <https://oecd.ai/en/transparency/>, <https://oecd.ai/en/transparency/>. [43]
- OECD (2026), *ICT Usage and Access Database*, <https://oe.cd/dx/ict-access-usage>. [6]
- OECD (2026), *OECD Due Diligence Guidance for Responsible AI*, OECD Publishing, Paris, <https://doi.org/10.1787/41671712-en>. [42]
- OECD (2026), *OECD Employment Outlook 2026: Geographic Disparities in Jobs and Incomes*, OECD Publishing, Paris, <https://doi.org/10.1787/7e710f54-en>. [69]
- OECD (2026), "Skills in the AI age", *OECD Artificial Intelligence Papers*, No. 60, OECD Publishing, Paris, <https://doi.org/10.1787/972bd15e-en>. [64]
- OECD (2026), "The OECD AI exposure measure: Mapping the OECD AI Capability Indicators to occupations", *OECD Artificial Intelligence Papers*, No. 59, OECD Publishing, Paris, <https://doi.org/10.1787/f3da0f0a-en>. [62]
- OECD (2026), *Venture capital investments in artificial intelligence through 2025*, OECD Publishing, Paris, <https://doi.org/10.1787/a13752f5-en>. [47]
- OECD (2025), *AI adoption by small and medium-sized enterprises: OECD discussion paper for the G7*, OECD Publishing, Paris, <https://doi.org/10.1787/426399c1-en>. [8]
- OECD (2025), *AI openness: A primer for policymakers*, *OECD Artificial Intelligence Papers*, No. 44, OECD Publishing, Paris, <https://doi.org/10.1787/02f73362-en>. [52]
- OECD (2025), "Algorithmic pricing and competition in G7 jurisdictions: Emerging trends and responses", *OECD Publishing, Paris*, <https://doi.org/10.1787/f36dacf8-en>. [53]
- OECD (2025), "Artificial intelligence and competitive dynamics in downstream markets", *OECD Roundtables on Competition Policy Papers*, Vol. No. 331, <https://doi.org/10.1787/ccf0624a-en>. [51]
- OECD (2025), *Artificial Intelligence for Advancing Smart Cities. Issue note of the 5th OECD Roundtable on Smart Cities and Inclusive Growth.*, <https://www.oecd.org/content/dam/oecd/en/about/programmes/cfe/the-oecd-programme-on-smart-cities-and-inclusive-growth/Issues-Note-AI-for-advancing-smart-cities.pdf>. [26]
- OECD (2025), "Competition in artificial intelligence infrastructure", *OECD Roundtables on Competition Policy Papers*, Vol. No. 330, <https://doi.org/10.1787/623d1874-en>. [49]
- OECD (2025), "Competition in the provision of cloud computing services", *OECD Roundtables on Competition Policy Papers*, No. 323, OECD Publishing, Paris, <https://doi.org/10.1787/595859c5-en>. [46]
- OECD (2025), *Generative AI and the SME Workforce: New Survey Evidence*, OECD Publishing, Paris, <https://doi.org/10.1787/2d08b99d-en>. [59]
- OECD (2025), *Governing with Artificial Intelligence: The State of Play and Way Forward in Core Government Functions*, OECD Publishing, Paris, <https://doi.org/10.1787/795de142-en>. [57]

- OECD (2025), "How are AI developers managing risks?: Insights from responses to the reporting framework of the Hiroshima AI Process Code of Conduct", *OECD Artificial Intelligence Papers*, No. 45, OECD Publishing, Paris, <https://doi.org/10.1787/658c2ad6-en>. [45]
- OECD (2025), "How can AI help make better regional development policies in Korea", *OECD Regional Development Papers*, No. 178, OECD Publishing, Paris, <https://doi.org/10.1787/be01f52d-en>. [22]
- OECD (2025), "Implementing the OECD Recommendation on Public Procurement in OECD and Partner Countries: 2020-2024 Report", *OECD Public Governance Reviews*, <https://doi.org/10.1787/02a46a58-en>. [56]
- OECD (2024), "Explanatory memorandum on the updated OECD definition of an AI system", <https://doi.org/10.1787/623da898-en>. [3]
- OECD (2024), "Artificial intelligence, data and competition", *OECD Artificial Intelligence Papers* No 18, <https://doi.org/10.1787/e7e88884-en>. [44]
- OECD (2024), "Defining AI incidents and related terms", *OECD Artificial Intelligence Papers*, Vol. 16, <https://doi.org/10.1787/d1a8d965-en>. [80]
- OECD (2024), *Fostering an inclusive digital transformation as AI spreads among firms*, OECD Publishing, Paris, <https://doi.org/10.1787/5876200c-en>. [11]
- OECD (2024), *Recommendation of the Council on Artificial intelligence*, <https://legalinstruments.oecd.org/en/instruments/OECD-LEGAL-0449>. [1]
- OECD (2024), "Shaping a rights-oriented digital transformation", *OECD Digital Economy Papers*, No. 368, OECD Publishing, Paris, <https://doi.org/10.1787/86ee84e2-en>. [65]
- OECD (2023), "Advancing accountability in AI: Governing and managing risks throughout the lifecycle for trustworthy AI", <https://doi.org/10.1787/2448f04b-en>. [41]
- OECD (2023), "Common guideposts to promote interoperability in AI risk management", <https://doi.org/10.1787/ba602d18-en>. [40]
- OECD (2023), "A blueprint for building national compute capacity for artificial intelligence", *OECD Digital Economy Papers*, Vol. No. 350, <https://doi.org/10.1787/876367e3-en>. [81]
- OECD (2023), *AI language models: Technological, socio-economic and policy considerations*, OECD Publishing, <https://doi.org/10.1787/13d38f92-en>. [78]
- OECD (2023), *OECD Employment Outlook 2023: Artificial Intelligence and the Labour Market*, OECD Publishing, Paris, <https://doi.org/10.1787/08785bba-en>. [72]
- OECD (2022), "Measuring the environmental impacts of artificial intelligence compute and applications: The AI footprint", *OECD Digital Economy Papers*, Vol. No. 341, OECD Publishing, Paris, <https://doi.org/10.1787/7babf571-en>. [20]
- OECD (2022), "OECD Framework for the Classification of AI systems", *OECD Digital Economy Papers*, No. 323, OECD Publishing, Paris, <https://doi.org/10.1787/cb6d9eca-en>. [73]
- OECD (2019), *Artificial Intelligence in Society*, OECD Publishing, <https://doi.org/10.1787/eedfee77-en>. [74]

- OECD (2015), “Recommendation of the Council on Public Procurement”, [55]
<https://legalinstruments.oecd.org/en/instruments/OECD-LEGAL-0411>.
- OECD (Forthcoming), *AI and Employment*. [61]
- OECD (Forthcoming), *AI and Work Organisation*. [60]
- OECD (Forthcoming), “Harnessing AI’s potential across key sectors”, *AI Horizontal Project*. [2]
- OECD (Forthcoming), “Powering AI Progress: The Future of Compute”, *OECD Digital Economy and Society Outlook*. [19]
- OECD (Forthcoming), *The Impact of AI on the Working Lives of Women*. [71]
- OECD.AI (2025), “Data from AI knowledge on Demand (AIKOD) database”, Vol. last updated 2025-05-16, accessed on 2025-10-24, <https://oecd.ai/>. [82]
- Powell, P. and I. Smalley (n.d.), *What is hyperscale?*, [83]
<https://www.ibm.com/think/topics/hyperscale#:~:text=Hyperscalers%2C%20an%20outgrowth%20of%20hyperscale,typical%20on%20premises%20data%20centers>. (accessed on 27 October 2025).
- The Alan Turing Institute (2023), *First Workshop on Multimodal AI*, [79]
<https://www.turing.ac.uk/events/first-workshop-multimodal-ai#:~:text=Multimodal%20AI%20combines%20multiple%20types,finance%2C%20robotics%2C%20and%20manufacturing>.
- Touzet, C. (2023), “Using AI to support people with disability in the labour market: Opportunities and challenges”, *OECD Artificial Intelligence Papers*, No. 7, OECD Publishing, Paris, [66]
<https://doi.org/10.1787/008b32b7-en>.
- Tracxn (2025), *Ximdex company profile*, [24]
https://tracxn.com/d/companies/ximdex/_BAXsYYrzSrE_wlWT7_IeVvYyPdAggxVXYga8WW_RwxVg#about-the-company.
- Trammell, P. and A. Korinek (2023), *Economic Growth under Transformative AI*, National Bureau of Economic Research, Cambridge, MA, [33]
<https://doi.org/10.3386/w31815>.

Notes

¹ Outputs include recognition (identifying and categorising data, e.g. image, video, audio and text, into specific classifications as well as image segmentation and object detection), event detection (connecting data points to detect patterns, as well as outliers, anomalies or imputing missing data), forecasting (using past and existing behaviours to predict future outcomes), personalisation (developing a profile of an individual and learning and adapting its output to that individual over time), interaction support (interpreting and creating content to power conversational and other interactions between machines and humans, possibly involving multiple media such as voice text and images), goal-driven optimisation (finding the optimal solution to a problem for a cost function or predefined goal) and reasoning with knowledge structures (inferring new outcomes that are possible even if they are not present in existing data, through modelling and simulation).

² *Agentic AI* generally refers to “systems composed of multiple co-ordinated AI agents that can break down tasks, collaborate, and pursue complex objectives autonomously over extended periods. Agentic AI systems are designed to operate in more open-ended, less predictable physical or virtual environments and to function with minimal human supervision” (OECD, 2026^[5]).

³ This builds on and extends previous OECD work (Filippucci, Gal and Schief, 2024^[84]; Filippucci et al., 2025^[29]) which relied on Acemoglu (2024)’s framework. Similar magnitudes were obtained based on the OECD calculations by Aghion and Bunel (2025).

⁴ The calculations relied on harmonised estimates of AI adoption by firms across OECD and G20 countries, relying on a concept of high intensity, systemic AI use in core business functions (the production of goods and services); see Figure 4 in (Filippucci et al., 2026^[27]).

⁵ The approach of the recent literature seeking to quantify macroeconomic gains, including the OECD work presented here, focuses strongly on the supply-side and do not quantify potential negative impacts on demand and ultimately growth through large scale automation and depressed aggregate labour demand. The challenge in modelling such impacts arises from the uncertain impacts of AI on the labour markets, where the evidence is only starting to emerge. This issue is actively researched in academia and policy institutions and is also the focus of future planned OECD work.

⁶ *Hyperscalers* can be defined as “hyperscale data centres primarily used to deliver and manage mega-sized applications. Hyperscalers are largely cut from the same cloth as traditional data centres—but geared to a much larger scale than typical on-premises data centres” (Powell and Smalley, n.d.^[83]).

⁷ The data underlying this paper (the AI knowledge on Demand, or AIKOD) features on the OECD.AI Policy Observatory (OECD.AI, 2025^[82]).

⁸ See for example [Tools for Trustworthy AI - OECD.AI](https://oecd.ai/en/catalogue/tools?objectiveids=2) at <https://oecd.ai/en/catalogue/tools?objectiveids=2>.