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Emerging divides in the transition to artificial intelligence

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Early divides in the transition to artificial intelligence

Sandrine Kergroach and Julien Héritier

Business adoption of artificial intelligence has markedly accelerated in 2023-24, with generative AI. Some places, sectors and firms have been faster in the uptake, so that gaps are forming and reinforcing existing cleavages. AI champions have stood out in the most innovative countries and regions, among larger firms and in knowledge-intensive services. AI is being used as a business solution for greater competitiveness. Applications are manifold and context-specific, often tied to local conditions for diffusion. Legal and data protection concerns, alongside skills shortages, cost or technology lock-ins, can slow adoption though, contributing to emerging divides.

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Keywords: artificial intelligence, innovation, technology diffusion, digitalisation, regions, SMEs, skills, jobs, place-based policies

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Table of contents

FIGURES

TABLES

BOXES

Executive summary

The diffusion of artificial intelligence (AI) accelerated in 2023 and 2024, with the release of generative AI. Compared to previous predictive, optimisation or decision-oriented AI technologies, generative AI enables more flexible applications, leveraging pre-trained models and low-code/no-code platforms, and bringing the technology within the reach of many. In 2024, 13.5% of enterprises in EU27 countries, and 13.9% in the OECD area, implemented AI solutions, with adoption rates doubling on the previous year in some countries.

Some places, sectors and firms are faster on the uptake, meaning that signs of fragmentation have appeared. Acceleration in AI diffusion is in fact more driven by leaders escaping the pack than laggards catching up, and divides form on existing fault lines. OECD/Eurostat statistics on business use of AI show that top adopters in Europe, such as the Nordic countries (Denmark, Sweden, Finland at 24%-28%), and Belgium (25%), have consolidated their lead. Korea (28% in 2022) has also emerged as a leader. Meanwhile, country gaps in business adoption have widened across the OECD area, with gaps of 14 percentage points in 2021 (a range of 2% to 16%) growting to 24 percentage points in 2024 (4% to 28%). AI uptake has also been much faster in knowledge-intensive services, larger firms and capital regions, meaning that gaps with bottom and middle range of adopters have grown. In information and communication services, the average adoption rate was at 44% in 2024 but, in Denmark, Sweden and Finland, more than two-thirds of ICT firms already use AI. In professional Science and Technology (S&T) services, the average OECD adoption rate was at 26%, but above 53% in Sweden. AI has also become more common in larger firms, with 39% of large firms in the OECD area, and over 70% in Finland, using AI as compared to 12% of small firms. The most advanced regions in the transition have also broken away between 2023 and 2024. Brussels capital, Vienna and Oslo, capital regions, reported between 32% and 26% of AI adopters, while Central Jutland and Region Zealand, non-capital regions in Denmark, lead at 35% and 28% of adoption rates. These regions are innovation leaders, standing out as global technology hubs. Conversely, as their innovation performance decreases, regions appear using less AI and being slower on uptake.

This fragmentation, and the speed at which divides appeared, raise concerns about competitiveness and territorial cohesion, especially since technology lags are difficult to overcome. Early adopters of a new technology secure benefits that increase exponentially as the technology becomes mainstreamed. The first mover advantages are difficult to break, markets get satured by incumbents, and costs to switch away from obsolete technologies increase. AI compounds these difficulties, because the growing use of AI can generate greater amounts of data, which in turn can improve AI systems and their outputs. It can also enable predatory practices and algorithmic collusion that might undermine the conditions of a fair competition, and make the gap even more difficult to bridge for late adopters.

For businesses, AI can improve processes, enhance productivity and quality, and support more responsible business conduct. AI is already used as a business solution for greater competitiveness, often in core business areas, e.g. for rationalising production in manufacturing firms, for improving digital security in network industries, or for research and development (R&D) in scientific services. Applications are highly context- and sector-specific, and tied to local conditions. In fact, differences in diffusion patterns across sectors, occupations and firms point to the co-existence of multiple pathways in the AI transition.

For workers, AI can create more interesting and better paid jobs, potentially eliminating some dangerous, dirty or demeaning ones. It can support training, career development, and preventive medicine, helping improve mental health and physical safety at work. And by permitting a better matching of skills demand and supply, AI can reduce job precarity. But not all workers will benefit in the same way. For them, gains are likely to be found in highly skilled occupations first, and where these occupations prevail. AI's impact on jobs will depend on complementarity between AI and workers, and upskilling to operate in AI-enhanced workplaces. Where AI cannot replace humans, either because tasks are difficult to replicate or because of the criticality and liability entitled in jobs, AI may lead to improvements in productivity and working conditions. In other places and jobs, AI may gradually replace humans, leading to lower wages and worker displacement. Certain groups of workers will be hit harder, given their over-representation in particular job families.

In practice, businesses may use agentic AI or smart robotics on needs that they combine with auxiliary technologies to embed AI in the (physical or virtual) workplace. Advanced automation, sensors, grippers and actuators, expand the range of actions AI can perform. Intelligent software is integrated into digital platforms, vehicles or production lines, to analyse information and take action. AI systems are often implemented together with business intelligence software.

Despite tremendous opportunities, AI poses challenges for broader adoption. Further diffusion requires overcoming barriers and accounting for local conditions. Firms report skills shortages, cost and risks of technology lock-in as major obstacles. In addition to these usual barriers to innovation, there are technical risks specific to AI. Low quality data, the opacity of AI models, human error or deficient infrastructure can compromise the integrity of AI systems, and harm predictions and decisions. Once compromised, AI systems and data degrade, sometimes with dramatic consequences. In the AI transition, regions face mounting digital security and data protection risks, heightened by hyperconnectivity and supply chains exposure.

AI uptake is tied to local industries, institutions and capacity. Local industries and economic specialisation will determine the skills and firm population structure, and therefore the capacity of places to transform. But firms in different regions, even located in the a same country and operating in a same sector, show large differences in AI uptake. A number of additional local factors may matter, such as: how regions source and manage AI assets (including data and digital infrastructure), the capacity of regional innovation systems and local vocational education and training (VET) systems to support the transition, the efficiency of technology transfers in regions, or their positioning in global value chains (GVCs) and channels of knowledge and capacity transfers. With AI however, GVC requirements on more or less captive suppliers are likely to expand significantly, posing challenges for domestic firms, particularly small and medium-sized enterprises (SMEs) to adapt.

Policy makers have a role to play in preparing people, places, and firms for a future with AI. The local factor in the AI transition cannot be ignored. This paper concludes with several work avenues for advancing the local AI agenda and developing place-based innovation and industrial strategies for AI.

Introduction

Artificial intelligence (AI) holds the potential to address complex challenges, from enhancing education and improving health care, to driving scientific innovation and climate action. But AI also poses risks to privacy, safety, security and human autonomy if used in unethical or untrustworthy ways.

Building on lessons from the past, it is essential to ensure this new technological wave is a source of progress for all, that it brings competitiveness and sustainability in all places, helps level the playing field among firms, notably vis-a-vis small- and medium-sized enterprises (SMEs), helps restore equity and cohesion among local communities, and does not further widen economic, social and territorial divides.

This paper reports on emerging gaps in the AI transition and the risks of exacerbating economic and territorial divides, especially considering the fast pace of change and lasting first-mover advantages. The study analyses recent trends and patterns in AI adoption across sectors, firms, workers and places based on the literature on innovation diffusion and a descriptive statistical analysis. The report highlights growing differences in the business deployment of AI and explores the drivers and barriers behind mainstreaming. In particular, it reflects on two-year evidence on business adoption since the release of generative AI; it analyses territorial aspects in AI diffusion and gaps; and it proposes several avenues of work to better prepare places, countries, regions and cities for a future empowered by AI.

This paper comes with two companion documents. The first one discusses the local factor in the AI transition (Kergroach, 2025 forthcoming[1]). The study builds on the literature and expert views to understand the local characteristics, and embeddedness of AI assets (i.e. data, models/algorithms, skills and infrastructure). It considers the scope, risks and limitations of the AI revolution, especially stemming from local opportunities and limitations, and policy implications. The second document explores how the AI transition is taking place in practice and locally (Kergroach, 2025 forthcoming[2]). The study follows a practical approach to compare real-world cases across industries and services, and in particular 24 place- and sector-specific examples of AI use (in agriculture, mining, low-tech and high-tech manufacturing, retail trade, arts and entertainment, tourism, and smart cities) to understand the variety of local approaches to AI development and deployment.

Altogether, these studies, combining quantitative and qualitative analysis, examine differences in the transition to AI across places. They present a rationale for differentiating policy approaches spatially in order to broaden the benefits, and better manage the risks, associated with AI. Tailoring public policies to local conditions will also help account for the still limited transferability of AI knowledge across environments and domains (OECD, 2021[3]), and the transformative capacity of places, local innovation systems, people and firms. This workstream draws on wider OECD work on AI and innovation and the OECD AI Principles (OECD, 2024[4]), in order to inform place-based industrial and innovation strategies for AI and support a cross-cutting policy agenda.

Different speeds of AI uptake

AI is a double-edged sword. It has the potential to unlock disruptive innovation at scale, boosting productivity and capacity to tackle global challenges. But change, especially of this magnitude, can exacerbate territorial, economic and social inequalities, jeopardise broad-based competitiveness and undermine trust and social cohesion, all conditions needed for policy to prepare a better future.

Technological change is a driver of progress and potentially fragmentation (Box 2). Gaps often emerge along pre-existing divides, stemming from former technological waves, and reflecting technology locks-in, or differences in dotations and capacity to adapt. The same way knowledge and technology stock accumulate during the innovation process for those who innovate, gaps and delays compound for those who do not.

Box 1. Technological change and inequalities

Technological change can create significant, overlapping, mutually reinforcing divides.

Some ***populations*** are more vulnerable to the economic shocks or job losses induced by technological change. Those with higher education and digital skills tend to adapt quicker. However, women remain underrepresented in tech careers, contributing to bias in technological developments, gender stereotypes, and weaker job conditions, including to access more secure high-level positions or training. Seniors may lack digital literacy which limits opportunities to benefit, and youth often enter the workforce in lower-skilled jobs that are more at risk of replacement. Disadvantaged backgrounds and low digital literacy worsen divides and reinforce mutually. Inequality people face in technological change reflect both jobs and economic impacts and social and cultural biases.

Economic opportunities tend to concentrate in ***places*** that attract businesses, talent and investment, and adjust faster. These places tend to offer better transport, energy and digital infrastructure, including broadband connectivity, and quality amenities and services, including education and housing. They are likely more urban, populated and wealthier, i.e. with a larger user/market base to amortise investments.

Among ***firms***, smaller enterprises face higher relative costs in sourcing inputs, and greater difficulties in coping with complex business environment, including deficient public institutions or market uncertainty. At the same time, they rely heavily on this same environment, and well-functioning networks and markets, to source strategic assets and scale up. Typically, SMEs lag behind in the digital transition.

Source : (OECD, 2024[5]) (Lee and Žarnic, 2024[6]) (OECD, 2024[7]) (OECD, 2023[8]) (OECD, 2023[9]) (OECD, 2021[3]) (OECD, 2019[10]).

This section looks into recent trends in AI diffusion. It compares business adoption rates over time, notably before and after the release of generative AI, and explores the different speeds of transition across places, sectors and types of firms. It benchmarks AI uptake among OECD countries and EU27 regions, among SMEs and large firms, and among industry and services, to identify nascent gaps in diffusion. It also compares AI adoption rates in regions with their innovation performance, and discusses the impact of emerging gaps in AI uptake on future adoption and outlook. The section uses business data on ICT use drawn from OECD-Eurostat surveys, that allow disaggregation at sectoral and subnational level (Box 3).

Box 2. Measuring AI progress and risks in regions

Defining AI

To support policy making and AI governance, the OECD has developed standards and definitions. 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*" (OECD, 2024[11]). The OECD also provides a framework for classification of AI systems that characterise them for specific projects and contexts, and helps assess their risks (OECD, 2022[12]).

Benchmarking AI progress: a variety of space-blind approaches

Internationally comparable data on AI are still scarce, reflecting the complexity and multidimentional nature of the AI transition and its novelty*.* A number of initiatives by international organisations, academia, global consultancies or media aim to monitor AI trends on a regular and comprehensive basis and propose international benchmarkings (see DSTI/DPC/GPAI(2024)6 for an overview). Among those are the Stanford AI Index (Maslej et al., 2024[13]), the IMF AI Preparedness Index (IMF, 2024[14]), the Oxford AI Readiness Index (Oxford, 2024[15]), the Tortoise Media's Global AI Index (Tortoise media, 2024[16]), the Latin America AI Index (CENIA/ECLAC, 2024[17]), the AI and Democratic Value Index (CAIDP, 2023[18]), or the Global Index on Responsible AI (GCG, 2024[19]), to name a few. The OECD has also convened an expert group to develop a composite OECD AI Index (OECD, 2025[20]). Instrumental for accessing data, analysis and guidance on AI metrics, policies, and practices (e.g. AI research, jobs, skills, and investment), the OECD.AI Policy Observatory serves as a hub for sharing information across over 70 jurisdictions (OECD, 2025[21]).

These initiatives differ in scope, data and country coverage, as well as in the extent to which metrics are AI-specific. They look at country or (supra-national) regional capabilities for AI development and deployment (adoption), technical performance (Stanford), enabling factors (IMF, Tortoise Media), economic and social impact (Stanford), or AI governance and policies (Oxford AIRI, CAIDP, GCG). In order to compile a comprehensive picture of AI progress, they combine metrics derived from existing measurement systems, including R&D and innovation surveys, patents applications, bibliometrics, venture capital investments, educational enrolment and attainment, broadband connectivity etc. And they leverage business and commercial data (e.g. Linkedin, business associations) or opinion surveys.

All these initiatives, however, converge in that none takes a subnational perspective.

Measuring AI adoption by businesses: business sample surveys

The OECD and Eurostat compile internationally comparable statistics on ICT use by businesses. For countries that are part of the European Statistical System, the data is sourced from Eurostat. For others OECD countries and key partners, the OECD gathers data. Data are collected on a yearly basis by the National Statistical Institutes (NSIs), based on the Eurostat and OECD *model questionnaires on ICT usage and e-commerce in enterprises* (Eurostat, 2024[22]).

On the basis of aggregated survey data transmitted by NSIs, Eurostat and OECD compute ratios. No estimates are made for missing data. The statistical unit is the enterprise and the survey population includes enterprises with 10 or more employees and self-employed persons. Breakdowns are provided by size class, by NACE Rev. 2 categories, and by NUTS 2 regions (on optional basis since 2023 for the latter). NUTS 2 level is retained as considered as the basic level for the implementation of regional policies, while more granular NUTS 3 data could support specific diagnoses. The enterprise as a statistical unit may however be less suitable for regional breakdowns, for which the local unit is generally used instead in enterprise statistics. The availability of regional data also depends on individual countries' participation and remains uneven across EU27 regions. For the regions covered in this report, there is no comparability issue reported among a same country's regions (see reference metadata in Annex B). There is no equivalent for such data for OECD non-EU regions.

Source: (Eurostat, 2024[22]), (Eurostat, 2023[23]); (Eurostat, 2025[24]), (Maslej et al., 2024[13]); (IMF, 2024[14]), (Oxford, 2024[15]), (Tortoise media, 2024[16]), (CENIA/ECLAC, 2024[17]), (CAIDP, 2023[18]), (GCG, 2024[19]),

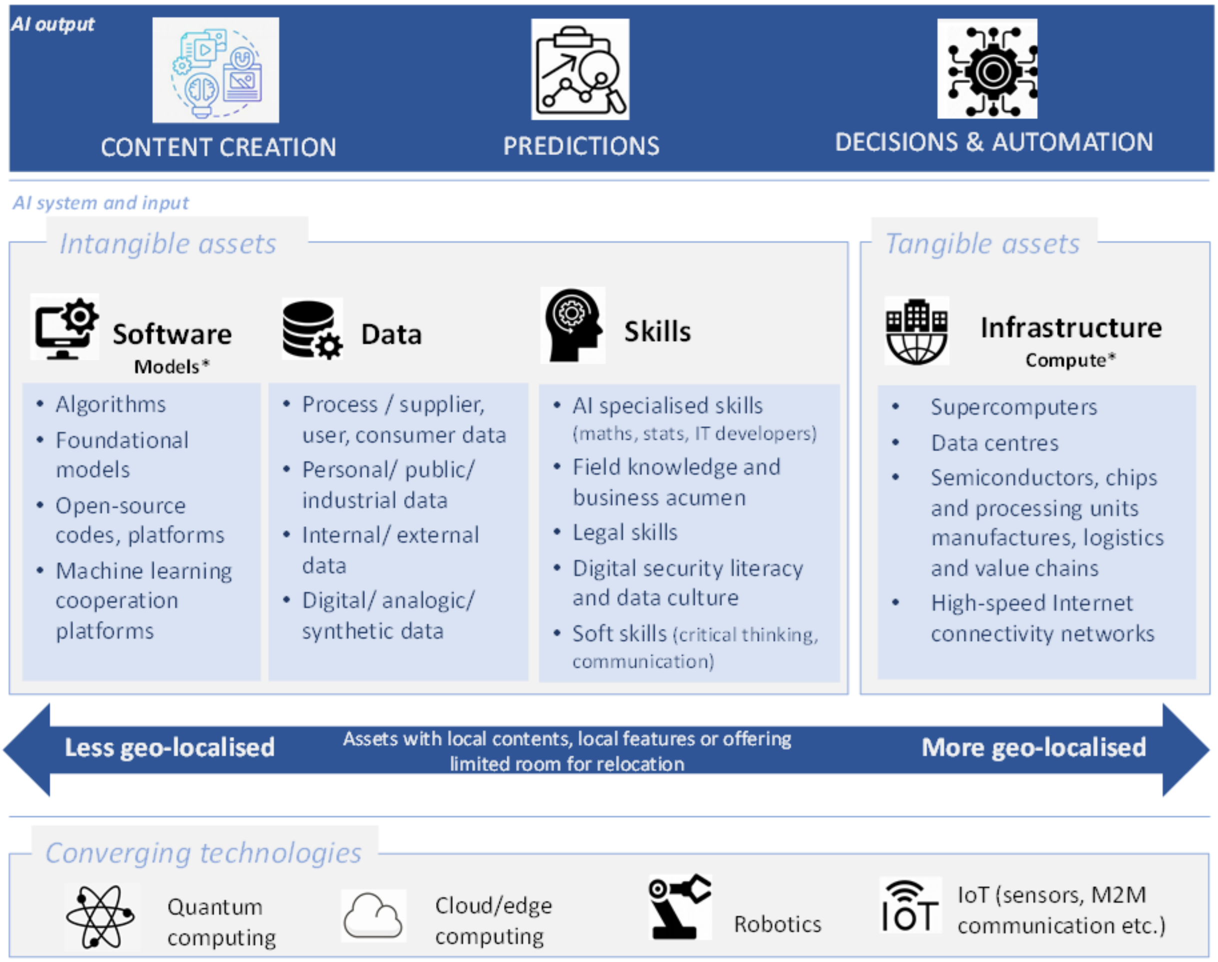
What AI technological change entails

Exploring trends in AI diffusion first requires to understand the fundamental basics of AI technology change. AI is data-driven, and essential assets include “soft” assets, i.e data, algorithms and skills, and “hard” assets, i.e. AI compute infrastructure (Figure 2).

- AI is trained by processing large amounts of **data** to identify patterns and infer responses. In general, the larger the volume of higher quality and relevant data, the better, although in some cases lean models can perform just as well as those trained on large amounts of data. There is a great variety of data, often categorised by ownership (e.g. personal, public or proprietary data) or by sourcing context (e.g. user, consumer, supplier or taxpayer data, process, industrial or government data, or product, technical, multimedia or communication data) (OECD, 2022[25]) (OECD, 2022[26]).
- **Algorithms** are step-by-step instructions that guide AI, with different degrees of complexity and supervision, on how to process this information. Once trained, the AI model can perform based on new data, and can keep improving with more training, better data and human feedback for *reinforcement learning* (E.U. and U.S Trade and Technology Council, 2023[27]) (OECD, 2024[28]).
- Advanced statistical, mathematical or programming **skills** are required for developing AI models. But non-AI, expert and soft skills, such as domain knowledge, business acumen, critical thinking and communication, are important to train the machine, interpret results and ensure a trustworthy and ethical use of AI. In addition, AI diffusion requires public acceptance, a collective data culture and digital security literacy (OECD, 2022[25]) (OECD, 2024[28]).
- **AI infrastructure (“AI compute”)** is the computational power required to train and run AI models. AI computing resources include one or more stacks (layers) of hardware and software used to support specialised AI workloads and applications, i.e. computing power (e.g. processors), data pipelines and storage facilities (e.g. data lakes, warehouses), high-speed networks and supporting software and platforms. AI compute requirements can vary significantly, depending on the application, AI system lifecycle stage, or size of the system (OECD, 2023[29]).

AI technological change remains complex to implement, because of the diverse technologies and applications it entails, the diversity of soft and hard assets it requires to perform, and because the frontier is in constant and fast evolution.

Figure 1. Infographics: input and output of an AI system



Source: Authors.

AI diffusion has accelerated with generative AI

AI diffusion accelerated in 2023 and 2024 which coincides with the advent of generative AI, a new generation of AI that brings the technology at the reach of all. Generative AI (GenAI) has burst into the public eye, with the launch of ChatGPT in November 2022, marking a milestone in public AI recognition (Maslej et al., 2024[13]). So named for its capacity to create content – including creative works, text, image, video or programming codes –, based on their training data and usually in response to prompts (i.e. natural -human- language queries) (Lorenz, Perset and Berryhill, 2023[30]), GenAI differs from earlier AI systems because of their lower deployment costs, reduced technical pre-requisites, and enhanced flexibility and modularity (Calvino, Haerle and Liu, 2025 forthcoming[31]). GenAI tailors output to users and contexts, across a wide range of domains and sectors. It allows to leverage pre-trained models and experiment on low-code/no-code platforms without the need for advanced technical skills, while predictive AI models require high computing power and deep expertise.

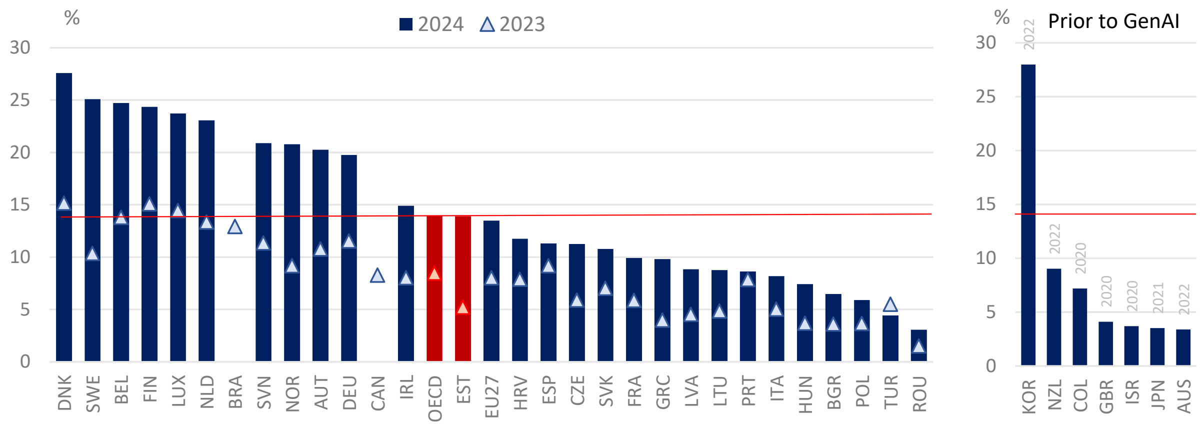
Recent OECD and Eurostat business surveys on AI use show that:

- In 2024, 13.5% of enterprises (with 10 or more employees) in EU27 countries use AI, compared to 8% in 2023 (Eurostat, 2024[32]), with similar shares of adopters in the OECD area (OECD, 2025[33]).

- This is a significant acceleration in AI uptake, adoption rates more than doubling in some countries, especially over 2024 (Figure 3). The most striking acceleration has been observed in Estonia (x2.7), Sweden and Greece (over x2.4) and Norway (x2.3).

Figure 2. AI adoption rates almost doubled in some countries over 2024

Businesses using AI as a share of total enterprises (%), 2023 and 2024, or nearest year available



Note : Based on sample surveys of firms with 10 or more employees. Total all activities. For countries with data anterior to 2023, adoption rates may be underestimated as not accounting for recent bursts, and are presented separately.
Source : Based on (OECD, 2025[33]) ICT Access and Usage by Businesses Database. Latest update and data retrieved on 07 May 2025.

National official statistics provide converging evidence, covering the most recent years, intentions of adoption or the adoption of GenAI more specifically:

- In the first quarter of 2024, 9.3% of businesses in Canada reported already using GenAI, and an additional 4.6% had plans to do so (StatsCan, 2024[34]). In the third quarter of the same year, 10.6% of firms had used AI in producing goods or delivering services, as compared to 6.1% in the previous quarter (StatCan, 2024[35]).
- The UK Office for National Statistics estimates that a low 9% of firms had adopted AI in 2023 but this share to increase to 22% in 2024 (ONS, 2025[36]). In addition, adoption by share of employment is expected to triple over the year, from 12% to 37%, reflecting faster deployment in larger firms.
- The US Census Bureau reported in April 2025 8.3% of firms using AI to produce goods or services, and 10.9% of intentions to do so in the next six months (US Census Bureau, 2025[37]).

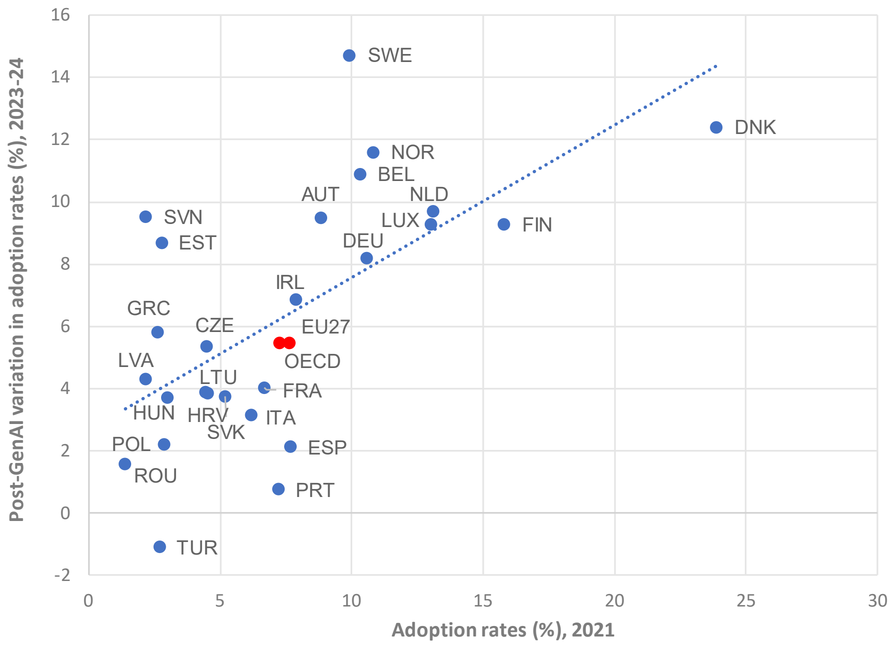
AI uptake is uneven and divides are forming on existing fault lines

Some places, sectors and firms have been slower on the uptake. This multi-speed acceleration reflects historical patterns in technology diffusion. Innovation is gradually adopted by firms or individuals, based on accumulated knowledge, capital (e.g. IT equipment and compute capacity) and intangibles (e.g. data, software) that enable to integrate the new technology into business workflows. Gaps in technological development form between sectors, firms, people and territories (Box 1).

With regards to AI, a literature has expanded in recent years to capture diffusion trends at firm- and worker-level. Early evidence indicates limited adoption prior to the GenAI era and disparities in diffusion, with a convergenge of results pointing to faster adoption by larger firms and knowledge-intensive sectors (i.e. ICT and professional S&T services). This literature compiles data from different sources, using different methods and coverage. Most of this research was conducted prior to the release of generative AI. Annex C provides an overview of selected OECD sources to illustrate the complementarities of data, methods and findings (Borgonovi et al., 2023[38]); (Calvino et al., 2022[39]); (Calvino and Fontanelli, 2023[40]); (Calvino et al., 2023[41]); (Calvino et al., 2024[42]); (Calvino et al., 2024[42]); (Calvino, Reijerink and Samek, 2025[43]); (Calvino, Haerle and Liu, 2025 forthcoming[31]); (Dernis et al., 2023[44]); (OECD, 2021[3]); (OECD, 2024[45]); (OECD, 2024[46]); (OECD, 2024[28]); (OECD, 2024[47]); (OECD/BCG/INSEAD, 2025[48]).

Figure 3. New AI generation has boosted deployment, increasing country divides

Share of total enterprises using AI in 2021 and post-GenAI variation in adoption rates in 2023-24 (%), EU27 countries with data available



Note : AI adoption rate is the share of enterprises using AI in total population of enterprises (firms with 10 or more employees). Total all activities. Post-GenAI variations are accelerations in adoption rates that took place between 2023 and 2024. Break in series in 2021 for most countries. The dotted line marks the trendline.
Source : Based on (OECD, 2025[33]) ICT Access and Usage by Businesses Database. Data retrieved on 07 May 2025.

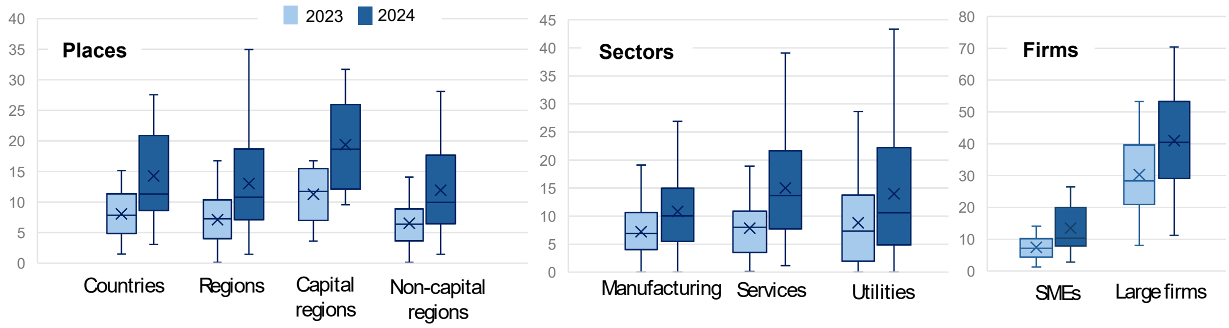
The recent, post GenAI, acceleration in AI adoption is more driven by leaders escaping the pack than laggards catching up. Gaps in AI adoption have therefore enlarged and added to existing divides between different segments of the economy and business population, at the risk of fueling a backlash as businesses, jobs and places are left behind.

Top country adopters have consolidated their lead (Figure 3). Korea, Nordic countries (Denmark, Sweden, Finland), and Belgium lead in AI adoption (Figure 2). Cross-country gaps in adoption rates have widened since 2021, increasing from 2% to 16% in 2021, to 4% to 28% in 2024 in the EU27 area. The recent acceleration (post-GenAI) has been universal, all countries reporting more firms using AI in 2024 than they did in 2023 (to the notable exception of Turkey). But the post-GenAI wave has been more intense in countries where AI adoption rates were already higher in the former period (2021-23, i.e. where more firms were already using predictive AI before the advent of generative AI). In fact, top country adopters have broken away in recent years only, capitalising on their advance in the first generations of AI technologies. This multi-speed deployment suggests, on the one hand, the existence of knowledge and technology diffusion channels between firms, and market mechanisms at play that enable spillovers, and, on the other hand, more efficient linkages in some countries than others.

Signs of fragmentation have appeared along the usual fault lines. The median AI adoption rates of OECD countries, EU regions, manufacturing, services and utilities sectors, and SMEs and large firms, have increased between 2023 and 2024, reflecting a general acceleration. But uptake has been much faster among capital regions, services and large firms, marking where AI leaders are emerging and where the first divides are forming (Figure 5). In addition, dispersions between top and bottom adopters, and within the middle range of adopters, have also increased sharply across all segments of the economy and business population, the largest gaps being observed among non-capital regions, large firms, and services and utilities.

Figure 4. Gaps in AI adoption rates have widened across places, sectors and firms

Dispersion of adoption rates across segments of total economy and business population (%), 2024 versus 2023



Note : The charts represents the dispersion of adoption rates in 2023 and 2024, and identifies the central tendency and variability across places, sectors and firms. Boxes represent the middle range (50%) of rates, the top and bottom of the box mark the upper and lower quartiles (Q3 and Q1, i.e. the interquartile) and the line inside marks the median. Whiskers extend from the upper and lower quartiles to the minimum and maximum values within 1.5 times the interquartile range. Outliers are not represented. Adoption rates are for firms with 10 employees or more. Data refer to OECD countries, plus Bulgaria, Croatia and Romania, for the segment of "countries", to EU27 countries for the segments of "SMEs" and "large firms, and to EU27 NUTS2 regions for the others. For Belgium data are NUTS1 level.
Source : Authors' calculations based on (Eurostat, 2024[49]) Artificial intelligence by NACE Rev. 2 activity and NUTS 2 region [isoc_r_eb_ain2]; (Eurostat, 2025[50]), Artificial intelligence by size class of enterprise [isoc_eb_ai]; and (OECD, 2025[33]) ICT Access and Usage by Businesses database. Data retrieved on 07 May 2025.

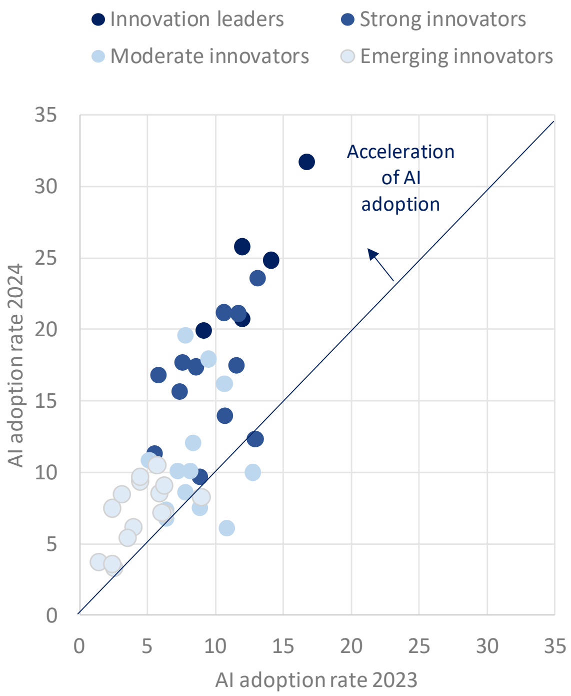
Leading regions in innovation are the first and fastest on uptake

Just as the leading countries in AI adoption have consolidated their advance with the advent of generative AI, so too the most advanced regions in the AI transition broke away between 2023 and 2024. Those with the highest adoption rates in 2023 saw the highest increases in adoption rates in 2024 (Figure 6).

In addition, the most innovative regions have been the fastest in uptake (Figure 6). Regions with the best performing innovation systems have experienced greater acceleration in business uptake between 2023 and 2024. Those regions stand as pockets of excellence, even in their own country, and combine highly educated and digital savvy population, efficient research systems, intensive production of intellectual assets (e.g. patents, trademarks) and a large population of innovative firms, including SMEs, engaging in cooperation, including with academia (EC, 2023[51]). Less innovative regions appear less likely to be using AI and have experienced a slower acceleration between 2023 and 2024.

Figure 5. The most innovative regions are prime AI adopters and the fastest in uptake

AI adoption rate by region and innovation performance (%), EU27, 2024 compared to 2023



Note : Values above the line signals an acceleration in AI diffusion, the higher, the faster.
Source : Authors' calculations based on (Eurostat, 2024[49]) Artificial intelligence by NACE Rev. 2 activity and NUTS 2 region, and (EC, 2023[51]) Regional Innovation Scoreboard.

Box 3. Innovation performance and AI uptake in regions: selected examples

The fastest EU27 regions on uptake are also the innovation leaders in Europe.

- Among capital regions, Brussels capital (Belgium), report more than 32% of business adopters in 2024, almost twice as many as in 2023. The region represents a highly skilled economy with over 90% of local jobs in services, especially in financial services and professional, S&T activities. Brussels capital is also home to the headquarters of European Institutions and serves as a hub for the country's integration into international service networks (OECD, 2024[52]).
- In Vienna, capital region of Austria, 26% of businesses use AI in 2024, up from 16% in 2023. The capital region is heavily service-oriented, playing in particular a major role in financial services, and in the digital transformation, including on AI. Vienna hosts numerous research instititions and universities, world-class research facilities and innovative firms, the region having developed an edge on renewable energy, smart city and environmental technologies.
- Oslo and Viken, the capital region of Norway, is the most innovative in the country and an innovation leader in Europe. It counts in 2024 almost 26% of AI business adopters, as compared to 12% the year before. The region is a key maritime and logistics hub, and a global centre for financial, and communication and media services. It has developed comparative advantages in

fintech, and green and health tech, with regional "innovation districts" supporting public-private collaboration and the integration of research and the start-up ecosystem.

- Among non-capital regions, Central Jutland and Region Zealand (DNK) at 35% and 28% of AI adoption are taking the lead, followed by Tirol, Vorarlberg and Upper Austria (AUT) and Southern Denmark at around 21% (Figure 7) (Eurostat, 2024[49]). These regions stands out as global hubs for green and healthtech, robotics and advanced manufacturing. The Flemish region in Belgium (25% adoption rate at NUTS1 level) hosts the most innovative universities in Europe and top business accelerators (Flemish Government, 2024[53]).
- Less innovative regions appear to be less likely to be using and have experienced a slower acceleration between 2023 and 2024. The rural and metallurgic regions of Great Plain and North Hungary, the agricultural lands of Romania, the low density region of Innlandet (Norway) rank the lowest in the EU for AI adoption.

Source: (EC, 2023[51]), (Eurostat, 2024[49]), (Flemish Government, 2024[53]), (OECD, 2024[52]).

Lagging places, sectors and firms may not be able to catch up

Technology diffusion is not homogeneous and universal at inception. Recent research shows that the adoption of general purpose technologies (GPTs) – such as computers, the internet and electricity – follows an initial period of acceleration and slows when a saturation point is reached in demand (Filippucci, Gal and Schief, 2024[54]) (Filippucci et al., 2024[55]). AI presents the features of a GPT for its pervasive impact across all segments of the economy, capacity for continuous improvement and potential to steer innovation and innovation complementarities at large scale (Calvino, Haerle and Liu, 2025 forthcoming[31]). For AI, firms who started sooner their journey are therefore likely to be on this accelerating path, which would lead to a natural rise of disparities in diffusion.

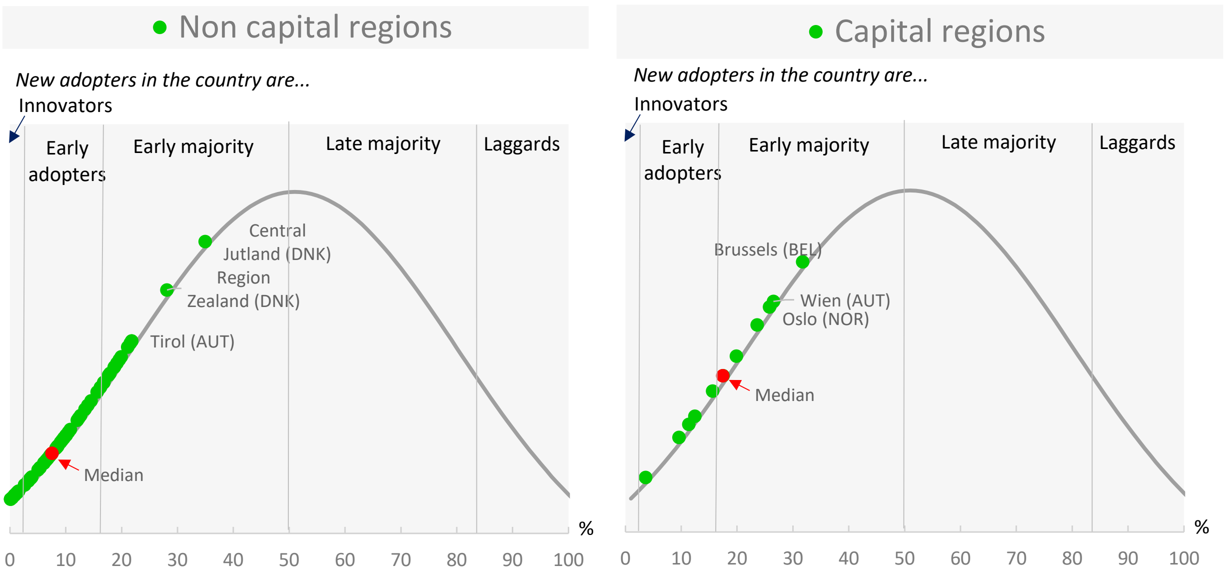
Delayed technology adoption is however hard to overcome. Early adopters of a new technology capture benefits that increase exponentially as the technology becomes mainstreamed. First (or second) mover advantages arise from the fact that they have already set industry standards, built reputation, and consolidated their markets and networks, when late adopters come in. For digital technologies in particular, network effects can be at play that increase the value and return on a technology as its number of users increases (e.g. matchmaking platforms). For later adopters and laggards, the potential benefits and returns on technology investment decrease rapidly. This is due to market saturation by incumbent competitors, higher costs to switch away from obsolescente technologies, or the unbreakable advantages gained by first and second adopters. Catching-up later may therefore not compensate for the lost opportunities at inception. In that vein, firms that would have been able to leverage AI solutions and implement a data governance to expand market base and boost productivity earlier, would be even better placed to leverage data and AI further and compete.

AI can compound these difficulties. By enabling the use of larger volumes of data, or even the creation of new data, it supports the development of more accurate and high-performing AI models, which generate more and higher-quality data. In other words, more AI can generate better AI and better outcomes. In addition, automation and deep learning techniques provide firms with powerful means to monitor prices, send market signals, implement common policies, create cartels or optimise joint profits that could be sustained above a fair competitive level, without necessarily any explicit agreement. Although it is still too early to say how competition conditions will evolve with the rapid deployment of AI, and even if few network effects have materialised so far, risks of algorithmic collusion and the strong AI asset concentration raise concerns for future business environment (OECD, 2024[56]) (Kergroach, 2025 forthcoming[1]). Risks for competition could in particular be amplified in specific sectors, e.g. sectors where market concentration is already high, or where early AI adopters can increase and consolidate their market shares, but at the same time bring new competition in currently highly concentrated markets, such as the ICT sector (OECD, 2025 forthcoming[57]).

Indeed, an early majority of AI adopters is emerging across regions, sectors, and firms, with likely decreasing returns on investment for next adopters (Figure 7) (Figure 8) (Figure 9).

Figure 6. In the race to AI, some regions are breaking away

Benefits of AI adoption by wave of adopters and NUTS2 regions, adoption rates (x-axis) and theoretical benefits for new adopters (y-axis), EU27 countries, 2024

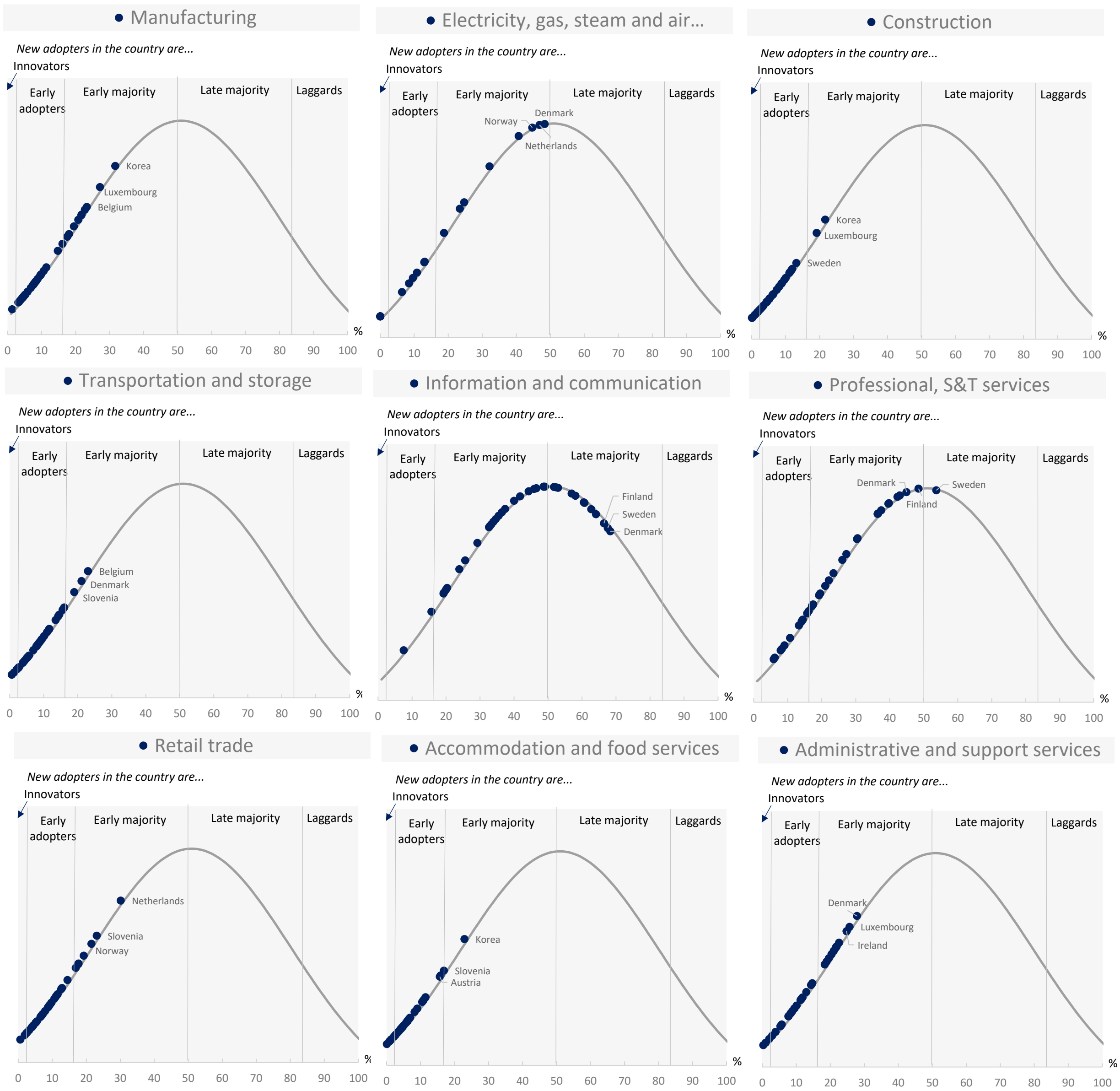


Note : Technology diffusion curves ("bell" shape) show that benefits of adoption accrue increasingly to early adopters and an early majority of adopters, and return on investments decreased for late majority and laggards. Benefits are represented in a stylised way on the y-axis. The adoption rate (represented on the x-axis) is the share of enterprises using AI, with innovators accounting for 2.5% of total business population, early adopters for an additional 13.5%, and early majority, late majority and laggards for additional 34%, 34% and 16%. Based on (Rogers, 1962[58]). Dots mark EU27 regions at NUTS2 level with data available, except Belgium (NUTS1).
Source : Authors' calculations based on (Eurostat, 2024[49]) Artificial intelligence by NACE Rev.2 activity and NUTS 2 region [isoc_r_eb_ain2] and (OECD, 2021[3]). Data retrieved on 08 April 2025.

Knowledge-intensive, digitally savvy services and network industries engage with AI faster. In information and communication services, OECD average adoption rate was at 44% in 2024, but in Denmark, Sweden and Finland, more than two-thirds of the firms operating in this sector were already using AI (Figure 8). In professional S&T services, OECD rate was at 26%, but in Sweden it was above 53%. In utilities services, the EU27 adoption rate was at 26% while, in Denmark, the Netherlands and Norway, it exceeded 44% (Eurostat, 2025[59]).

Figure 7. Firms in knowledge-intensive services and networks industries are quicker on AI uptake

Benefits of AI adoption by wave of adopters and sector, adoption rates (x-axis) and theoretical benefits for new adopters (y-axis), OECD countries, 2024 or latest year available



Note : Technology diffusion curves ("bell" shape) show that benefits of adoption accrue increasingly to early adopters and an early majority of adopters, and return on investments decreased for late majority and laggards. Benefits are represented in a stylised way on the y-axis. The adoption rate (represented on x-axis) is the share of enterprises using AI, with innovators accounting for 2.5% of total business population, early adopters for an additional 13.5%, and early majority, late majority and laggards for additional 34%, 34% and 16%. Based on (Rogers, 1962[58]). Dots mark OECD countries with data available. All countries for which the latest year available is anterior to 2023 may be underestimated.

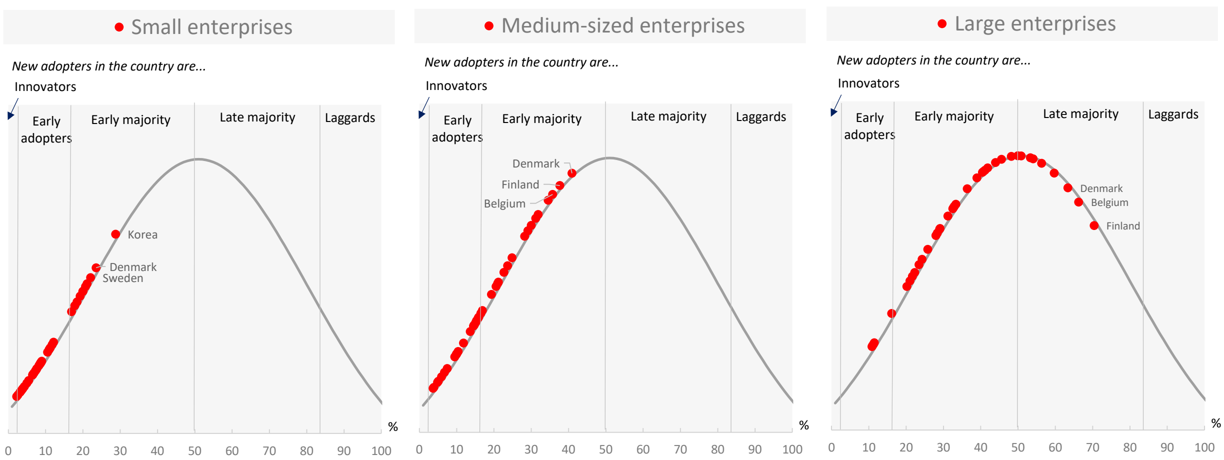
Source : Authors' calculations based on (OECD, 2025[33]) ICT Access and Usage by Businesses Database, (Eurostat, 2025[59]) Artificial intelligence by NACE Rev. 2 activity [isoc_eb_ain2] for utilities industries and (OECD, 2021[3]). Data retrieved on 07 May 2025.

Large firms have deployed AI models quicker, reflecting their larger capacity for investing in technology and complementary skills and organisational changes (Figure 9). In 2024, 12% of small firms used AI in the OECD area compared to 39% of large firms, i.e. a difference factor of 3.3 (also due to the low rates of SMEs). But in Finland, Belgium and Denmark, over 60% of large firms are already operating AI (70%, 66% and 63% respectively, for an EU27 average of 41%) (OECD, 2025[33]).

The adoption gap between small and large firms is sizable compared to the adoption pathway of other technologies. SME lag in the digital transition is not new and observed in all technologies. But in mainstreamed technologies, such as social media, or in platform technologies that support leapfrogs, such as cloud computing, the difference factor between SME and large firm adoption rates is lower, i.e. inferior to 2 (1.3 and 1.7 respectively based on 2023 data). In more advanced technologies, such as big data analytics, or for technologies requiring a minimum scale for amortising costs, such as customer relationship management and enterprise resource planning software, the difference factor between SME and large firm adoption rates increases, being around 2.5 (OECD, 2025[33]). At more than 3, the SME gap in AI adoption is striking.

Figure 8. Large firms took the lead in the AI transition

Benefits of AI adoption by wave of adopters and firm size class, adoption rates (x-axis) and theoretical benefits for new adopters (y-axis), OECD countries, 2024 or latest year available



Note : Technology diffusion curves ("bell" shape) show that benefits of adoption accrue increasingly to early adopters and an early majority of adopters, and return on investments decreased for late majority and laggards. Benefits are represented in a stylised way on the y-axis. The adoption rate (represented on x-axis) is the share of enterprises using AI, with innovators accounting for 2.5% of total business population, early adopters for an additional 13.5%, and early majority, late majority and laggards for additional 34%, 34% and 16%. Based on (Rogers, 1962[58]). Dots mark OECD and EU27 countries with data available. All countries for which the latest year available is anterior to 2023 may be underestimated.

Source : Authors' calculations based on (OECD, 2025[33]) ICT Access and Usage by Businesses Database and (OECD, 2021[3]). Data retrieved on 07 May 2025.

Different patterns of diffusion

Examining patterns of AI diffusion across places, sectors and firms provides first insights into the possible pathways of transformation and the causes of emerging divides.

Innovation is a business response to constraints and opportunities. Firms innovating seek a competitive advantage, such as a new customer base or increasing sales. Innovation can lead to greater efficiency and productivity, and higher cost competiveness, as it can also be needed to adapt to a changing environment, when new regulations, technological change or global challenges, such as climate change or ageing population, impact markets and value chains.

This section looks into the expected benefits of AI adoption for firms and workers. It explores how AI can transform firms and employment conditions, and how different benefits can incentivise different forms of adoption. It discusses the current patterns of deployment across regions, sectors, occupations and firms, i.e. how various AI technologies are used and combined, including with complementary technologies, and what business applications are made of them. The analysis also highlights context- and business-specific practices. The section combines business statistics on ICT use and occupational data.

AI can unlock substantial corporate efficiency gains

AI can transform businesses, their internal processes and cost structure, ultimately unlocking productivity and quality gains (Box 5**)**. Table 1 shows how AI can be applied along the internal value chain of the firm, and improve operations from pre-production to post-production.

Predictive and generative AI increase capacity for business decision making and corporate planning, budgeting and management, by reinforcing knowledge management and business intelligence systems, supporting scenario analysis and forecasting, and by automating central corporate functions, such as accounting, financial affairs, or human resources (HR). New AI applications are also found for IT security. Face recognition based on computer vision is used for authentication of ICT users, or machine learning for better and faster detection and prevention of cyber-attacks.

Performance and optimisation gains can be achieved in supply chain management, logistics and inventories, or production lines and workforce planning. AI helps predict and anticipate disruptions, shortages or maintenance, and reduce losses, uncertainty and volatility (e.g. in price and procurement).

Applications can transform customer relationships and marketing, by improving market segmentation and raising capacity to “Know Your Customer” (KYC), by automating basic customer services and enabling a 24/7 attendance, or by supporting content creation at lower cost, such for communication or advertising.

AI is finding promising uses in R&D and design by raising significantly corporate capacity for data analytics and experimentation, and by lowering the costs and risks of innovation. Simulations, prototyping and a parallel improvement in market knowledge and corporate business intelligence could indeed reduce the time to market and facilitate the organisational changes needed (e.g. in production or workers training).

Table 1. How AI can change internal operations, cost structure and performance of the firm

Business functions	AI applications and business improvements
Direction, strategy, planning and management	Support in decision-making; increased predictive capacity, with automate real-time analytics, business projections and scenario analysis. Strategic recommendations, including for effective transitions and organisational changes. Greater ability to integrate and coordinate operations and functions, within the firm or intra-group. Refocus activities on higher value-added functions, as productivity gains are achieved in other less strategic functions.
General administration (including HR, accounting, finance and internal communication)	Automation of administrative and routine tasks (e.g. accounting, reporting, payroll etc.) and enhanced capacity to overcome organisational bottlenecks and comply with tax and regulatory obligations. E.g. HR analytics to better profile and attract talent; monitor individual performance, provide personalised feedback, and tailor on-the-job training; differentiating in terms of working conditions (e.g. disabled workers), wages, fringe benefits or responsibilities. Boost worker engagement, by granting them greater autonomy, and improve mental health and physical safety at work, by supporting preventive medicine to reduce risks and prevalence of occupational diseases. E.g. financial projections based on historical and real-time data, cost optimisation, risk assessment and fraud detection.
IT systems and networks	Increased capability of detecting data breaches and cyber-attacks, and repairing and analysing vulnerabilities. Increased digital security risk management capacity.
Pre-production functions (including R&D, design, exploration)	Data analytics on corporate, production and customer/user data to identify areas of productivity and quality improvement. Automation of scientific processes and identification of cheaper experiments, e.g. for the development of new products, devices or processes. Greater capacity for factoring costs, identifying the best design and prototyping, especially if combined with 3D printing or Generative AI, or assessing patenting opportunities.
Sourcing, procurement and supply-chain management	Data analytics on contract management and strategic sourcing. Optimisation of resource allocation through better anticipation of shortages and better management of purchases. Enhanced capacity of supply chain risk management, e.g. vis-à-vis supplier reliability, price volatility (commodity and intermediary pricing), market disruptions and fluctuations etc. Enhanced capacity in identifying invoicing errors, tracking assets and input, and strategic routing in real-time, especially when combined with IoT. Greater ability for supply chain audits, sustainability reporting, and due diligence.
Production and operations, including stock management and maintenance	Better planning capability through optimisation of operations, production/process/quality control and product availability. Lean management, increased capacity for just-in-time delivery, greater responsiveness to end-use market variations. Use of predictive maintenance to reduce risks of incidents and costs associated with production disruption. Enhanced overall safety and increased cost efficiency, e.g. regarding intermediary or energy consumption.
Logistics and content delivery	Automation of warehouses and vehicles. Seamless connection between factories, distribution platforms and end markets, especially when combined with IoT. Increased reliability and integrity of the supply chains. Smart roads reducing congestion and time (and cost) for transportation, and improving safety conditions (less casualties, damages and insurance cost). Automation of back office and administrative tasks for increased cost efficiency.
Marketing, sales, advertising, branding, customer services and external communication	Greater market segmentation, sales forecasting, price differentiation and targeted advertising for more efficient marketing. Automation of basic and repetitive customer services (eg. chatbots, videobots) and content curation and generation, e.g. for websites or reporting. Cost cut in marketing, branding or visual communication (e.g. content creation, images, narrative, video, and etc.).

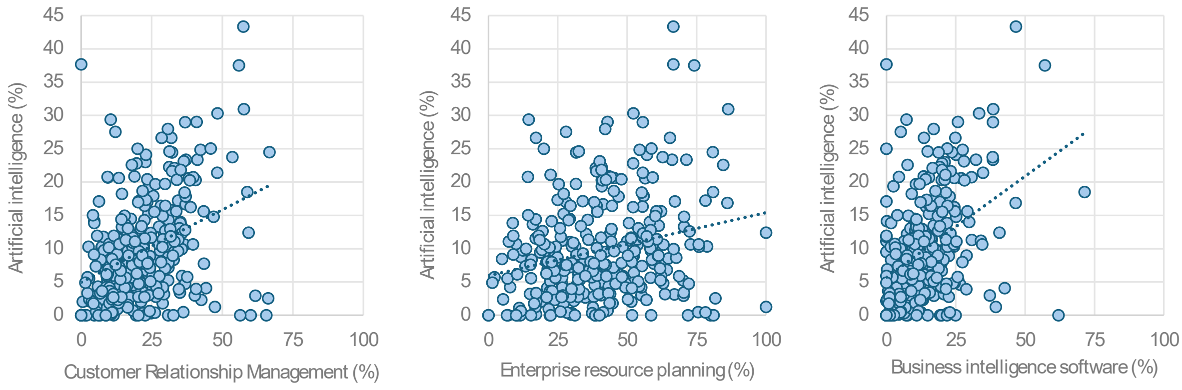
Source : Authors, update based on (OECD, 2021[3]).

AI is implemented together with software for process integration and business intelligence. Often, there are complementary dynamics in the digital transformation as a digital technology supports other -or further- digital technology adoption (OECD, 2021[3]). Pairplots of digital adoption rates across 480 EU27 regions and sectors, shows that AI deployment is linked to firms' efforts to improve process efficiency, with a great variability of uptake across places and sectors (Figure 10).

This technology complementarity could however contribute to enlarge digital divides, as some businesses and places are trapped into a vicious circle, while others, more digital-savvy and already engaged in digitalising activities, are able to step up to new digital environment and practices quicker. Technology complementarity also increases the risks of benefits accruing to early adopters.

Figure 9. Enterprises adopt AI with software for process improvement and business intelligence

Adoption rate of AI and business process integration software (%) by EU27 region and sector, 2024



Note : Firms with 10 employees or more, by NACE sector and NUTS2 regions for which data are available. 2024 or latest year available.
Source : (Héritier and Kergroach, 2025 forthcoming[60]). Based on (Eurostat, 2025[61]) Integration of internal processes by NACE Rev. 2 activity and NUTS 2 region [isoc_r_eb_iipn2] and (Eurostat, 2024[49]) Artificial intelligence by NACE Rev. 2 activity and NUTS 2 region [isoc_r_eb_ain2]. Data retrieved on 08 April 2025.

Box 4. Impact of AI on productivity: early empirical evidence

AI can yield substantial performance gains, especially among early adopters of the latest AI generation. Since the 2000s, academic studies have aimed to assess AI impact on various performance measures, in different countries and economic contexts, and by using different metrics for AI use. Before the advent of Generative AI, empirical research examined the impact of AI adoption primarily at the firm level. Estimated effects on firm-level labour productivity vary from 0 to 11%, gains somehow comparable to those obtained from other digital technologies (Brynjolfsson and Hitt, 2003[62]) (Gal et al., 2019[63]). Following the introduction of GenAI, and LLM in particular, attention has focused on effects at worker level, and on performance in specific tasks. Gains are estimated ranging from 10% to 56%, suggesting significant returns for early GenAI adopters but also very different assessments on the capacity of GenAI to revive sluggish productivity growth (Filippucci et al., 2024[55]) (Filippucci, Gal and Schief, 2024[54]). These findings are consistent with other research using qualitative worker and business surveys and sectoral case studies (OECD, 2024[64]) or experimental research on GenAI (Calvino, Reijerink and Samek, 2025[43]).

The broad economic impact of AI is yet to be seen. AI advances have not been associated with higher productivity growth at the macroeconomic level or with a significant change in job levels or wages either (Filippucci et al., 2024[55]) (OECD, 2023[65]). Acemoglu (2024[66]), using existing estimates on exposure to AI and productivity improvements at the task level, showed that macroeconomic effects have been nontrivial but modest - less than a 0.66% increase in total factor productivity (TFP) over 10 years. In addition, these estimates could be inflated, because early evidence is from easy-to-learn tasks. Future effects may come from hard-to-learn tasks, for which many context-dependent factors also matter, and no objective measure of outcome could inform about successful performance and conditions. Consequently, the same research predicts TFP gains over the next 10 years to be less than 0.53%.

Slow productivity effect is a common feature of General Purpose Technologies that require initial investment in complementary inputs before they can bring productivity gains (Brynjolfsson, Rock and

Syverson, 2018[67]). In the first stage of adoption, both output and input are systematically underestimated because of unmeasured intangible investment. As a matter of fact, a large amount of AI investments is made on intangible assets that are currently incompletely measured and integrated into macroeconomic statistics, starting with the valuation of “data” as a key AI asset. As a result, their overall aggregate effects are difficult to capture.

Source: (Acemoglu, 2024[66]), (Brynjolfsson and Hitt, 2003[62]), (Brynjolfsson, Rock and Syverson, 2018[67]), (Filippucci, Gal and Schief, 2024[54]) (Filippucci et al., 2024[55]), (Gal et al., 2019[63]), (OECD, 2024[64]), (OECD, 2023[65]).

Firms use AI for competitiveness

Patterns in AI adoption suggest that firms use AI to increase competitiveness, especially in core business areas. Internationally comparable and comprehensive data lack to assess AI return on investment (ROI) and impact on firms performance. So far, investment in AI is likely driven by speculation on future competitiveness-enhancing effects. Adoption rates are used in Figure 12. AI benefits are perceived and seized differently across and Figure 12 as proxies to signal where firms have anticipated sufficient benefits from AI integration to engage the investments needed.

The share of AI adopters increases differently across sectors and the purposes of adoption pursued. But the most frequent motives reported often relate to the core business of enterprises, as opposed to general affairs or administrative functions, indicating where firms see the ROI. The following numbers stand for firms using at least one AI technology (including those that may combine several AI technologies).

In accommodation services (49%), retail trade (53%) and travel agencies (59%), AI is used in the first place for marketing and sales. In manufacturing, AI aims to improve production processes and sales (26-27%). Over 40% of enterprises in sectors providing strategic critical infrastructure and products, such as energy supply (42%) and pharmaceuticals (42%), use AI for digital security. In professional S&T services, especially legal, accounting and management services, the main purpose to implement AI is accounting and finance (35%), but in scientific R&D, this is for R&D, problem-solving and innovation (57%).

Figure 10. AI benefits are perceived and seized differently across sectors

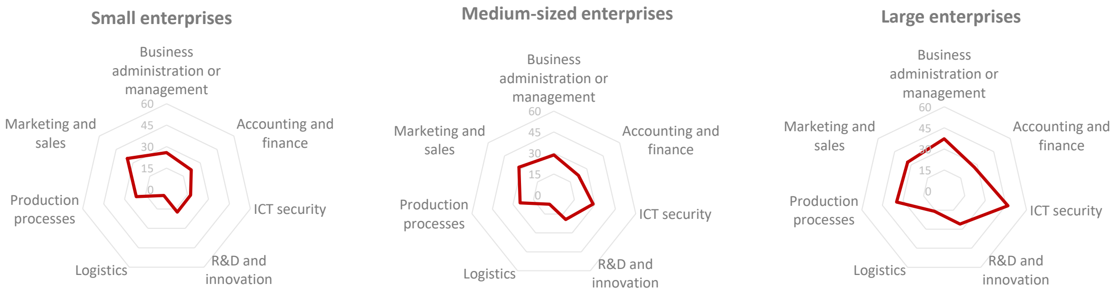
Share of firms using AI by main purpose of use and sector (%), EU27, 2024

Note : The "highest/lowest rate" categories refer to the sectors with the highest/lowest AI adoption rates. Enterprises with 10 or more employees using at least one AI technology. EU27 average. Multiple responses possible by firm.
Source : Based on (Eurostat, 2025[59]).

Differentiation in purposes of use across firm sizes is less striking than across sectors (Figure 12). Gaps in adoption rates increase with firm size, in this case towards improving production processes, management and ICT security. This reflects the over-representation of larger firms in manufacturing and networks industries, their longer and more complex decision lines, and their greater exposure to cyberattacks (OECD, 2023[8]).

Figure 11. AI benefits are perceived and seized differently across firms

Share of firms using AI by main purpose of use and firm size class (%), EU27, 2024



Note : Enterprises with 10 or more employees using at least one AI technology. EU27 average. Multiple responses possible by firm.
Source : Based on (Eurostat, 2025[50]).

Large sectoral differences in the diffusion and combination of digital technologies, point out to different paths in the AI transition. This is in line with prior studies that showed that digital adoption and the mix of digital technologies are more closely linked to industrial specialisation and inherent business models in the sector, than firm size. While the former rather determines the patterns of digital transformation, the latter affects adaptability capacity and transformative prospects (OECD, 2021[3]).

Reconciling productivity, sustainability and inclusiveness

By transforming firms and industries, AI can create the ground for more sustainable and responsible business conduct, and help conciliate economic and environmental, social and governance (ESG) performance. There is a large range of AI applications that could help firms improve their ESG performance, assuming that the related harmful impacts are appropriately managed (OECD, 2021[3]) (Box 6). This section discussed the expected benefits arising from AI (the "bright" side). Harmful impacts are further explored in the last section of the report (the "dark" side).

Box 5. AI for improving ESG performance (the "bright" side)

Environment: AI enables more acute ***environmental impact analysis*** by leveraging corporate data on ***energy or water consumption, and waste generation***, creating room for more optimal resource management and ***eco-savings***. Predictive maintenance that limits overconsumption due to malfunctions, smart buildings that balance energy needs with weather conditions and actual occupancy, smart circular factories that ease sorting, ***recycling*** and the repurposing of materials, or satellite data analysis that track ***leakages*** in the natural environment and degradation due to business activities, could reduce emissions and the environmental footprint of business operations.

Social: AI helps enhance people data analytics and improve ***well-being and diversity*** in the workplaces, e.g. through more inclusive and fairer ***hiring***, promotion and access to ***training*** (OECD, 2023[65]) (OECD, 2019[68]). An AI-powered ***performance management*** system can support career development. AI offers means for skills reinforcement and improve workplace ***accessibility*** (e.g. for workers with special needs or disabilities) and can support ***preventive medicine*** at work to reduce the risks of occupational diseases. Likewise, data analytics on social media or customer/stakeholder reviews or records could help track public sentiment and reinforce ***local community engagement*** and corporate reputation.

Governance: By the same token, AI can help monitor the ***ethical and sustainable sourcing*** of input, and enhance corporate governance and ***due diligence*** (OECD, 2018[69]). The larger scale AI permits in the collection and processing of (financial, corporate, supply chain, legal and media) data increase firms' capacity to assess ***double materiality*** (i.e. impact of the firm on the environment and society, and environmental and social impact on the firm), identify patterns and risks (e.g. environmental harm, violation of human rights or governance issues) and act for mitigation. AI tools can help strengthen ***supplier intelligence*** and incentivise more ethical and sustainable practices along global value chains (GVCs). Similarly, supply chain audits and ***reporting*** can be streamlined with AI-powered platforms that aggregate data, or automatically generate reports that meet international standards (e.g. EU Corporate Sustainability Reporting Directive and EU Taxonomy), reducing the burden on firms, including SMEs. Natural language processing could also help analyse allegations (e.g. of abuses or corruption) and stakeholder sentiment to enhance transparency and accountability in markets. Chatbots and human-machine communication tools can assist in ***engaging stakeholders***, also gathering additional feedback for more AI input. Finally, AI can fulfil a function of ***regulatory monitoring***, tracking and analysing changes in regulations and standards to help firms remain compliant.

Source: (OECD, 2023[65]), (OECD, 2019[68]), (OECD, 2018[69]).

AI for better working conditions

AI can change the world of work. It alters the tasks and competences required of workers, and modifies the working conditions and functioning of labour markets (OECD, 2024[45]) (OECD, 2023[65]) (OECD, 2019[68]) (OECD, 2019[70]) (Box 7).

Box 6. AI for better jobs and working conditions (the "bright" side)

AI is creating more complex, interesting and better paid tasks, and can in turn eliminate the dangerous, dirty or demeaning ones ("3D s"). Robots are likely to take over cleaning, maintenance, heavy load carrying, or operations in risky environments. Combined with robotics and autonomous vehicles, AI can reach places and handle tasks that reduce human exposure to hazardous, harmful or unsanitary conditions (e.g. in construction, emergency responses, waste management). In a broad range of sectors where workers interact with users or customers, chatbots can assist in providing basic information or intermediary management tasks. This is likely to change jobs and the skills that are required to carry them out (OECD, 2023[65]). Yet, the balance human-augmenting vs. human-substituting AI (i.e. complementarity vs replacement) is still uncertain. According to employers, AI has increased the importance of specialised AI skills, but it has increased the importance of human skills even more. For "bottleneck skills" like complex problem-solving, high-level management and social interaction, replacement is not possible (Lassébie and Quintini, 2022[71]). Workers will be called to more complex social interactions, such as hyper-personalised attendance, complaint or crisis management, or just-in-time decision taking. This will require critical thinking, empathy and psychology, creativity, and a deep field knowledge, including knowledge of customers.

AI brings novel solutions for training workers and improving careers. It enables the monitoring of individual performance and personalised feedback, and the tailoring of on-the-job training or massive open online courses. In addition, an AI-enhanced performance management system can better support skills certification and career development, e.g. through the deliverance of micro-credentials and the validation of experience. Noteworthy are AI applications in education and adult learning services, such training with interactive augmented and virtual reality (simulation), on-demand concrete examples (illustration), conversational sessions or mini quizzes (gaming). AI offers also means for skills reinforcement among workers with special needs (e.g. disabilities, impairments in social skills, foreign language).

AI can improve job quality, beyond remuneration and training, by boosting worker engagement, giving them greater autonomy, and improving mental health and physical safety at work. On the latter, AI can become an useful tool for preventive medicine at work. It enables real-time monitoring of the work environment. It can anticipate on unsafe conditions or practices to suggest immediate corrections (Table 2). It can help design more ergonomic workstations, better protective equipment, or train workers through simulations of occupational hazards. AI applications range from personalised health monitoring and diagnosis (e.g. smart wearable devices, health trackers, medical imaging, possibly coupled with medical records), to occupation health data analytics (e.g. machine learning for pattern recognition), to personalised assistance (e.g. NLP-assisted counselling, real-time alerts) etc. AI applications for preventive medicine will depend on the types and prevalence of occupational diseases in sectors and places.

Table 2. AI to reduce local risks of occupational diseases

Occupational Diseases	Sectors of prevalence	AI Applications
Respiratory Diseases	Construction, Mining, Manufacturing	AI-powered environmental sensors to monitor air quality and detect hazardous particles, gas or chemicals; predictive analytics to identify high-risk areas and thresholds.
Musculoskeletal Disorders	Healthcare, Manufacturing, Agriculture, Construction, Office work, Warehouses	AI-driven ergonomic analysis tools to optimise workstations and reduce repetitive strain and unsafe postures; wearable devices monitoring posture and movement.
Hearing Loss	Construction, Manufacturing, Transportation (aviation), Music and Entertainment	AI-based noise monitoring systems to identify and reduce exposure to harmful noise levels.
Skin Disorders	Healthcare, Chemical Industry, Agriculture	AI systems for early detection of skin conditions through image recognition; personalised risk assessments for chemical exposure.
Cancers	Construction, Chemicals, Healthcare	AI algorithms for analysing occupational exposure data to identify risks of cancer; wearable devices to monitor exposure to carcinogen.
Infectious diseases	Sanitation work, Agriculture	AI-powered surveillance systems to detect and track infectious outbreaks in workplaces; predictive models for infection control and risk mitigation.
Mental Health Issues, Stress Sleep disorders	All sectors, particularly high-pressure environments, such as front-desk customer service, event organisers, flight attendants etc.	AI-based mental health chatbots for early intervention; predictive analytics to identify stress-prone environments.

Source : Authors.

AI can reduce work precarity and times of joblessness, by permitting a better matching of skills demand (needs) and supply (skills available). Better matching will increase transparency in labour markets, limit times out of job and without income, and raise opportunities of mobility within larger firms or groups etc. (Lane and Saint-Martin, 2021[72]). As AI brings solutions for better predicting and managing labour market volatility, the employment outlook of workers in sectors of high seasonality (e.g. agriculture, retail trade, tourism, arts and entertainment) could become more stable, working conditions less informal and contracts less precarious. With greater stability should come greater investment in the workforce training.

Source: (Lane and Saint-Martin, 2021[72]), (Lassébie and Quintini, 2022[71]), (OECD, 2023[65]).

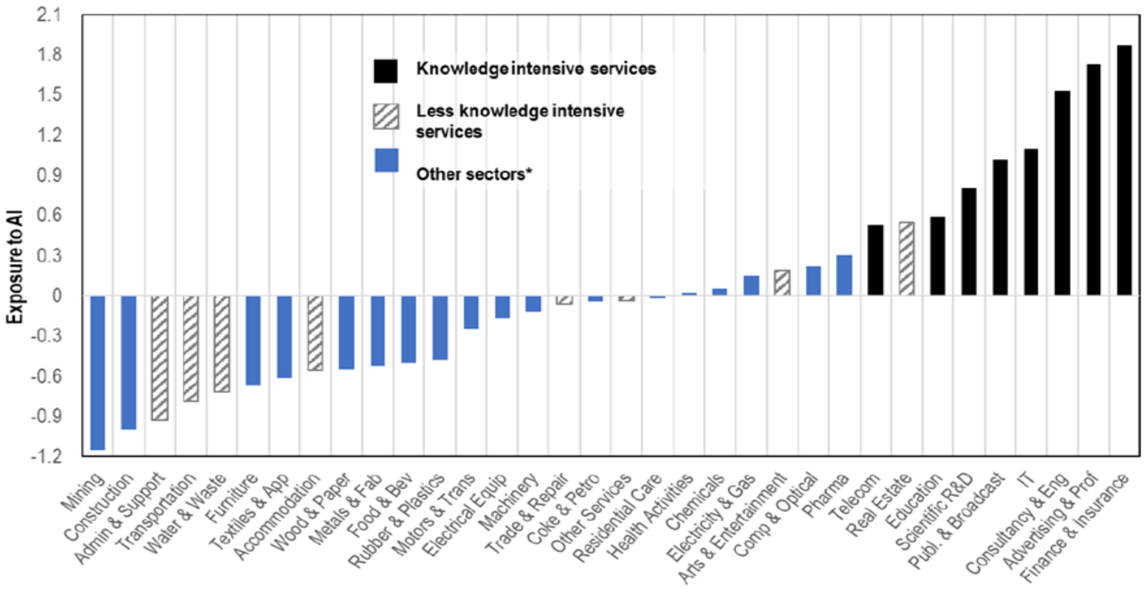
AI gains are likely to be found in highly skilled occupations first

Not all occupations are exposed to AI the same way. Unlike former technological waves where machine-human substitution was rather taking place in low-skilled occupations and fears of automation were stronger on lower-range-skilled workers, AI is likely to affect expert, knowledge-intensive, highly skilled occupations first. Several studies have aimed to look at main AI applications and their possible impact on the abilities needed to operate in different occupations and sectors.

- AI exposure is stronger in knowledge-intensive services, such as ICT, telecommunications, finance, marketing and professional services, including scientific R&D (Figure 13).
- Almost 40% of global employment could be exposed to AI. Advanced economies face higher risk (60% of employment exposed) due to the prevalence of cognitive-task-oriented jobs in more knowledge-based economic structures, but they are also better placed to benefit (Cazzaniga, 2024[73]).
- Across the OECD, around a quarter of workers are exposed to Generative AI, but only 1% are considered to be highly exposed. As GenAI further enters the workplace, up to 70% of workers could be exposed in the near future (and 39% highly exposed) (OECD, 2024[45]).

Figure 12. AI is expected to affect knowledge-intensive highly skilled occupations first

Index of AI exposure at worker level, standard deviation from means by sector, 2019 (before GenAI)



Note : AI exposure is estimated by mapping 10 AI applications, such as image recognition and text creation, with 52 occupational abilities like oral comprehension and inductive reasoning. Each occupation is then viewed as a weighted combination (bundle) of these 52 abilities. Values in the chart are standardized with mean zero and standard deviation 1 at the occupation level, and matched to sectors. Data on AI applications come from the Electronic Frontier Foundation, and on abilities from the US Occupational Information Network (O*NET) database.
Source : (Filippucci et al., 2024[55]) based on OECD Global Forum of Productivity and (Felten, Raj and Seamans, 2021[74]).

AI, job killer or co-worker?

The impact of AI on jobs will depend on the degree of AI complementarity with human skills. In highly exposed jobs with low task complementarity, AI may gradually replace humans leading to substitution, wage decrease and worker reconversions. In highly exposed jobs with high task complementarity, such as those that still require human supervision, or where AI cannot reproduce human tasks (e.g. in interpersonal interactions or complex decision-making), AI may lead to improvements in productivity and working conditions. In addition, higher human-AI complementarity in a job does not guarantee no risks of eviction for workers either. Those employed in a highly complementary occupation, but who do not possess the skills needed to engage with AI, would likely face lower employment opportunities and wages.

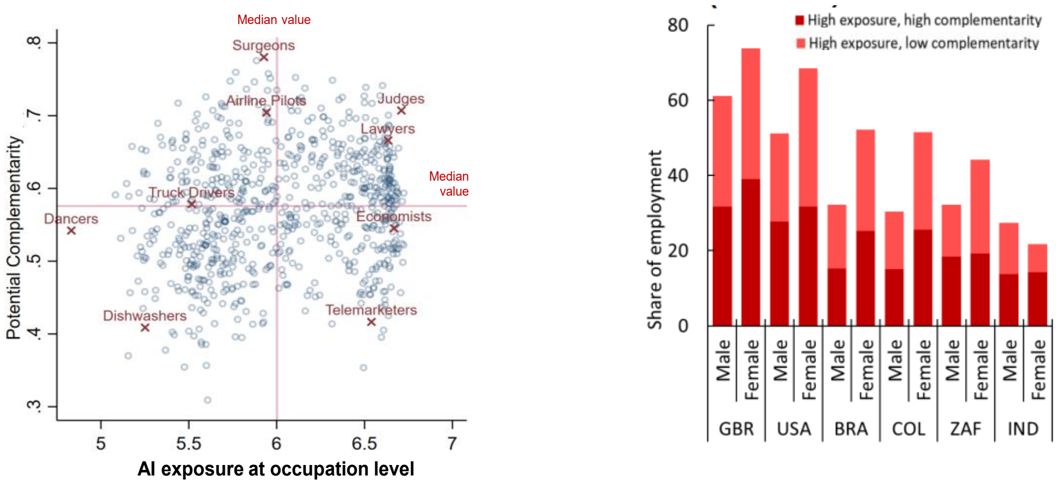
AI impact on jobs and labour markets is therefore complex and still uncertain. Job exposure to AI alone cannot predict employment and income outcomes, as other factors such as liability, criticality or converging technological developments also matter. The articulation of labour markets and (re)training systems will also be instrumental in the AI transition.

Figure 13. AI will hit jobs and affect employment and income outcomes asymmetrically

Job exposure and complementarity at occupation level in the US and as a share of employment in selected countries

Panel 1. AI exposure and complementarity at occupation level, US indices

Panel 2. Employment shares in high-exposure occupations by gender, selected countries



Note : Panel 1. AI exposure is drawn from (Felten, Raj and Seamans, 2021[74]) and adjusted to reflect complementarities at occupation level. Potential complementarity reflects lower risk of job displacement. The index account for physical and social factors that influence the nature of work and the likelihood that activities within an occupation could be assigned to AI without human supervision (substitution). It also reflects the amount of education and training required to perform an occupation in order to factor for the level of expertise and ability to integrate the knowledge needed to operate AI into the skillset of an occupation. Both indices build on the Occupational Information Network (O*NET) repository. For instance, telemarketers, despite a relatively similar level of AI exposure with judges, display minimal complementarity, likely because of the greater possibility of capturing customer data with AI applications and limited decision-making and liability in their tasks. As a comparison, judges may harness AI for analysing documentation and informing their decisions which have the force of Law. Surgeons, although considered less exposed to AI than most occupations, have the highest potential of AI complementarity.
Panel 2: IMF calculations based on American Community Survey, Gran Encuesta Integrada de Hogares, India Periodic Labour Force Survey, Labour Market Dynamics in South Africa, Pesquisa Nacional por Amostra de Domicílios Contínua (Brazil), and UK Labour Force Survey.
Source : (Pizzinelli et al., 2023[75]) for Panel 1 and (Cazzaniga, 2024[73]) for Panel 2.

AI will affect jobs and employment areas asymmetrically (Figure 13).

- Fully delegating critical decisions to AI may be difficult in contexts in which errors could have grave consequences, like piloting an airplane or diagnosing diseases (Figure 13 Panel 1).
- AI is also likely to hit certain populations harder, reflecting existing demographic biases in employment and potential biases brought by labour market search and matching tools. Women

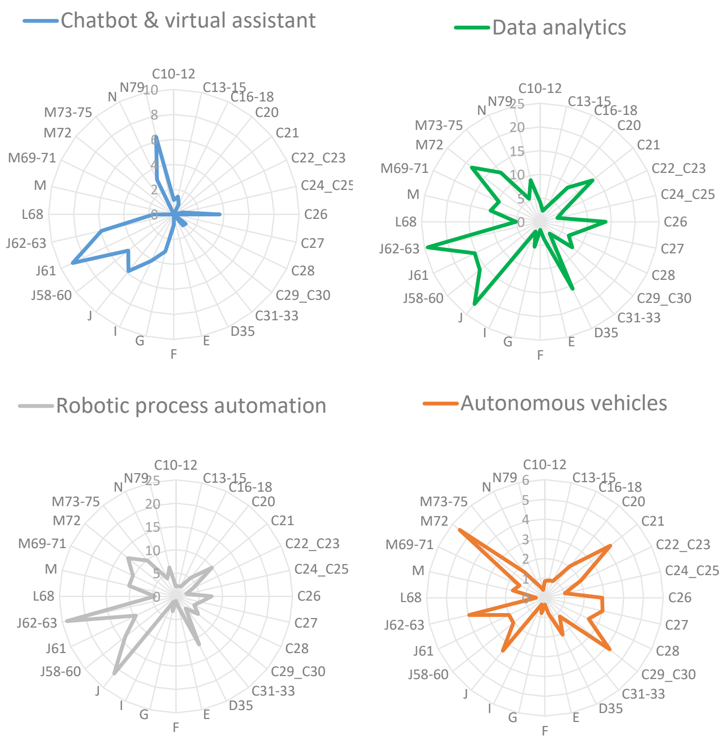
tend to be more often employed in high-exposure jobs than men, but also in jobs with higher complementarity, which could result in both greater risks and greater opportunities for them (Figure 13 Panel 2).

Agentic AI or smart robotics, increasingly integrated into workplaces

Not only is AI deploying at different speeds across sectors, firms and places (as measured above by business use of any type of AI technology)**, but it is also deploying differently depending on how diverse AI and complementary technologies are combined in the workplace**. In fact, AI is spreading in hybrid forms, with businesses combining agentic AI, robots and human intervention as required. In addition, auxiliary technologies require to embed AI in the (physical or virtual) workplace imply advanced automation and developments in sensors, grippers and actuators, to expand the range of actions it can perform. This also means integrating intelligent software into digital platforms, apps, vehicles or production lines, to enable AI systems analyse information and take action.

Figure 14. AI is offering multiple applications across sectors

Share of enterprises using AI by type of applications and sector (%), EU27, 2024 or latest year



Note : Firms with 10 or more employees. NACE classification. C- Manufacture of : C10-12 beverages, food, tobacco; C13-15: Textiles, wearing apparel, leather; C16-18: Wood, cork, paper & printing; C20: Chemicals; C21: Pharmaceuticals; C22-23: Rubber, plastic, & non-metallic mineral; C24-25: Basic metals & metal; C26: Computer & electronic; C27: Electrical equipt; C28: Machinery & equipt; C29-C30: Motor vehicles & transport equipt; C31-33: Furniture & other manufacturing; D35: Electricity, gas, steam & air conditioning supply; E: Water supply; sewerage, waste management; F: Construction; G: Wholesale & retail trade; I: Accommodation & food services; J: Information & communication services; J58-60: Publishing, programming & broadcasting; J61: Telecommunications; J62-63: Computer programming & information services; L68: Real estate; M: Professional, S&T services; M69-71: Legal & accounting, management, architectural & engineering services; M72: Scientific R&D; M73-75: Advertising, other professional & veterinary services; N: Administrative & support services; N79: Travel agency. To note, the Eurostat survey covers agent-like applications, but does not use the term "agentic AI" or classify technologies under this category.
Source : Based on (Eurostat, 2025[59]) Artificial intelligence by NACE Rev.2 activity [isoc_eb_ain2].

Different forms of AI, purely software-based or embedded in devices, find different business applications (Box 8). They support customer chatbots and virtual assistants in telecommunications or in travel agencies and tour operators; robotic process automation in pharmaceuticals or electricity supply; autonomous vehicles in the car industry or scientific research; or data analytics in professional S&T services (Figure 14). Recent estimates suggest that 75% of agentic AI systems have been used to interact with computer interfaces, stressing their increasingly pervasive role in the digital infrastructure.

Box 7. Agentic AI and cobots increasingly integrated in the workplaces

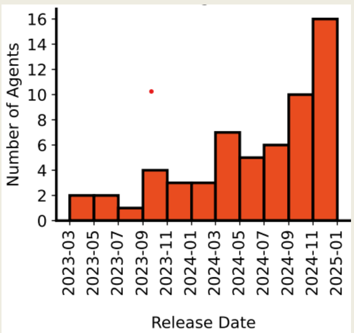
Agentic AI systems are used in a growing number of domains (Casper et al., 2025[76]). At the time of drafting, there is no widely agreed definition of agentic AI. In this paper, it is therefore understood as a type of AI system designed to pursue specific goals within a specific context and some degree of autonomy. Agentic AI systems may possess capabilities to make decisions, take actions, and adapt strategies based on feedback from the environment where they operate, often requiring limited human involvement. Applications of agentic AI span areas such as software and computer use, robotics, autonomous vehicles, and decision-support systems.

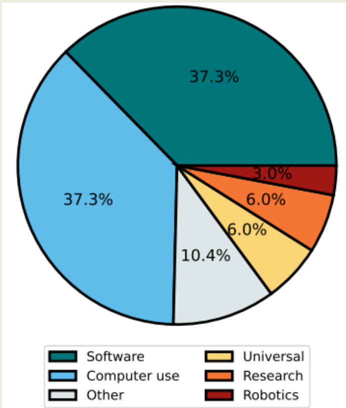
It is estimated that:

- Half of agentic AI systems were deployed in the second half of 2024 only. In fact, new developments in the agentic AI product ecosystem occur weekly.
- 75% of agentic AI systems have been used to assist in coding and software engineering or in computer use, i.e. to interact with computer interfaces, stressing the increasingly pervasive role of agentic AI in the digital infrastructure.

Figure 15. Agentic systems are increasingly deployed and across multiple domains

Number of agentic AI systems deployed and share by application domain (%), world, as of 31 December 2024





Note : Based on work by the Massachusetts Institute of Technology to document the technical and safety features of deployed agentic AI systems. A comprehensive sample of 67 agentic AI systems has been identified as of 31 December 2024, using publicly available information from web searches, academic literature, benchmark leaderboards, and compiled lists of agentic systems, complemented with correspondence with developers. The characteristics of artificial agency are drawn from (Chan et al., 2023[77]). Excluding systems that are not open source.
Source : (Casper et al., 2025[76]).

Cobots, i.e. collaborative robots that act as assistants capable of learning and interacting with humans, have emerged as a new trend in robotics amidst a booming market (Figure 17). The global number of robots in factories has doubled in seven years, 2023 being a record year with over 4 million **industrial** robots in operation worldwide. Korea and Singapore head by far, with the highest density of industrial robots in the world.

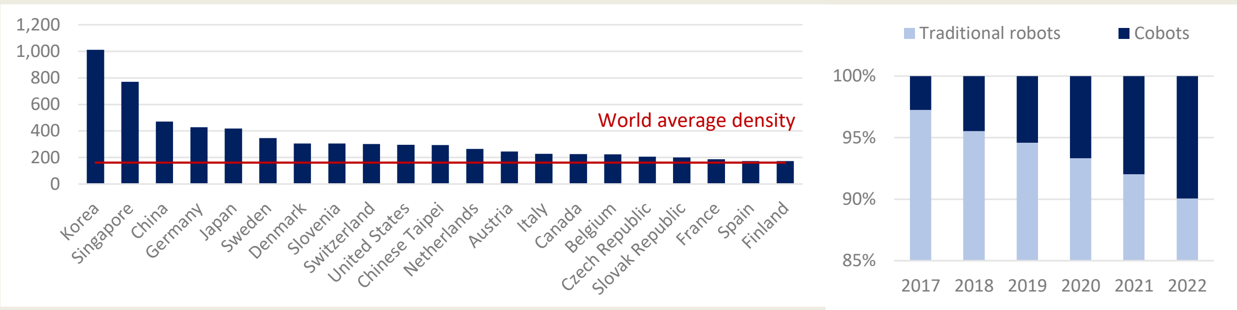
- Most industrial installations are in automotive, electricals/electronics and metals/machinery sectors. **Service robots** are also spreading for a broad range of consumer uses and professional applications, e.g. in transportation and logistics (56%) and hospitality (27%) (Annexes C and D).
- **Robot-as-a-Service** (RaaS) is a new model that allows enterprises, notably SMEs, to benefit from low-cost robotic automation without high initial investment and unpredictable maintenance costs. Businesses can rent or lease robots based on (time- or task-) needs to RaaS providers who handle maintenance, updates and software integration. RaaS solutions enable quick scale up, e.g. during peak seasons, or to smooth workflows. Applications can be found in agriculture, logistics, manufacturing, or healthcare etc.

Figure 16. Robotics is increasingly leveraging AI

Density of industrial robots in 2023 and share of cobots in global robot fleet, 2017-23

Panel 1. Industrial robot density in major countries of installations (number of robots in operation per 10,000 employees), 2023

Panel 2. Share of cobots in global robot fleet (%), 2017-23



Note : Industrial robots are "automatically controlled, reprogrammable multipurpose manipulator, programmable in three or more axes, which can be either fixed in place or fixed to a mobile platform for use in automation applications in an industrial environment" (ISO, 2025[78]). "Cobots", or collaborative robots, acts as assistants capable of learning and interacting with humans. Data is collected from industrial robot suppliers worldwide either as primary data or as secondary data through national robotics associations.
Source : (International Federation of Robotics, 2024[79]).

Different outlooks for broader adoption

Despite tremendous opportunities, AI poses challenges for broader adoption. Further uptake depends on existing and perceived barriers and how they are overcome. Broader deployment, the type and mix of technologies used, and practical business applications, will also depend on local industries, institutions and capacities (Box 9).

Box 8. Innovation diffusion: barriers and local conditions

Commonly identified barriers to business innovation include cost, and difficulties in sourcing and integrating knowledge and innovation assets, such as skills or technology, into existing business models and processes. Firms tend to underinvest in innovation if returns are low, i.e. when markets fail to compensate for the risks taken. This happens when innovation leaks to competitors, e.g. due to imitation or misappropriation, or when innovation brings negative externalities and costs, e.g. environmental degradation. Obstacles also come from inefficient innovation systems that hinder knowledge flows and cooperation, the existence of lock-ins, path dependency and legacy infrastructure, that prevent switching technology, or poor policy frameworks. Weak intellectual property protection or weak entrepreneurial ecosystems could for instance hamper innovation diffusion and discourage risk taking. Solutions for strengthening the business and policy conditions for AI deployment, for improving the efficiency of innovation and entrepreneurial systems, or for mitigating environmental impact, are to be found locally.

In fact, there is a strong geographic dimension in the innovation process, especially the knowledge accumulation behind. AI innovation is no exception. Codified, scientific and technical, knowledge, is by nature more universal and could be more easily shared across cultural contexts and geographical distance (Fitjar and Rodríguez-Pose, 2013[80]). More tacit, experience-based and experimental, knowledge is gained by doing and using, and through informal interactions within and between organisations. Cooperation and practice-sharing require however a common vision and understanding of problems among partners, and often a close geographical and cultural proximity among actors (Iammarino, 2005[81]) (OECD, 2013[82]). Benefits arising from agglomeration, including resource and infrastructure sharing, provide further rationale for clustering.

Source: (Fitjar and Rodríguez-Pose, 2013[80]), (Iammarino, 2005[81]), (Kergroach, 2020[83]), (OECD, 2013[82]), (OECD, 2015[84]), (Weingarden and Lembcke, 2024[85]).

This section discusses the conditions for enabling broader AI adoption and addressing early divides in the AI transition. It presents an overview of AI innovation barriers, AI associated risks, and how these barriers are perceived among firms and sectors, and can hamper further deployment. It develops notably on the rising digital security risk in regions, considering the close intrication of AI with software systems and the physical world. The section also presents some insights on the local conditions that are likely to affect business conduct and decision to implement AI, going beyond considerations around economic specialisation and the occupational structure of places.

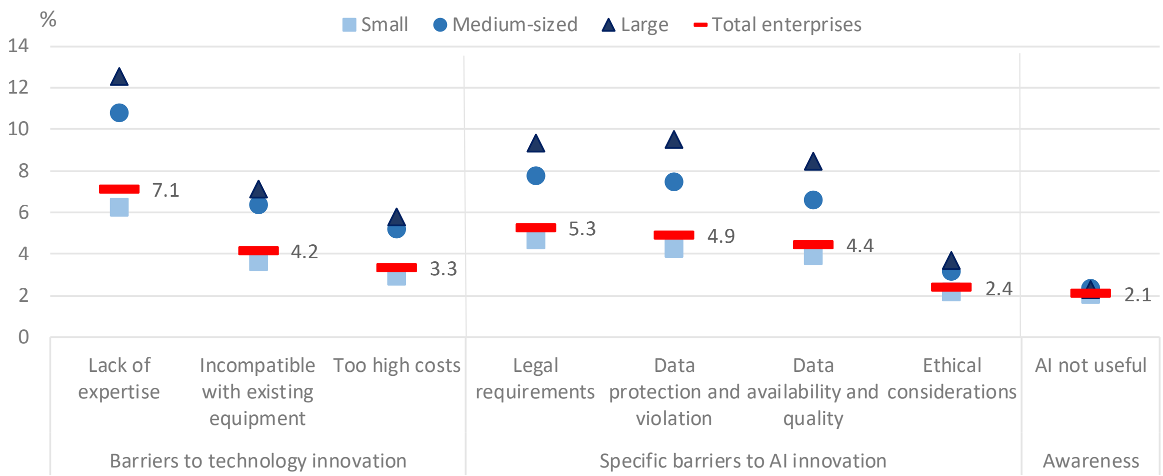
Common innovation barriers hold AI adoption back

Common barriers to innovation are often reported as a major obstacle to AI adoption (Eurostat, 2024[32]). The AI transition - like most other innovations - requires capital upgrading and complementary organisational and skills investments to integrate AI systems and converging technologies into business practices and workflows. These changes induce costs, imply workers' acceptance and engagement, sometimes retraining, and call for appropriate corporate strategies and management.

- 7.1% of EU27 enterprises report a lack of relevant expertise as a reason for not using AI (2024). 4% bring up incompatibility with existing equipment, software and systems and 3% too high costs. This means common barriers to innovation remain relevant for AI adoption (Figure 18 Panel 1).
- The skills gap has become apparent across a majority of sectors, and is larger (over 11%) in high-tech sectors, e.g. computer and electronics manufacturing, in utilities, and in knowledge-intensive services, e.g. telecommunications, and travel agencies.
- Technology locks-ins are of higher concern in high-tech manufacturing, such as pharmaceuticals (9%) and electrical equipment (7%) (Figure 18 Panel 2).
- A very large majority of enterprises, including amongst the small ones, are aware of the usefulness of AI, which suggests that more adoption by more businesses in the years to come.

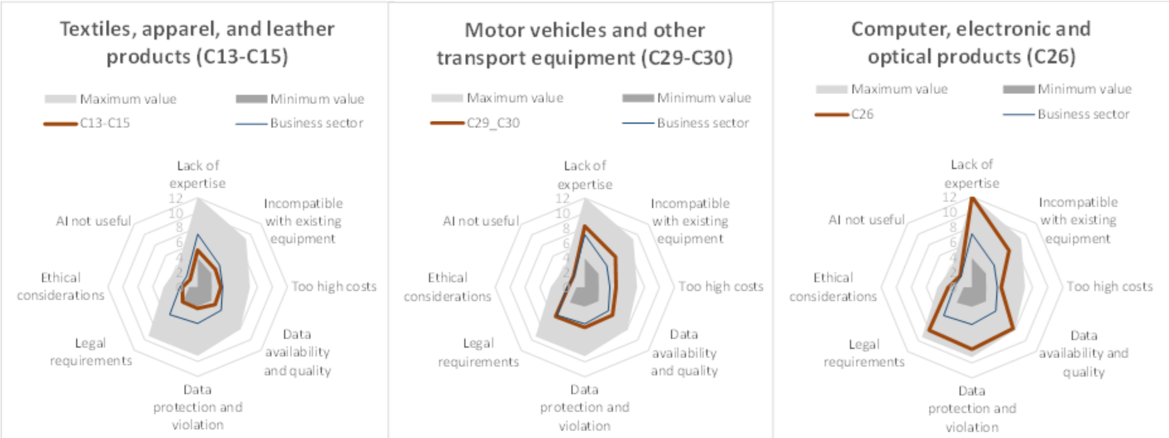
Figure 17. AI-specific barriers add to common innovation barriers to slow deployment

Panel 1. Share of enterprises not using AI technologies by motive and firm size class (%), total EU27, 2024

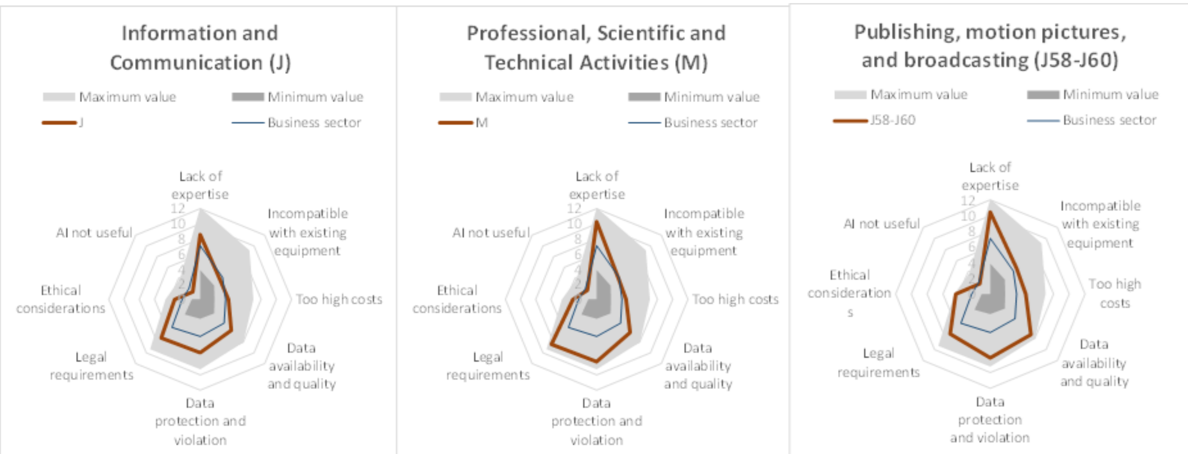


Panel 2. Share of enterprises not using AI technologies by motive (%), selected sectors, total EU27, 2024

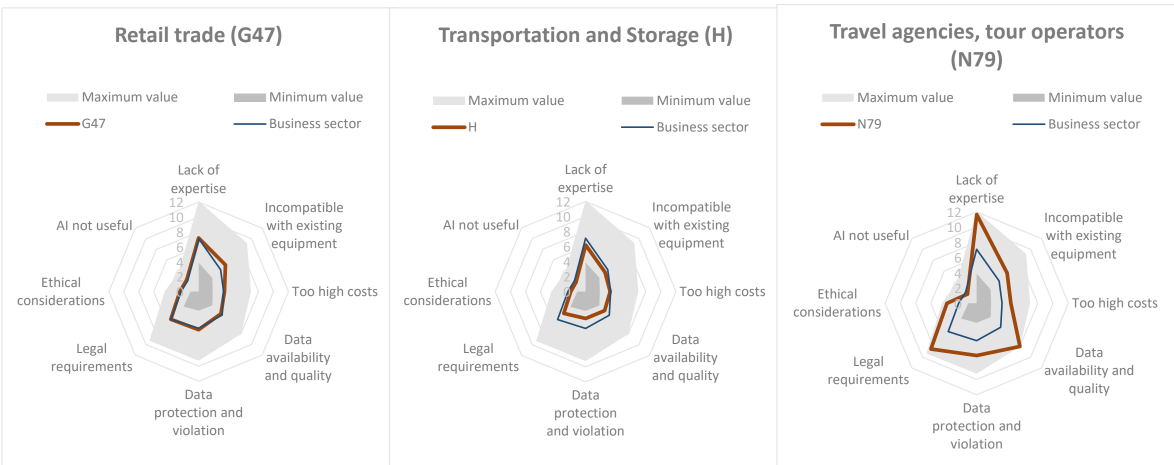
Selected manufacturing sectors



Selected knowledge-intensive services



Selected other services



Note : The "Maximum/minimum values" categories refer to the sector with the highest/lowest share of firms not using AI. Based on business surveys to firms with 10 or more employees. The question on barriers to adoption is optional and only raised to enterprises that do not use any of AI technologies, which can explain the small numbers reported (see model questionnaire in (Eurostat, 2024[22])). NACE classification.
Source : Based on (Eurostat, 2025[59]).

The "dark" side of AI raises additional barriers to adoption

Key challenges in AI uptake consist in managing the technical risks associated with AI and managing their socio-economic implications to make sure AI does not impact fairness, human rights or environment negatively. Unethical or untrustworthy misuse of AI can have far-reaching and detrimental consequences for societies, economies, markets and environment (Box 10 and see (Kergroach, 2025 forthcoming[1]) for more detailed discussion on local aspects in AI externalities. This section explores the possible harmful impact of AI (the "dark" side) and how related risks can hamper business AI adoption.

Box 9. AI risks: echo chamber and chains of risks (the "dark" side)

There are significant risks associated with the use of AI and failures can have wide-reaching impacts, affecting the security and integrity of people, institutions and markets. Several harms are already well established, new ones are gradually emerging at systemic scale (Bengio et al., 2025[86]). To name a few:

AI works as an echo chamber. In ***profiling***, AI systems can mimic and amplify inequalities, leading to ***discriminatory*** decisions in critical areas to people's rights (such as hiring, healthcare). AI-powered stratification can also enable predatory marketing targeting more vulnerable consumers, borrowers or workers. In addition, we are not all equal in the eyes of AI. GenAI has proved to sexualise women and professionalise men. Facial recognition has become a "high-risk" case, with actions worldwide to limit usage in public spheres (OECD, 2021[87]).

AI increases the risks of ***privacy*** violation due to misuse, abusive inference or data leaks. AI can for instance infer health conditions by analysing apparently unrelated data, such as social media activity or web search history. Employers using AI can base hiring decisions on applicants' online activity, behaviour or personal preferences outside of work contexts. Harmful and invasive worker surveillance practices have also been reported (such as tracking worker moods and behaviour for pro-union indicators, or tracking of screentime and bathroom breaks, etc) (OECD, 2024[88]) Algorithmic management, while increasingly more widespread, can negatively impact workers' job satisfaction, workloads and stress levels and health (Milanez, Lemmens and Ruggiu, 2025[89]). Risks of data leaks (e.g. of personal data, medical or financial records) or identity theft, are growing with hyperconnectivity. There are also misuses of AI for ***misinformation and disinformation*** (e.g. deepfakes generated to manipulate media), that can harm freedom of expression, democracies and public institutions.

Untrustworthy AI can endanger the ***safety and security*** of the real world, either because of malfunctions or because of malicious use. A failure can have dramatic consequences in damages and fatalites: e.g. failure of autopilot systems in transportation; mistargeting or unpredictable behaviours of combat drones in defense; misdiagnosis or defaillance of surgical robots in healthcare; non-detection of human presence in unsafe zones in industry; etc. The risk of hacking critical infrastructure cannot be excluded either, causing outages, accidents, massive disruptions in supply chains or public services, a health crisis, or all of those. AI has also become a tool for cyberespionage and information theft.

AI can compromise the ***fair functioning of markets*** and weaken the conditions of innovation and entrepreneurship. By manipulating pricing, AI enables ***algorithmic collusion*** and predatory practices, at the risk that (likely large) firms sustain profits and prices above a fair competitive level, or develop strategies to evict competitors, to the detriment of smaller businesses with less AI capacity (OECD, 2024[56]) (OECD, 2023[90]). Predatory practices and dark commercial patterns can also harm the most vulnerable consumers through excessive pricing, aggressive profiling or discrimation (e.g. children, elderly or population with lower digital literacy and -likely- disadvantaged socio-economic background (OECD, 2023[91])).

AI tools can also raise issues around ***intellectual property***, for the content it creates, and for the (un)protected content it can misuse. Generative AI in particular is trained on massive amounts of data scraped from the Internet, that can include unlicensed content or copyrighted data, without the permission of the rights-owners. Numerous court cases are under way to discuss the legitimacy of the approach, setting precedents for the AI industry in the way models will be trained in the future (Zirpoli, 2023[92]). As legal systems worldwide differ in their treatment of intellectual property rights, the treatment of AI-generated works also varies internationally (Murray, 2022[93]).

AI systems finally raise ***sustainability*** concerns due to the energy they consume, the environmental damage they cause, and the carbon emissions they produce. AI requires massive computational power, and power behind, to process data. Despite efficiency gains and efforts to shift to carbon-free energy sources, AI environmental pressure is likely to increase as the AI transition gets momentum and energy-intensive models such as generative AI spread Firms, especially in countries where emissions are capped, will need to restructure their business models accordingly.

The OECD AI Principles provide recommendations to promote trustworthy and human-centric AI.

Source : Based from (OECD, 2024[28]), (Bengio et al., 2025[86]), and (Kergroach, 2025 forthcoming[1]).

Technical risks are integral features of AI assets.

- Low quality ***data*** affect the training of AI models and biased algorithms, resulting in poor outcomes and harms in predictions and decisions. Data can also be poisoned or sabotaged.
- The opacity of ***AI models*** makes it difficult to correct algorithmic biases and mitigate risks, which compromises the integrity of AI systems and input data. Countermeasures are difficult to implement because AI algorithms are complex and often protected by copyrights or trade secrets.
- ***People*** also raise technical risks. They can introduce biases in interpretation, make mistakes during AI training or deployment, or do not ensure proper oversight.
- Deficient ***infrastructure,*** faulty hardware, power outages, or network disruptions can also harm AI systems.

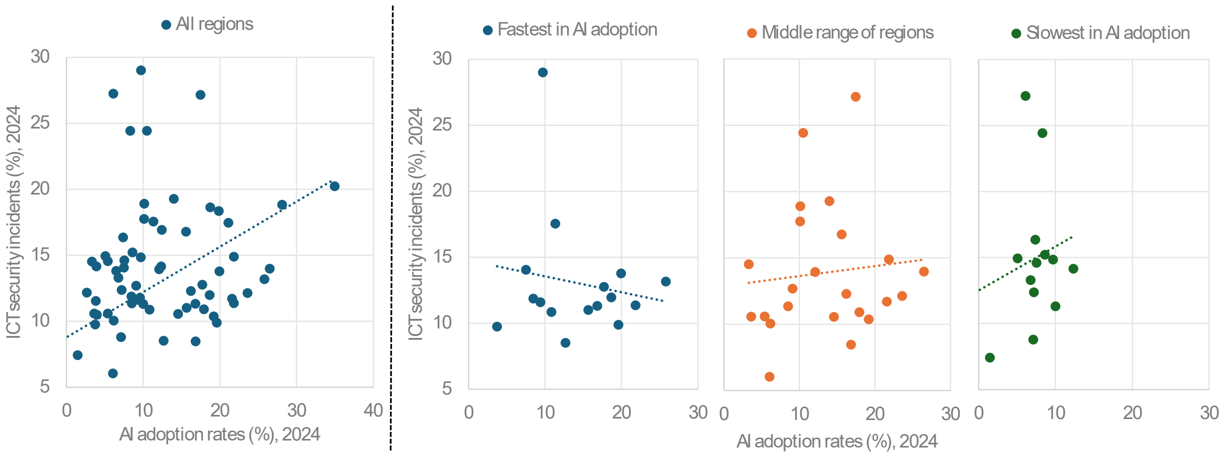
The digital security risk is a major threat to factor with, considering the close entanglement of AI with software systems and the physical world. Hyperconnectivity and the growing number of actors operating online, often with insuficient preparedness and digital hygiene, have increased global vulnerability to cyberattacks and data breaches (OECD, 2021[3]). Even firms with good defences can be victim of a supply chain attack, as interdependencies and weak points in GVCs increase the “surface attack”. Cybersecurity has become a major challenge in global production systems, with attacks occurring more often, being more sophisticated and difficult to detect and counter, and generating more disruption in operations along value chains (OECD, 2023[8]).

The frequency of ICT security incidents in firms tends to increase with AI adoption rates. In 2024, 21.5% of EU27 enterprises report having experienced interruption of services, destruction or corruption of data, or disclosure of confidential data. In Finland, the share of firms affected peaks at 42%. As regions advance in the AI transition, the prevalence of digital security breaches increases (Figure 19). Greater breach incidence may be related to higher level of digitalisation, connectivity and exposure in these regions, but also to the easiness and worthiness for hackers to capture value and data. The frequency of

ICT incidents signals mounting risks for AI systems to be altered, data to be stolen or corrupted, and possibly ICT and software systems to be compromised due to AI. At the same time, the relationship between AI adoption and ICT security incidents seem stronger among the regions slower on uptake, which may indicate a better preparedness of the leaders and fast movers, and would reinforce the risks of technology complementarity driving further digital divides.

Figure 18. Regions may face mounting cybersecurity and data protection risks in the AI transition

AI adoption rates and prevalence of digital security breaches in enterprises (%), EU27 NUTS2 regions, 2024



Note : The prevalence of digital security breaches is measured by the percentage of enterprises having experienced ICT security incidents during 2023. ICT security incidents include any incidents leading to: unavailability of ICT services, destruction or corruption of data, disclosure of confidential data (for any reason). Firms with 10 or more employees. Fastest regions in adoption have seen AI adoption rates among firms more than doubling between 2023 and 2024. Slowest regions in adption have . NUTS2 regions for which data are available. Total activities.
Source : Based on (Eurostat, 2024[49]) and (Eurostat, 2024[94]).

Once the integrity of the AI infrastructure is compromised, a vicious circle of AI system and data degradation is ignited. The liability and reputation of the firm are then engaged. These AI- and data-specific barriers add complexity and uncertainty in the transition, circumstances that are rarely favorable to risk taking and innovation.

- 5.3% of EU27 enterprises report a limited understanding of legal obligations in using AI. This is almost twice as many as the year before (albeit from low levels). About 4-5% also mention data as a challenge, either because of difficulties in accessing the quality data needed (4.4%), or because of concerns regarding data protection and privacy and risks of violation (4.9%). Ethical considerations (2.4%) come next (Figure 17 Panel 1).
- Legal and data governance concerns appear more prevalent in sectors that are more advanced in the transition and where an early majority of adopters has already emerged, i.e. professional, S&T services and utilities (8-9%), manufacture of computers (8%) or publishing, motion pictures and broadcasting (7%-8%) (Figure 17 Panel 2). This suggests that business awareness of AI-specific risks increases as applications are deployed within their sector, including competitors, supply chains and business networks.

AI uptake is tied to local conditions

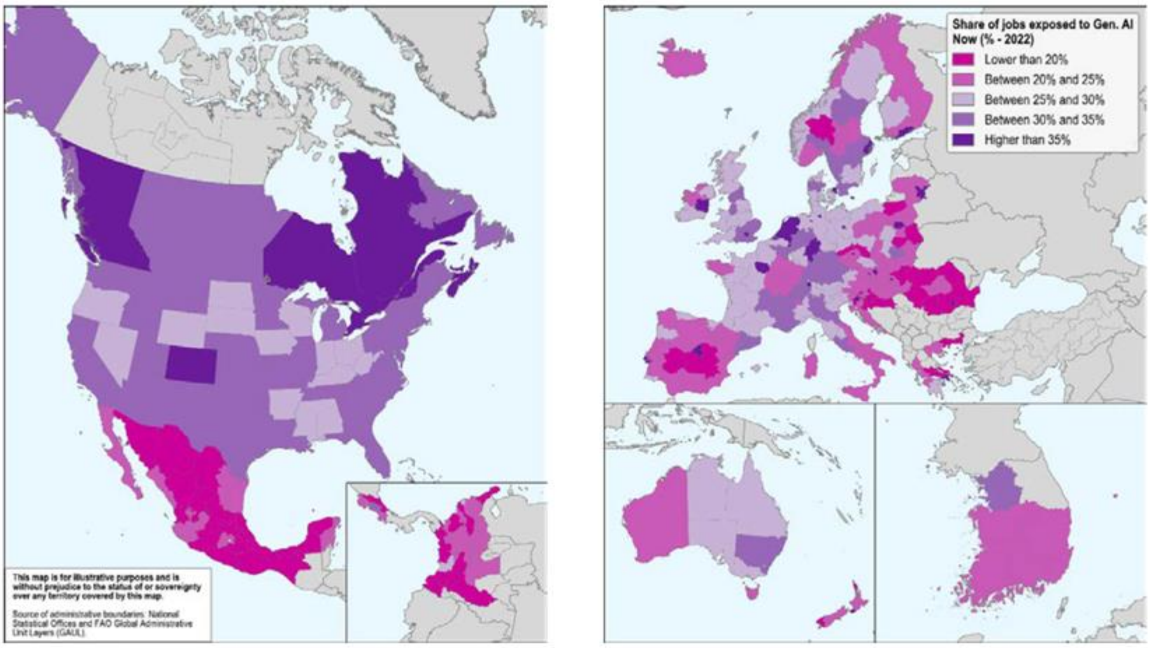
AI diffusion is polymorphic and sector- and context-specific. AI-powered business applications reflect the adaptation of different AI technologies with different auxiliary technologies, to propose solutions to different business models under different industry and environmental constraints. The descriptive analysis above highlights the diversity of trajectories, across sectors, firms and places.

There is often an alignment between the local skills structure and dominant industries and specialisation. The local skills structure, i.e. composition and distribution of skills across occupations and sectors, will determine the degree of job exposure to AI and the degree of substitution-complementarity between AI and workers locally, i.e. the actual impact of AI on local employment. Again, the trajectories of transformation in skills markets will differ across places. For instance:

- Looking at automation risks due to predictive AI (before the release of generative AI), city workers in European countries (4%) were estimated less exposed than those in towns and semi-dense (7.5%) or rural (9%) areas (2022 data) (OECD, 2024[5]). The urban-rural divides in job exposure were already apparent.
- Focusing on generative AI (after 2022), job exposure was estimated to range from 16% in Guerrero (Mexico) to 77% in Greater London (United Kingdom) (Figure 20) (OECD, 2024[45]). Within-country, the most exposed region is on average 1.6 times more at risk compared to the least exposed region. In Colombia, the country with the highest regional dispersion, the top region (Bogotá Capital District) is over 3 times as exposed as the bottom region (La Guajira). And, across the full range of OECD regions for which data are available, capital regions tend to account for most of the within-country dispersion, pointing to a new urban-rural divide growing in generative AI as well.

Figure 19. Industrial specialisation and local skills composition will shape AI diffusion

Share of jobs exposed to generative AI by TL2 region, 2022 or nearest year available



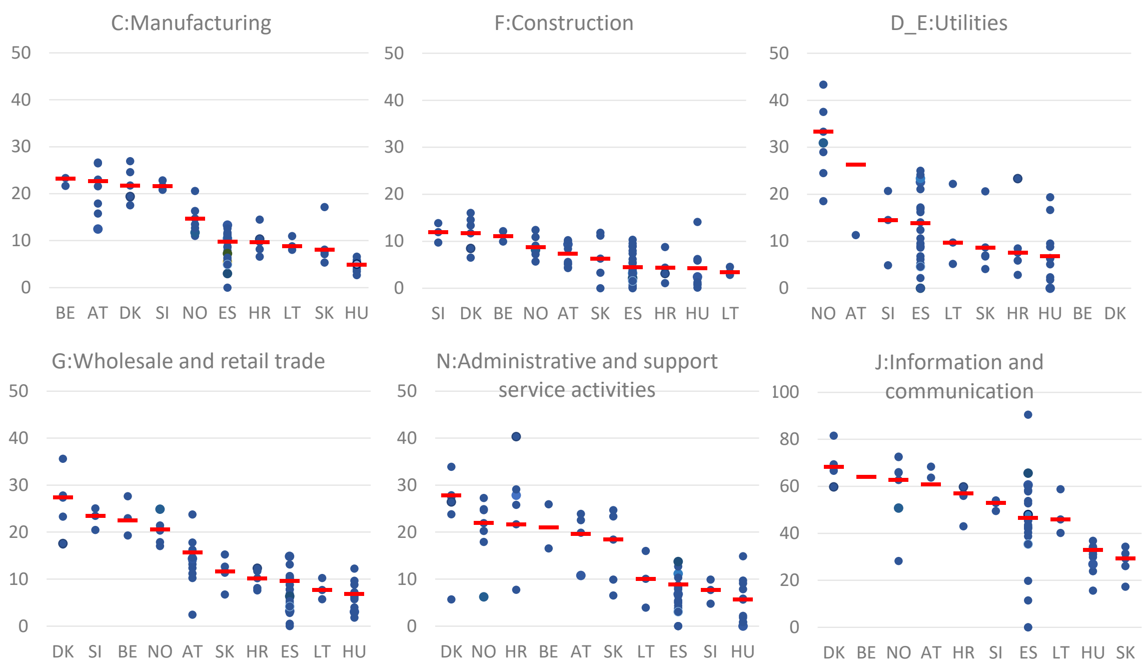
Note : A job is estimated exposed to Gen AI if the time required for a human to perform a task can be reduced by at least 50% when using a large language model (LLM), provided the quality of output is not compromised. Estimates for TL-2 regions (TL-3 for Slovenia). Last available year: 2024 for Canada and Korea, 2023 for Australia, Colombia, Costa Rica, Mexico, New Zealand, the UK and the US, 2022 otherwise.
Source : (OECD, 2024[45]), OECD calculations based on (Eloundou et al., 2023[95]) , labour force survey and employment by occupations tables.

However, firms in different regions, even located in a same country and operating in a same sector, show large differences in AI uptake, suggesting that more is at stake locally than specialisation and skills composition.

- Large gaps in business uptake of AI are observed in Spain in wholesale and retail trade (1.9%-16.7%); in Austria, in transportation and storage services (1.5%-12.4%), in Norway in information and communication services (9.2%-38.9%); and in Slovakia in professional S&T services (2.6%-18.1%) (Eurostat, 2024[49]).
- Some of the largest within-country gaps in adoption take place in the most AI advanced sectors, i.e. information and communication services, or network industries, indicating that leaders are fast distancing followers even in a same sector (Figure 21).
- In information and communication services, looking at Spain in particular, there is a significant gap between the top performing region (Extremadura at 90.5% of AI adoption rate) and a bottom performing region (La Rioja at 11.4% adoption rate). Extremadura hosts two large scale and carbon neutral data centres aimed to serve the rising demand for computing power for generative AI and cloud computing. The region has become an AI hub capitalising on high speed fiber connectivity, the proximity of major submarine cables and large European markets, and the availability of low-cost renewable energy sources locally. The region has also developed supercomputing facilities and university research in the fields of AI, virtual reality, digital twins or cobot technologies. The local government provides financial incentives to attract digital nomads, and aims to support a nascent start-up ecosystem, e.g. through public procurement (Edged US, 2025[96]) (Tracxn, 2025[97]) (Computaex, 2025[98]).

Figure 20. Regions move to AI at different speeds, even in a same country and in a same sector

AI adoption rates at firm level (%), NUTS2 regions (dots) and national total (bar), selected sectors, 2023



Note : The AI adoption rate is the share of enterprises using at least one AI technology in total enterprises with 10 or more employees. NACE industrial classification. Utilities include electricity, gas, steam and air conditioning supply; water supply; sewerage, waste management and remediation activities. EU countries and regions for which data are available.
Source : Based on (Eurostat, 2024[49]) [isoc_r_eb_ain2].

How regions source and manage AI assets is likely to be key for future deployment. The analysis above, the extensive literature on innovation diffusion and an emerging literature on the factors of AI adoption suggest some aspects to consider in the discussion (OECD, 2023[99]) (OECD, 2015[84]) (Weingarden and Lembcke, 2024[85]) (Kergroach, 2020[83]).

Boosting the capacity and coordination of local vocational education and training (VET) systems and active labour market policies will be critical to respond to emerging demand and support structural change and worker reconversion. The pace and nature of the change will vary across places, with no one-fits-all solution. Recent research shows that in the UK, the demand for AI skills (pre-GenAI) has spread to most industries, but remains concentrated in the South of the country, around London in particular, and in Northern Ireland, most likely due to the concentration of ICT and financial services and the proximity of research activities in Cambridge and Oxford (Schmidt, Pilgrim and Mourougane, 2024[100]).

Regional innovation systems are emerging as critical drivers of transformation. Regional innovation systems bring together universities, research institutions, businesses, and government agencies to faciliate knowledge exchange, leverage local capacities, such as infrastructure, and pool resources together, including finance and data. Collaboration and interdisciplinarity aim to identify areas of technology convergence, including with non-AI technologies, and accelerate the development and marketing of tailored AI solutions (Kergroach, 2025 forthcoming[2]). Regions with strong manufacturing sectors might focus on AI applications in automation and robotics, while regions with a competitive advantage in healthcare might prioritise AI in medical diagnostics and treatment.

Technology transfer in regions requires access to specialised knowledge networks and marketplaces, where, increasingly, firms seek to source from a broader portfolio of assets at reduced costs. Knowledge marketplaces centralise software, technology or databases (e.g. cloud computing services), solutions (e.g. crowd-sourced specialised software solutions), or user data (e.g. e-commerce). They are often accessible online. Local start-ups are however likely to play a key role in responding to niche demand for bespoke AI systems, demand that hyperscalers and larger AI industry actors may see as less profitable. Knowledge intermediaires also include professional S&T services and consultancy providers, who may help bridge the AI adoption gaps, e.g. by designing AI integration solutions. Those intermediaires are often locally based and operate in close proximity of their clients.

The positioning of regions in GVCs will also matter in the AI transition. Through trade, firms can access cheaper or more sophisticated input and services, or the technology embodied in purchases and imports. Through international investments, and the supply chains and linkages of foreign affiliates in regions, knowledge spillovers can also take place (OECD, 2023[99]) (OECD, 2019[10]), especially since foreign firms tend to use digital tools and processes more intensively than their domestic counterparts.

In fact, multinationals increasingly serve as vehicles for the diffusion of digital technologies globally, and play an increasing role in building the global digital infrastructure. In particular, foreign firms play a pivotal role in digital sectors, significantly more so than in the rest of the economy, and overall more in non-OECD countries than in the OECD area. The share of foreign firms in digital sectors' output, or gross value added, is nearly double those of domestic firms in OECD countries, and more than three times greater in non-OECD countries (OECD, forthcoming[101]).

However, GVC integration does not automatically translate into technology or chain upgrading. Various factors can affect the scope of spillovers such as the qualities and knowledge intensity of investments, the economic competencies and absorptive capacity of local firms, notably SMEs, the mode of governance of the value chains, and structural factors, such as local economic geography and business and policy environment (OECD, 2023[8]) (OECD, 2023[99]). Typically, the governance in a value chain is dictated by the MNE leading the chain and the sector in which it operates, which determine the type of relationships that bind it to more or less "captive" suppliers.

In other words, the opportunities of spillovers and the intensity of knowledge transfers from FDI to places will depend on the quality of foreign firms' linkages with local firms and markets. In practice, foreign firms in non-digital sectors tend to source a larger share of their inputs locally compared to those operating in digital sectors, that rely more on specialised inputs less readily available from domestic suppliers (e.g. software, advanced hardware, ICT components). In OECD economies, for every 1 unit of input imported, foreign firms source 1.7 units from local suppliers in digital sectors as opposed to 2.6 units in non-digital sectors. However, in order to tap into GVC knowledge flows, domestic firms often need to meet certain preconditions, such as product quality, supply and storage capacity, technology maturity or adequate skills. With AI, GVC requirements are likely to expand to include data integration and security, interoperability standards, AI model transparency and system reporting, AI risk mitigation, skills upgrading, or AI and data regulatory compliance.

Ways forward?

The adoption of high-performing, trustworthy and ethical AI at scale will be critical for the competitiveness and future growth of places. Yet, not all regions are engaging in the transition with the same needs and from the same basis. In the race to AI, some places are even not on the starting line. This asymetrical shift raises concerns about the foundations of a broad-based competitiveness and territorial cohesion. The question of the local factor cannot remain unanswered, especially since AI diffusion is tied to local conditions. As early divides are forming on existing fault lines, the risk of further deepening the growth trap and exacerbating inequalities across places has heightened.

Policy makers, including at subnational level, have a role to play in better preparing people, places, and firms for a future empowered by AI. This paper concludes with several areas where work could be advanced to inform policy making, improve our understanding of AI transitions and promote a broader uptake of trustworthy and ethical AI.

- **More empirical evidence is needed on AI adoption across sectors, places and firms**, and the approaches taken. The descriptive statistical analysis carried out in this paper could be extended with empirical and multivariate analysis (Héritier and Kergroach, 2025 forthcoming[60]).
- **More internationally comparable metrics** are needed to monitor AI transitions and gaps, especially in non-EU27 countries. Developing a coherent set of statistics to measure AI deployment at firm- and worker-levels would help inform policy making on progress, and would require a better harmonisation of metrics of AI use and adoption across countries and places. Emerging divides call for more granular evidence on places' and sectors' trajectories of transformation.
- **More evidence on the impact of AI adoption** on business performance, notably of SMEs, on workers' well-being, on the fair functioning of markets and competition, and on people's lives would help seize future policy intervention in the area. Assessing the environmental impact of AI, including at local level, and investigating mitigation and adaptation solutions are greatly needed.
- **A reflection on the localisation and embeddeness of AI assets** would usefully elaborate on (g)local considerations, to ensure places do not evolve in a legal and geopolitical vacuum (Kergroach, 2025 forthcoming[1]). This closely relates to the international debate on industrial sovereignty, the AI risk landscape, and the strategic positioning of places in a changing international context.
- **Better understanding the impact of AI on employment and local skills pools**, in terms of exposure, complementarity and mismatches, will be critical to inform local labour policies, and calibrate mitigation and transformation efforts. This may include exploring synergies between local VET systems and knowledge networks and markets to outsource skills, especially for SMEs.
- **Practical examples of AI diffusion** across regions could inform policy makers about different strategies adopted locally. Comparative case studies could look into the role of regional innovation systems and local economic conditions in the transition (Kergroach, 2025 forthcoming[2]). **These practical cases could be enriched with more comprehensive and forward-looking studies**, adressing with more granularity the complex and interconnected issues of AI transitions locally.

These studies could support differentiated transitions in places, through multi-stakeholder dialogue, consensus building and policy coordination towards a trustworthy and ethical AI for all.

- **Establishing a forum for discussion** to support peer learning and policy dialogue, including with non-OECD countries and regions, and that could advise on work orientations for better policy advice, and encouraging broader discussions and policy analysis on AI diffusion at a subnational level in international AI fora, such as the Global Partnership on Artificial Intelligence (GPAI).
- **More policy analysis on the role of subnational governments** in promoting trustworthy and ethical AI in businesses, public services and society (e.g. regional development policy making, or smart cities governance) is needed. Issues range from their role in promoting AI development, financing and deployment locally, and the means and tools available; to their contribution to risk management along the AI value chain; to their participation, as AI spreads, in policy coherence, alignment and interoperability for AI regulation; to their place in multi-disciplinary and multilevel collaboration, e.g. with competition, security, trade or S&T authorities, at national and supranational levels, in order to account for the local conditions of AI transitions. A stronger knowledge base is a prerequisite to develop policy recommendations for advancing the local AI agenda and the implementation of place-based innovation and industrial strategies for AI.

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Annex A. Glossary

Terminology	Definitions
Algorithm	Set of step-by-step instructions to solve a problem (not including data). Can be abstract and implemented in different programming languages or software libraries (E.U. and U.S Trade and Technology Council, 2023[27]).
Application Programming Interface (API)	Set of rules and protocols, including data formats, that allows software applications to communicate with each other, request and exchange information. APIs are essential for integrating different systems and enabling them to work together seamlessly.
Artificial intelligence (AI)	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. AI systems vary in their levels of autonomy and adaptiveness (OECD, 2024[11]).
Agentic AI	In the absence of widely accepted definition, the term of agentic AI designates in this paper a type of AI systems that can operate with minimum human oversight or intervention, take actions, and adapt strategies based on real-time environmental feedback. Use cases include self-driving cars, recommender systems, customer support chatbots, AI-powered robots etc. Contemporary agentic AI systems are generally compound systems comprised of a base model augmented by external resources, e.g. software, databases, storage ("scaffolding"), communicating through APIs and natural language dialogue (Casper et al., 2025[76])
Cloud computing services	Services that are delivered over the internet, can be accessed from anywhere and remove the need for near physical hardware. Allows accessing extra processing power, storage capacity, databases and software, at a more affordable cost, along a "pay-as-you'-go" model, i.e. in quantities that suit needs, without incurring upfront investment in hardware and recurrent expenses on maintenance, IT staff and certification. Include Software-as-a-service (SaaS), platform-as-a-service (PaaS) and infrastructure-as-a-service (IaaS). Cloud computing is instrumental in the digital transition as it reduces costs of technology upgrading (OECD, 2021[3]).
AI compute	Computational power required to train and run AI models, including processing power, memory and storage. AI computing resources ("AI compute") include one or more stacks (layers) of hardware and software used to support specialised AI workloads and applications in an efficient manner. Efficient interaction between the hardware and software stacks is crucial for AI compute, such as for optimised execution time and energy usage. AI compute requirements can vary significantly, depending on the application, AI system lifecycle stage, or size of the system. Therefore, the AI compute needed can vary from large, high-performance computing clusters or compute hyperscale cloud providers, to smaller data-science laptops and workstations (OECD, 2023[29]).
Data	Refer to recorded information. Data can be in any structured or unstructured format, including text, images, sound and video, from analogue formats like paper, to emerging quantum forms like qubits. The widespread of digital technologies has enabled the growth of digital data, i.e. information stored in binary format, that are specific insofar as they can also be processed by digital technologies (OECD, 2022[25]). (OECD, 2022[26]).

Data lake	Model of data storage allowing to integrate, in flexible and scalable ways, large volumes of raw (non-processed) data, i.e. in both structured and unstructured formats, e.g. for big data and real-time analytics. As opposed to data warehouses that operate on a ridig schema (schema-on-write) with structured data that require pre-processing, but could make data analysis simpler, especially for limited volumes of relatively uniform data. The challenges of the data lakes include dataswamp, performance issues, and ensuring compliance with data protection legislation. Both models are complementary and increasingly mixed into data lakehouses (Heritier and El Hani, 2024[102]).
Deep learning (or deep neural networks)	Subset of neural networks. Allows machine-based systems to "learn" from examples to make predictions or "inferences", based on the large amount of data processed during their training phase. Deep neural networks are distinct mostly in that they are general and require little adaptation (or "cleaning") of input data to make accurate predictions. Deep learning has enabled leaps in technological AI developments.
Edge computing	Hardware developed "at the edge" of the network, i.e. near the user or data source (such as Internet of Things -IoT- devices or local databases), to reduce the resources needed for data management, improve network performance and connectivity, reduce data processing latency and increase real-time response, and eases compliance with jurisdictional requirements for security and privacy. Typical use cases are billions of IoT devices used in advanced warehouse and inventory management solutions, vision- and sensor-enhanced robotic manufacturing lines, or advanced smart city traffic control systems.
General-purpose technology (GPTs)	Technology that can have a significant and long-term impact on an entire economy, and have pervasive effects across various sectors and industries. Examples of GPTs include electricity, the internet, and the steam engine. AI is considered as a GPT for its wide range of applications in workplaces and daily lives, or its transformative impact to address global challenges like climate change and access to quality medical care.
Generative AI (GenAI)	AI systems capable of creating content – including creative works, text, image, video – based on their training data, and usually in response to prompts, in turn serving as AI input data (Lorenz, Perset and Berryhill, 2023[30]).
Hyperscalers	Providers of large-scale cloud computing and data management services that operate networks of high computing data centers around the world, with extensive processing and storage capacity, allowing for scalable and flexible infrastructure. Major hyperscalers include companies like Amazon Web Services (AWS), Google Cloud, Microsoft Azure, IBM Cloud, and Alibaba Cloud.
Industrial policies	Policies that aim to structurally improve business performance and boost and transform specific economic activities, especially in areas where markets cannot address key challenges on their own, e.g. green transition, resilience or strategic sovereignty (Criscuolo et al., 2022[103]). Government support could be provided through a range of horizontal and targeted, supply-side and demand-side, measures ("policy mix") that are combined to create complementarities, and especially aimed at firms, or certain types of firms, based on their activity, technology, location, size or age. Beyond traditional sectoral or place-based orientations, "new" industrial strategies increasingly focus on specific technologies or "missions".
Internet of Things (IoT)	Sets of (physical) sensors, devices, and systems that are connected and support machine-to-machine (M2M) communication, creating bridges between the physical and virtual worlds, and increasing dramatically the volume of data available. Key transformative technology of the Industry 4.0 revolution, with more frequent applications in transport and logistics, manufacturing, wholesale and retail trade, and supply chains tracking. IoT contributes to hyper-connectivity and takes more and more hybrid forms by incorporating terrestrial and non-terrestrial (satellite or aerial) network technologies (OECD, 2017[104]) (OECD, 2024[28]).

Machine learning	Branch of artificial intelligence (AI) and computer science, which focuses on the 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 (E.U. and U.S Trade and Technology Council, 2023[27]). The "learning" process using machine-learning techniques is known as "training".
Open source AI software	Open-source AI software models that can be modified and freely used by anyone. As opposed to closed models, open source models are valued for the possibilities they offer to counteract market concentration, foster innovation, and enhance transparency within the AI ecosystem. They are questioned for security reasons, e.g. to facilitate disinformation or the creation of bioweapons (Maslej et al., 2024[13]).
Places	Spatial areas (or sub-units) within countries with human settlements and communities of various sizes that include, but are not limited to, remote areas, rural areas, small and intermediary cities and their neighbourhoods, and large urban, peri-urban and metropolitan areas (cities and their commuting zones) and the rural areas within them. The term 'region' is used with a spatial dimension and does not refer to any administrative or political entity (OECD, 2025[105]).
Place-based policies	Policies that account for the local conditions and the asymmetric impact of shocks and transitions, including technological change, on places, to tackle the nexus of productivity, sustainability and inclusiveness and transform the local development trajectory. Place-based policies leverage local assets, knowledge and networks, especially key for innovation, address local market and system failures responsible for labour and business mismatches, and support the provision of public goods locally [CFE/RDPC(2024)8/REV1]. Place-based policies are spatially targeted within a jurisdiction and imply a higher level of government support (as opposed to regional and local public policies); do not involve transfer of powers or responsibilities (as opposed to decentralisation policies); do not aim to reduce subnational fiscal capacity gaps (as opposed to fiscal equalisation); and they are cross-cutting insofar as they cut across different policy domains (as opposed to local education, health or transport policies) (OECD, 2025[105]).
Subnational government	Refer to all levels of government below the national level, including regional and state governments, other intermediary government levels (e.g., départements, counties, provinces) and municipal/local/metropolitan governments (OECD, 2025[105]).
Synthetic data	Data generated from data/processes and a model that is trained to reproduce the characteristics and structure of the original data (aiming for similar distribution), and to serve as a proxy when original data are scarce (E.U. and U.S Trade and Technology Council, 2023[27]).

Annex B. Eurostat national reference metadata

Table A B.1. Country notes (A-D)

	AUT	BEL	BGR	DNK
National Statistics Institutes	Statistics Austria	Statistics Belgium	National Statistical Institute	Statistics Denmark
Statistical unit	Enterprise	Enterprise	Enterprise	Enterprise
Business population				
Enterprises [10+ employees[	Yes	Yes	Yes	Yes
Micro-entreprises	No	Yes (incl. [2-9])	No	No
Self-employed	No	No	Yes	No
Total population size	42,791	115,700	27,498	18,422
Survey/census				
Sample size	10,512	7,331	5,169	4,236
Response rate	63%	61% (10+) - 37% (micro)	89.3%	97.7%
Voluntary/mandatory survey	Voluntary	Voluntary	Mandatory	Mandatory
Random sampling stratification	Yes	Yes	Yes	Yes
by firm size (employment-based)	x	x	x	x
by economic activity	x	x	x	x
by region	x	x	x	
Regions NUTS2	9 regions Burgenland - Kärnten - Niederösterreich - Oberösterreich - Salzburg - Steiermark - Tirol - Vorarlberg - Wien	3 regions (NUTS1) Brussels Capital - Flemish region - Wallonia	6 regions Severozapaden - Severen tsentralen - Severoiztochen - Yugoiztochen - Yugozapaden - Yuzhen tsentralen	5 regions Hovedstaden - SjÃ¦lland - Syddanmark- Midtjylland - Nordjylland (Greenland and the Faroe Islands are not included).
Comparability across the country's regions	**Yes**	**Yes**	**Yes**	**Yes**
National reference metadata link	(1)	(2)	(3)	(4)

Note:
(1) https://ec.europa.eu/eurostat/cache/metadata/EN/isoc_e_simsie_at.htm
(2) https://ec.europa.eu/eurostat/cache/metadata/EN/isoc_e_simsie_be.htm
(3) https://ec.europa.eu/eurostat/cache/metadata/EN/isoc_e_simsie_bg.htm
(4) https://ec.europa.eu/eurostat/cache/metadata/EN/isoc_e_simsie_dk.htm

Table A B.2. Country notes (E-L)

	ESP	HRV	HUN	LTU
National Statistics Institutes	Instituto Nacional de Estadística	National Bureau of Statistics	Central Statistical Office	Statistics Lithuania
Statistical unit	Enterprise	Enterprise	Enterprise	Enterprise
Business population				
Enterprises [10+ employees[	Yes	Yes	Yes	Yes
Micro-entreprises	Yes	No	No	No
Self-employed	Yes	Yes	Yes	Yes
Total population size	2,719,686	14,491	34,681	14,265
Survey/census				
Sample size	25,000	4,500	7,278	3,103
Response rate	95,3 % (10+ and self-employed) - 78,7 % (micro)	66%	99.9%	99.4%
Voluntary/mandatory survey	Mandatory	Mandatory	Mandatory	Mandatory
Random sampling stratification	Yes	Yes [10-49] - census [50+[	Yes	Yes
by firm size (employment-based)	x		x	x
by economic activity	x	x	x	x
by region	x		x	
Regions NUTS2	19 regions Galicia - Principado de Asturias - Cantabria - País Vasco - Comunidad Foral de Navarra - La Rioja - Aragon - Comunidad de Madrid - Castilla y León - Castilla-La Mancha - Extremadura - Cataluña - Comunitat Valenciana - Illes Balears - Andalucía - Región de Murcia - Ciudad de Ceuta - Ciudad de Melilla - Canarias	4 regions Panonska Hrvatska - Jadranska Hrvatska - Grad Zagreb - Sjeverna Hrvatska	8 regions Budapest - Közép-Dunántú -, Nyugat-Dunántúl - Dél-Dunántúl - Észak-Magyarország - Észak-Alföld - Dél-Alföld - Pest megye	2 regions Central and Western Lithuania
Comparability across the country's regions	**Yes**	**Yes**	**Yes**	**Yes**
National reference metadata link	(5)	(6)	(7)	(8)

Note:
(5) https://ec.europa.eu/eurostat/cache/metadata/EN/isoc_e_simsie_es.htm
(6) https://ec.europa.eu/eurostat/cache/metadata/EN/isoc_e_simsie_hr.htm
(7) https://ec.europa.eu/eurostat/cache/metadata/EN/isoc_e_simsie_hu.htm
(8) https://ec.europa.eu/eurostat/cache/metadata/EN/isoc_e_simsie_lt.htm

Table A B.3. Country notes (N-S)

	NOR	ROM	SVN	SVK
National Statistics Institutes	Statistics Norway	National Institute of Statistics	Statistical Office of the Republic of Slovenia	Statistical Office of the Slovak Republic
Statistical unit	Enterprise	Enterprise	Enterprise	Enterprise
Business population				
Enterprises [10+ employees[	Yes	Yes	Yes	Yes
Micro-entreprises	No	No	No	No
Self-employed	Yes	Yes	Yes	Yes
Total population size	27,700	51,920	8,729	14,286
Survey/census				
Sample size	5,686	11,487	1,794	2,828
Response rate	99.9%	85.3%	88.2%	90.7%
Voluntary/mandatory survey	Mandatory	Mandatory	Mandatory	Mandatory
Random sampling stratification	Yes	Yes	Survey/ census	Yes
by firm size (employment-based)	x	x	x	x
by economic activity	x	x	x	x
by region				x
Regions NUTS2	6 regions (mainland) Innlandet - Trondelag - Nord-Norge - Oslo og Viken - Agder og Sor-Ostlandet - Vestlandet	8 regions Nord-Vest - Centru - Nord-Est - Sud-Est - Sud-Muntenia - Bucuresti-Ilfov - Sud-Vest Oltenia - Vest	2 regions Eastern Slovenia (Vzhodna Slovenija) - Western Slovenia (Zahodna Slovenija)	4 regions Bratislava Region - Western Slovakia (Západné Slovensko) - Central Slovakia (Stredné Slovensko) - Eastern Slovakia (Východné Slovensko)
Comparability across the country's regions	**Yes**	**Yes**	**Yes**	**Yes**
National reference metadata link	(9)	(10)	(11)	(12)

Note:
(9) https://ec.europa.eu/eurostat/cache/metadata/EN/isoc_e_simsie_no.htm
(10) https://ec.europa.eu/eurostat/cache/metadata/EN/isoc_e_simsie_ro.htm
(11) https://ec.europa.eu/eurostat/cache/metadata/EN/isoc_e_simsie_si.htm
(12) https://ec.europa.eu/eurostat/cache/metadata/EN/isoc_e_simsie_sk.htm

Annex C. Evidence on AI adoption by firms

Table A C.1. Comparative meta-analysis of selected references on business use of AI

Authors	Level of analysis	Source and method					**Pre/ post-GenAI**
		Source	Country coverage	Comparability	Timeliness	Granularity	
Borgonovi, F. et al. (2023)	Worker-level	Lightcast data (online job vacancies and skills description)	14 OECD countries (English speaking and EU)	With cautious across countries (good representativeness for the US)	Real-time data from Jan 2019 to Oct 2022	- Occupation - Skills - Sector (US)	**Pre-GenAI**
	Key findings: AI-related online vacancies represent a small share of all vacancies posted online (less than 1%), but this share grew steadily between 2019-22 (+33%), especially in ICT and professional services, and particularly in programming, data analysis, and machine learning. Demand and skill profiles vary across countries, reflecting different economic structures. Skills related to Machine Learning were the most sought after.						
Calvino, F., et al. (2022)	Firm-level	Matching of data on IPRs (patents, trademarks), company website information (GlassAI), online job postings (Lightcast), and firm-level financials and performance (Orbis) using string-matching algorithms	Exploratory analysis on UK only	Not applicable	Variable across measures (from 2012-20)	- Sector - Firm size	**Pre-GenAI**
	Key findings: A significant share of AI adopters is active in ICT and professional services, and located in the South of the UK, particularly around London. Adopters tend to be highly productive and larger firms, while young adopters tend to hire AI workers more intensively. Significant differences in the characteristics of AI adopters emerge when distinguishing between firms carrying out AI innovation, those with an AI core business, and those searching for AI talent.						
Calvino, F. and L. Fontanelli (2023)	Firm-level	Distributed microdata analysis on official firm-level surveys collected through NSOs (OECD AI diffuse project)	11 OECD countries (7 EU plus CHE, ISR, JPN, KOR)	Harmonised statistical code, but differences in national survey design and implementation may affect cross-country comparability.	Varies across countries (from 2016 to 2020, with a few data points for some countries)	- Sector	**Pre-GenAI**
	Key findings: Polarised AI adoption which is more prevalent in ICT and professional services sectors, and among large and, to some extent, younger firms. AI adopters tend to be more productive, especially larger firms. Complementary assets, including ICT skills, high-speed digital infrastructure, and the use of other digital technologies, which are significantly related to the use of AI, appear to play a critical role in the productivity advantages of AI users.						
Calvino, F. et al. (2024)	Sector-level	Combining online job vacancies (Lightcast), AI-related patents, sector-level AI exposure adjusted for barriers, and firm-level AI usage surveys	OECD countries, depending on data availability	Differences in data availability and sectoral classifications may affect comparability	From 2017-23, with online job vacancies (2018–22), AI-related patents (2017–21), sector-level AI exposure adjusted for barriers, and firm-level AI usage	- Sector	**Pre-GenAI**

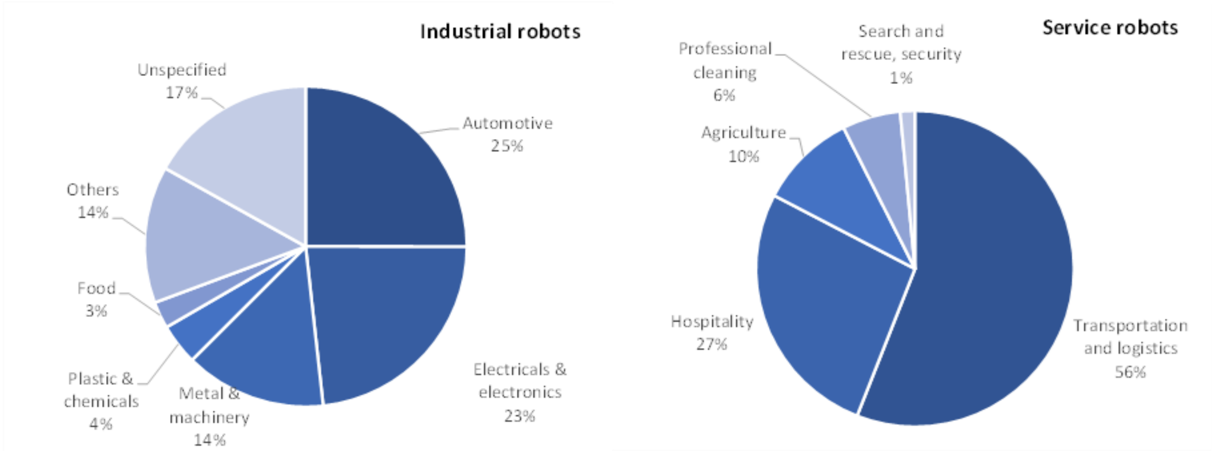
					surveys (2021–23)		
	Key findings: Taxonomy to assess AI intensity across sectors, considering AI human capital, innovation, exposure, and usage. Sectors like IT services, media, and telecommunications exhibit high AI intensity across all dimensions. Sectors such as pharmaceuticals show high AI human capital but lower innovation output. Low-intensity sectors include food products, textiles, construction, and hospitality.						
Dernis, H., et al. (2023)	Firm- and organisation-level	Company/university website information (web-scraped information by GlassAI using semantic analysis and topic ontology)	Canada, Germany, UK, US	Variations in website content and language may affect cross-country comparability	2020	- Firm size - Firm age - Sector	**Pre-GenAI**
	Key findings: AI firms are predominantly young, small, and operate mainly in the information and communication sector. These firms often have AI at the core of their business models, focusing on customer solutions. Universities engaged in AI activities are concentrated in urban areas, but this does not necessarily correlate with the intensity of AI-related activities.						
OECD (2021) The Digital Transformation of SMEs	Firm-level	ICT use by businesses (firm-surveys)	OECD countries, depending on data availability	Differeces in sampling and survey method may affect cross-country comparisons	Up to 2020	- Firm size - Sector - Technology and AI usage type	**Pre-GenAI**
	Key findings: AI adoption among SMEs remains limited, with a significant gap compared to larger firms. SMEs face multiple challenges, including limited financial resources, lack of digital skills, and inadequate infrastructure. The adoption of AI is often linked with other digital technologies, such as cloud computing and data analytics, and SMEs that have embraced these complementary technologies are more likely to adopt AI. In-depth analysis of SME digital adoption challenges and support policies.						
OECD (2024) Digital Economy Outlook	Firm-level	ICT use by businesses (firm-surveys)	OECD countries, depending on data availability	Differences in sampling and survey method may affect cross-country comparisons	Up to 2023	- Firm size - Sector - Technology and AI usage type	**Pre-GenAI and early GenAI trends**
	Key findings: There is a significant AI adoption gap between SMEs and larger enterprises. Mulitple barriers hinder business ability to implement and benefit from AI technologies, inlcuding funding, digital skills or infrastructure. High-level synthesis of major trends in digital transformation globally and across sectors.						
OECD (2024) Fostering an inclusive digital transformation as AI spreads among firms	Firm-level	Synthesis of existing work and data	..	..	..	- Firm size - Firm age - Sector	**Pre-GenAI and early GenAI trends**
	Key findings: AI adopters outperform other firms, the highest rates of AI adoption being found among the most productive firms, and productivity advantages are linked to complementary assets, such as ICT and management skills, digital capabilities, and digital infrastructure. AI adoption remains highly concentrated in the ICT sector and among larger firms. In some countries, among young firms as well.						
OECD (2024) Job Creation and Local Economic Development 2024: The Geography of GenAI	Worker-level	Worker exposure to AI estimated by the share of tasks within an occupation that could be completed in half the time with LLMs, based on national statistics on occupations and task exposure by (Eloundou et al 2023))	35 OECD countries, depending on data availability	Differences in labour survey methods, sampling and occupational classifications may affect country and region comparisons..	2024 or latest year available	'- Regions NUTS2 - Degree of urbanisation - Occupation - Sector	**Post-GenAI**
	Key findings: Regions previously considered to be at lower risk of automation are the most exposed to Generative AI. Technology-led automation, including through other forms of AI, particularly affected non-metropolitan and manufacturing regions. In contrast, GenAI has the potential to alter a higher share of jobs in metropolitan regions, and exposure is greater for high-skilled workers and women, unlike precedent technological waves.						
OECD (2025) SME	Firm-level	D4SME business survey conducted via	10 OECD countries	Differences in sampling affect cross-country	Q4 2024	- Firm size - Business	**Post-GenAI**

digitalisation for competitiveness	(SMEs)	online retail platforms (Amazon, Intuit, Kakao, Rakuten, Sage)	(AUS, CAN, FRA, GER, ITA, JPN, KOR, ESP, UK, USA)	comparisons. Non-randomised and small size samples limit business representativeness.		owner age - Sector - Digital maturity - AI usage type	
	Key findings: SMEs with higher digital maturity levels are more likely to adopt AI technologies. Among SMEs using generative AI, 91% report productivity improvements, and 76% note enhanced innovation capabilities. SMEs led by younger CEOs demonstrate a higher propensity for AI adoption, suggesting that leadership demographics influence digital transformation strategies.						
OECD/BCG/INSEAD (2025)	Firm-level	Literature review, business survey to active AI users and structured interviews	G7 countries and Brazil	Not available	Survey conducted between Nov 2022 and Jan 2023	- Sector (only ICT and manufacturing) - Firm size	**Pre-GenAI**
	Key findings: Prior to the advent of generative AI, the adoption of AI in firms is an exception rather than the norm. Single-digit adoption rates for entire sectors are common in many countries. A universal finding is that adoption is highest in larger firms. Yet, there are significant diversity in the state of AI deployment across countries. More work is needed to understand the reasons, which, among other things, are likely to reflect methodological issues in measurement.						
Calvino, F., J. Reijerink and L. Samek (2025)		Literature review of experimental research on the impact of GenAI	..	..	..	..	**Post-GenAI**
	Key findings: AI's effectiveness depends on the user's experience and the task carried out, with human-AI collaboration being key to maximising its potential. The review identifies knowledge gaps , particularly regarding long-term business effects and workers' understanding of its limitations.						
Calvino, F. et al. (2023)	Patent-level	Patent data (based on forward citations of AI-related patents, identified by AI keywords retrieved in patent documents and selected International Patent Classification (and CPC) codes. Top 1% cited patents are core AI patents)	World applicants	High within USPTO data. Citation counts are normalised by the average number of forward citations received by patents from a reference cohort.	Patent applications filed at US Patent and Trademark Office (USPTO) between 2000-18	..	**Pre-GenAI**
	Key findings: AI patents tend to be broader in technological scope. Technologies related to general AI, robotics, computer/ image vision and recognition/detection are consistently listed among core AI patents, with autonomous driving and deep learning having recently become more prominent. Finally, core AI patents tend to spur innovation across AI-related domains, although some technologies – likely autonomous driving or robotics – appear to increasingly contribute to developments in their own field.						
Calvino, F., D. Haerle and S. Liu (2025)	Patent-level	Patent data (based on forward citations of GenAI-related patents, identified by WIPO combining keywords and technology classes on documentation. Top 1% cited patents are core GenAI patents)	World applicants	High within USPTO data. Citation counts are normalised by the average number of forward citations received for a reference cohort.	Patent applications filed at US Patent and Trademark Office (USPTO) between 2010 and 2020	..	**Post-GenAI**
	Key findings: GenAI exhibits characteristics of general-purpose technologies: 1) being pervasive and having a widespread diffusion across sectors; 2) continuously improving over time; and 3) resulting in innovation in products and processes.						

Note: This table was prepared with generative AI for classifying publicly accessible information. Key findings are abridged from abstracts.
Source: (Borgonovi et al., 2023[38]); (Calvino et al., 2022[39]); (Calvino and Fontanelli, 2023[40]); (Calvino et al., 2023[41]); (Calvino et al., 2024[42]); (Calvino et al., 2024[42]); (Calvino, Reijerink and Samek, 2025[43]); (Calvino, Haerle and Liu, 2025 forthcoming[31]); (Dernis et al., 2023[44]); (OECD, 2021[3]); (OECD, 2024[45]); (OECD, 2024[46]); (OECD, 2024[28]); (OECD, 2024[47]); (OECD/BCG/INSEAD, 2025[48]).

Annex D. Industrial and service robots

Figure A D.1. Global industrial and service robot fleet by sector of use, 2023



Note : Industrial robots are “automatically controlled, reprogrammable multipurpose manipulator, programmable in three or more axes, which can be either fixed in place or fixed to a mobile platform for use in automation applications in an industrial environment" (ISO, 2025[78]). Service robots are "robot in personal use or professional use that performs useful tasks for humans or equipment". They require a certain degree of autonomy, which ranges from partial autonomy - including human-robot interaction - to full autonomy - without active human robot intervention. See classification in Annex B. Data is collected from industrial robot suppliers worldwide either as primary data or as secondary data through national robotics associations. Data cover service robots for professional use only.
Source : (International Federation of Robotics, 2024[79]).

Annex E. Classification of service robots

Figure A E.1. Classification of service robots

AP	Professional service robots	Robots intended for use by trained professionals.
AP1	Agriculture	Robots for agricultural and farming applications
AP11	Cultivation	Plowing, seeding, harvesting, weeding, fertilizing, pesticide spraying of/for crop plants and fuit indoors (greenhouse) and outdoors (field, vineyard)
AP12	Milking	Milking
AP13	Other livestock farming	Livestock farming, except milking, e.g. feeding, barn cleaning
AP19	Other agriculture	Agriculture, but none of the above
AP2	Professional cleaning	Robots for professional cleaning applications
AP21	Floor cleaning	Cleaning of horizontal areas, e.g. floors in offices, hotels, public buildings, streets and sidewalks. Note: Robots for barn cleaning are included in class AP13
AP22	Window and wall cleaning	Cleaning of windows, walls and other vertical areas
AP23	Tank, tube and pipe cleaning	Inside cleaning of tanks, tubes or pipes
AP24	Hull cleaning	Outside cleaning of hulls (aircraft, train, other vehicles, tank, container)
AP25	Disinfection	UV, spray, wiping or other disinfection methods
AP29	Other professional cleaning	Professional cleaning other than above
AP3	Inspection and maintenance	Robots for inspection and maintenance
AP31	Buildings and other construction	Outside detection of damage in buildings, plants, bridges, tunnels and other civil construction
AP32	Tank, tubes, pipes, sewers	Inside detection of leakage in tanks, pipes, or sewers
AP39	Other inspection and maintenance	Inspection and maintenance, but none of the above
AP4	Construction and demolition	Robots for construction and demolition
AP41	Construction	Installation of buildings and other constructions, earthwork
AP42	Demolition	Tear-off of buildings and other constructions
AP5	Transportation and logistics	Mobile robots for transportation of goods or cargo and other logistics functions
AP51	Indoor environments without public traffic	Cargo/goods transportation in indoor environments without public traffic only, e.g. warehouses, factories, non-public areas of hospitals, airports, etc.
AP52	Indoor environments with public traffic	Cargo/goods transportation in indoor environments with public traffic, e.g. hospitals, hotels, restaurants
AP53	Outdoor environments without public traffic	Cargo/goods transport in outdoor environments without public traffic only, e.g. harbors, airports
AP54	Outdoor environments with public traffic	Cargo/goods transport in outdoor environments with public traffic, e.g. home delivery, parcel delivery in the streets
AP55	Inventory	Counting and refilling of stock and inventory
AP59	Other transportation and logistics	Mobile robots for transportation and logistics applications not mentioned above. No passenger transportation.
AP7	Search and rescue, security	Robots for emergency situations
AP71	Firefighting	Robots for Firefighting. Includes robotic devices.
AP72	Disaster relief	Robots for detection or rescue of survivors. Includes robotic devices.
AP73	Security services	Robots for security functions, e.g. surveillance, bomb squad support. Includes robotic devices.
AP8	Hospitality	Robots for interaction with guests or visitors
AP81	Food and drink preparation	Robots for food or drink preparation
AP82	Mobile guidance, information, telepresence	Robotic information desks or guides, e.g. in museums, shops, hotel receptions. Robots for virtual participation in real-world events. Note: Telepresence robots specifically designed for the medical field are covered in AP69
AP9	Other professional service robots	Robots that do not fit into any of the above classes
AP99	Other professional service robots	Robots that do not fit into any of the above classes

AC	Consumer robots	Robots intended for use by everyone. No professional training required.
AC1	Robots for domestic tasks	Robots for housekeeping and similar tasks around the house
AC11	Domestic floor cleaning (indoor)	Wet and dry cleaning of floors, e.g. vacuuming and wiping of floors
AC12	Domestic window cleaning	Cleaning of windows
AC13	Gardening	Gardening tasks, e.g. lawn mowing
AC14	Domestic cleaning (outdoor)	Outdoor cleaning tasks around the home, e.g. pool cleaning, yard cleaning
AC19	Other domestic tasks	Domestic tasks other than AC11 to AC14
AC2	Social interaction, education	Robots with social interaction functions, robots for children and student education
AC21	Social interaction, companions	Main purpose of the robot is to interact with and entertain users at home
AC22	Education	Robots desigend specifically to educate children or students
AC3	Care at home	Robots that support people in need of care (e.g. seniors or handicapped people) in their homes or home-like environments (e.g. retirement homes)
AC31	Mobility assistants	Robotic wheelchairs, robotic rollators/walkers, exoskeletons for walking disabilities. Includes robotic devices.
AC32	Manipulation aids	Robots that support seniors or disabled people in the manipulation of their environment (e.g. meal assistance robot, manipulators mounted to wheelchairs). Includes robotic devices.
AC39	Other care robots	Robots for care at home that do not fit into AC31 or AC32. Includes robotics devices.
AC9	Other consumer robots	Consumer robots that do not fit into any of above classes
AC99	Other consumer robots	Consumer robots that do not fit into any of above classes