CHAPTER 3

BUILDING THE AI ECONOMY

Advanced AI relies on a capital-intensive supply chain of chips, data centres, electricity and specialised research. Economies in the EBRD regions play a limited role in these upstream segments: their AI-related hardware exports, frontier-model development and AI firm valuations lag those of global leaders considerably, while power constraints restrict their capacity to host large-scale data centres. Greater opportunities lie downstream in the development of AI-enabled applications and the use of AI to boost productivity. As adoption capacity varies widely, benefits are likely to be uneven. Policymakers could facilitate successful AI adoption by prioritising infrastructure, skills, access to computing capacity, data governance and international cooperation.





INTRODUCTION

Unlike previous waves of automation, generative AI primarily affects knowledge-intensive work, such as writing, developing software (coding) and analysing data. AI capabilities continue to improve rapidly, giving firms and workers less time to adjust to innovation than in the past. In the United States, workplace adoption of generative AI has been faster than that of the personal computer (relative to their respective mass-market launches), while its overall adoption has outpaced the rollout of both personal computers and the internet.[1]

The capacity to build AI systems remains concentrated: a handful of economies and firms dominate the fields of advanced semiconductor chips, data infrastructure and frontier models. Economies in the EBRD regions play a limited role in these upstream segments of the AI supply chain, and the potential for expanding that role is frequently limited by the size and structure of those economies. The potential is stronger in the application layer, where AI models are turned into products and services for end users. The barriers to entry are lower in this market segment, and firms in the EBRD regions are already active in many areas relating to AI applications.

The biggest opportunity lies in AI adoption. While the potential economic gains from AI are substantial, they are likely to be distributed unevenly across economies and sectors. Economies with strong digital infrastructure and the skills needed to adopt and use new technologies effectively are best positioned to benefit; those starting from a lower level of digital economy development, including many in the southern and eastern Mediterranean (SEMED) and sub-Saharan Africa (SSA) regions, risk falling further behind.

Realising gains from AI will depend first and foremost on the ability of firms, workers and governments to use AI effectively and on policy choices governing digital infrastructure, data use, the upgrading of skills and international cooperation.

This chapter starts by documenting the supply chain underpinning the production and use of AI, including the participation of the EBRD regions in those networks. It then estimates the potential productivity gains from AI adoption and reviews early evidence on affected workers, particularly new entrants into the labour market. Lastly, it considers policies that can facilitate the effective adoption of AI.

THE AI SUPPLY CHAIN

Recent progress on AI capabilities rests on specialised hardware or accelerators, such as AI semiconductor chips. These form the basis of processors suited to the computations involved in training and running AI models, which consist of very large numbers of simple arithmetic operations carried out in parallel. For such workloads, AI chips are faster and use far less energy than the general-purpose central processing units (CPUs) found in ordinary computers. Most AI computing capacity comes from graphics processing units (GPUs), which were originally designed to render images for video games.

The computing power used to train leading models has grown more than fourfold per year since 2010,[2] and training a frontier model now requires tens of thousands of chips working together for months. This expansion is visible in the global stock of AI computing capacity, which reached the equivalent of about 20 million H100 chips[3] at the end of 2025, around a threefold increase relative to its level a year earlier (see Chart 3.1).

The supply of AI chips has struggled to keep pace with demand, however.[4] Semiconductor fabrication is one of the most exacting industrial processes, with each step, from the design of production equipment to chip fabrication, dominated by a handful of specialised firms. As a result, output can only grow as fast as the weakest link in the chain.

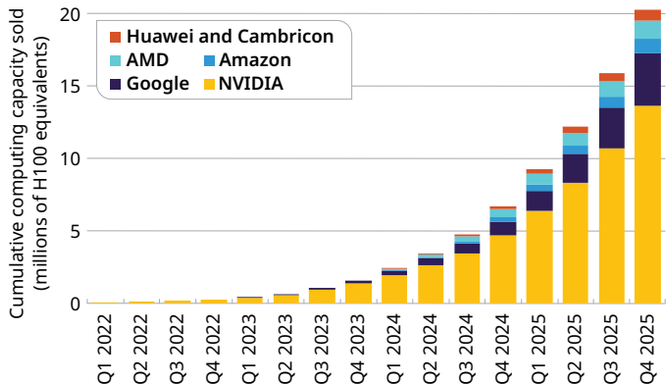
[1] See Bick, Blandin and Deming (2026).

[2] See Epoch AI (2026a).

[3] H100 is a widely used AI accelerator produced by NVIDIA.

[4] See Epoch AI (2026b).

CHART 3.1 The global stock of AI computing capacity is growing exponentially



SOURCE: Epoch AI (2026c).

DESIGNING CHIPS: THE "FABLESS" MARGIN

Chip design involves deciding how its transistors are arranged, depending on the unit's purpose. For a frontier AI accelerator, this stage can take several years of engineering work and hundreds of millions of dollars in R&D expenditure.[5]

A few "integrated device manufacturers" design and fabricate their own chips, while most other chip designers are "fabless": they design chips and contract manufacturers, known as foundries, to build them based on the blueprints provided. The fabless model now dominates the supply of AI accelerators: NVIDIA, the world's largest fabless designer, accounted for an estimated 79 per cent of global spending on AI chips in 2025.[6] Designers also capture most of the value, with the margins retained by the designers of leading chips estimated at between 58 per cent and 90 per cent of the chip's selling price.[7]

MAKING CHIPS: A FEW FOUNDRIES

At the fabrication stage, a polished silicon wafer passes through several hundred steps in which layers of material are deposited, patterned with light and etched away. Each new generation of this technology, known as a process node, makes chips more powerful and energy efficient. Frontier accelerators are built on the most advanced nodes, overwhelmingly produced by foundries.

The entire supply chain is highly concentrated. Most leading AI chips flow through a single foundry, TSMC. Based in Taipei China, it accounts for around 70 per cent of the global foundry market for all chips.[8] The extreme ultraviolet lithography machines needed to produce leading-edge chips are, in turn, supplied by a single firm, ASML of the Netherlands. High-bandwidth memory, which allows data to move rapidly between memory and the processor, is produced at scale by just three firms: SK Hynix, Samsung and Micron. Advanced packaging, which integrates processor and memory into a working unit, is dominated by a single TSMC process, chip-on-wafer-on-substrate (CoWoS). High-bandwidth memory and advanced packaging were the main bottlenecks constraining AI accelerator supply in 2025.[9]

TSMC in Taipei China accounts for around **70%** of the global foundry market

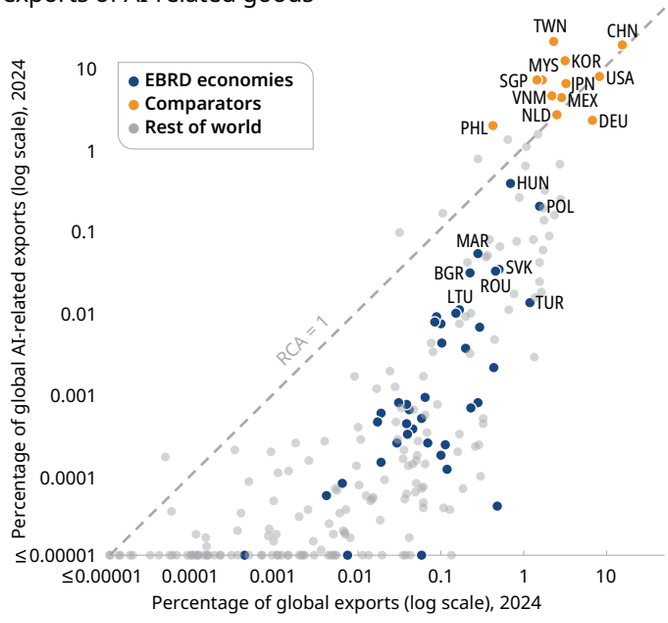
[5] See SIA and BCG (2022).
[6] See Epoch AI (2026c).
[7] See Silicon Analysts (2026). This calculation covers 12 AI accelerators sold by NVIDIA, AMD, Intel and Groq.
[8] See TrendForce (2026).
[9] See Epoch AI (2026b).

TRADE IN AI-RELATED PRODUCTS

Analysis of global trade in AI-related inputs for this year's *Transition Report* identifies a basket of 24 product codes at the six-digit level of the WCO Harmonized System (HS6),[10] the most detailed level at which trade data are internationally comparable. This basket covers the chips, boards and servers that AI workloads run on, along with chip fabrication equipment and manufacturing materials (see Box 3.1). These product codes are not always specific to AI: servers and processing units (HS 847150), for instance, include both ordinary business servers and AI accelerators.

Together, the 24 AI-related products accounted for an estimated 6.4 per cent of world merchandise trade in 2024.[11] As in Chapter 1, this analysis uses the concept of revealed comparative advantage (RCA): an economy holds an RCA in a product if it exports more of that product than its overall share of world trade would suggest.

CHART 3.2 EBRD economies are underrepresented in exports of AI-related goods



SOURCE: CEPII (2026) (HS17 version) and authors' calculations.
NOTE: AI-related goods comprise 24 HS6 codes linked to the AI hardware supply chain. Comparators are economies above the 95th percentile of world AI-related export shares.

AI-related goods accounted for an estimated **6.4%** of world merchandise trade in 2024

By this measure, EBRD economies are underrepresented in trade in AI-related goods (see Chart 3.2). In 2024, they supplied around 8 per cent of world goods exports, but only 0.8 per cent of AI-related goods exports, and no EBRD economy holds an RCA in the AI-related basket as a whole. In contrast, Taipei China's share of exports of AI-related goods is around 9 times its share of world trade; for South Korea, this ratio is almost 4 to 1.

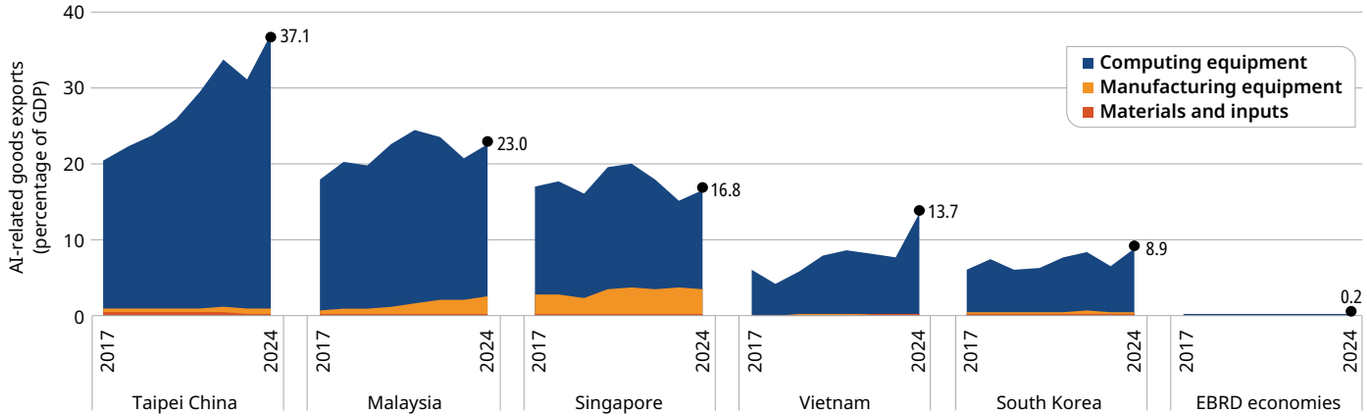
In 2024, AI-related exports in the EBRD regions amounted to 0.2 per cent of GDP, compared with 37.1 per cent in Taipei China and 8.9 per cent in South Korea (see Chart 3.3). Singapore, which ranks among the five largest economies by wafer capacity in mature logic and specialty memory chips,[12] has the highest exports of semiconductor manufacturing equipment as a share of GDP, at 3.3 per cent.

Malaysia and Vietnam specialise in hardware assembly, with AI-related exports reaching 23 per cent and 13.7 per cent of GDP, respectively, in 2024. Their leading positions were cemented by anchor investments by foreign firms. Malaysia's industry grew around Intel's Penang plant, opened in 1972 as the firm's first assembly site outside the United States.[13] In Vietnam, investments by Intel and Samsung from the mid-2000s made electronics the country's largest export sector (see Chapter 1).

Current exports also provide information on the products an economy might be able to produce in future, as discussed in Chapter 1. For each AI-related product,

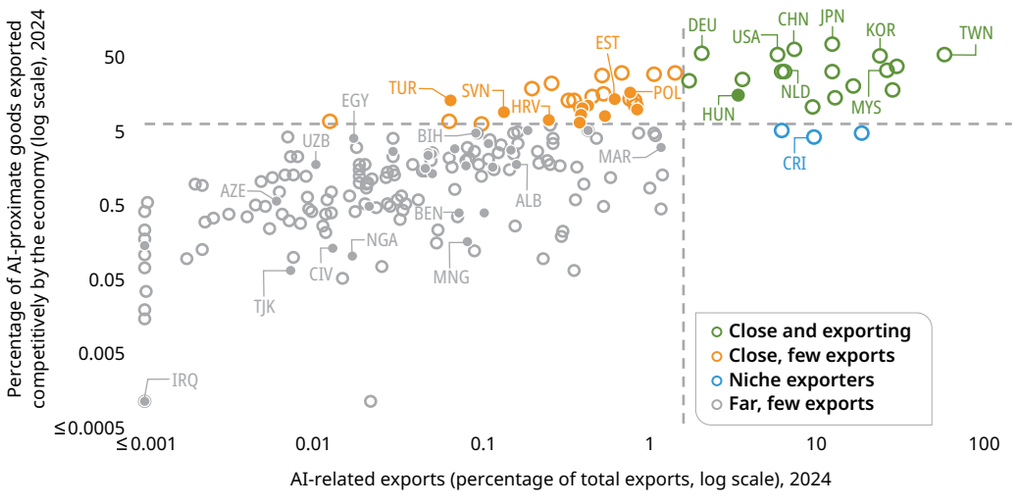
[10] See WCO (2022).
[11] Authors' calculations based on CEPII (2026) (HS17 version).
[12] See OECD (2025a).
[13] See Intel (n.d.).

CHART 3.3 Exports of AI-related goods remain small relative to GDP in EBRD economies



SOURCE: CEPII (2026) (HS17 version), IMF (2026) and authors' calculations.
NOTE: AI-related goods comprise 24 HS6 codes linked to the AI hardware supply chain. Weighted average for the EBRD regions.

CHART 3.4 Most EBRD economies export few AI-related goods and hold few proximate capabilities



SOURCE: CEPII (2026) (HS17 version) and authors' calculations.
NOTE: AI-related goods comprise 24 HS6 codes linked to the AI hardware supply chain. The product links defining each product's neighbourhood are validated against exports pooled over 2022-24 (see Box 3.1). Niche exporters are economies whose exports of AI-related goods consist largely of a single product, while few of the AI-proximate goods are exported competitively. Quadrants are split at the sample mean for each measure. Filled circles denote economies in the EBRD regions.

the analysis identifies its neighbouring or proximate products – those typically exported alongside it – and measures how much of that neighbourhood an economy already exports competitively, giving greater weight to products that are more closely linked. Higher coverage of that neighbourhood indicates that an economy has a stronger position, potentially enabling it to develop a comparative advantage in the AI-related product itself (see Box 3.1).

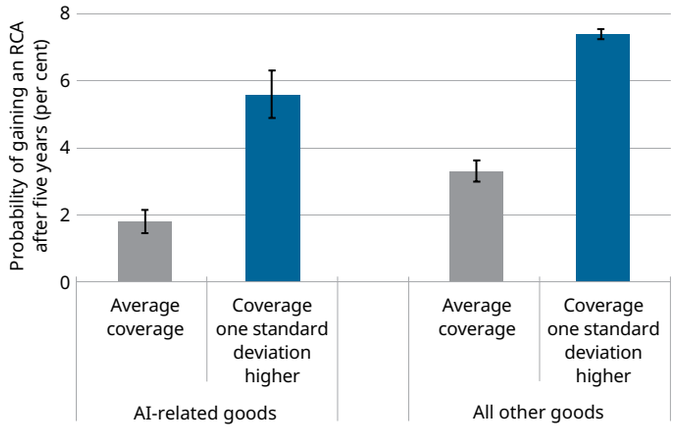
Most EBRD economies export few products that are typically exported alongside AI-related goods (see Chart 3.4 and Chapter 1). In Central Asia, eastern Europe and the Caucasus (EEC), SEMED and SSA, only 2 per cent of AI-proximate products are exported competitively, compared with a global average of 5.7 per cent. In contrast, China, Germany, Japan, South Korea, Taipei China and the United States each export competitively some 50 per cent or more of AI-proximate products.

Hungary is the only EBRD economy with sizeable AI-related goods exports and relatively high coverage of proximate products. This reflects the presence of several major foreign manufacturers: Lenovo has built servers and workstations at its Üllő plant since 2022,[14] alongside contract manufacturers such as Foxconn, Flex and Jabil. Processing units and servers (HS 847150) are Hungary's largest AI-related export line, at nearly four times the level implied by Hungary's share of world trade. Hungary is further specialised in instruments for measuring and checking semiconductor wafers and devices (HS 903082), hosting a domestic supplier in that niche, Semilab, which sells metrology and inspection tools to wafer and device manufacturers. Hungary is also a competitive exporter of related products, such as desktop computers.

Some EBRD economies that lack sizeable AI-related goods exports are already competitive in proximate products. Poland holds an RCA in complete data-processing systems (HS 847149) and desktop computers (HS 847141), while Estonia has an RCA in parts for electrical measurement instruments (HS 903090) and other precision measuring instruments (HS 903190), components closely related to semiconductor manufacturing and testing equipment.

Expertise in proximate goods more than triples the likelihood of developing an RCA in AI-related products, from 1.8 per cent to around 6 per cent (see Chart 3.5 and Box 3.1).

CHART 3.5 Economies are more likely to develop an RCA in products close to their existing capabilities, including AI-related goods



SOURCE: CEPII (2026) (HS02 version) and authors' calculations.
NOTE: Estimates are from a linear probability model relating an economy's holding of an RCA in a product five years after the baseline year to its coverage of that product's neighbourhood at baseline. The product links defining each product's neighbourhood are validated against exports over the three years up to and including the baseline year (2002-04 for a 2004 baseline, and so on). The sample pools economy-product pairs without an RCA in the baseline year with baseline years from 2004 to 2019 and products classified under HS02 throughout. The model is estimated jointly, with separate slopes for AI-related and all other goods, and includes economy-year and product-year fixed effects. AI-related goods comprise 22 HS6 codes linked to the AI hardware supply chain. Whiskers show 95 per cent confidence intervals, with standard errors clustered by economy.

AI INFRASTRUCTURE

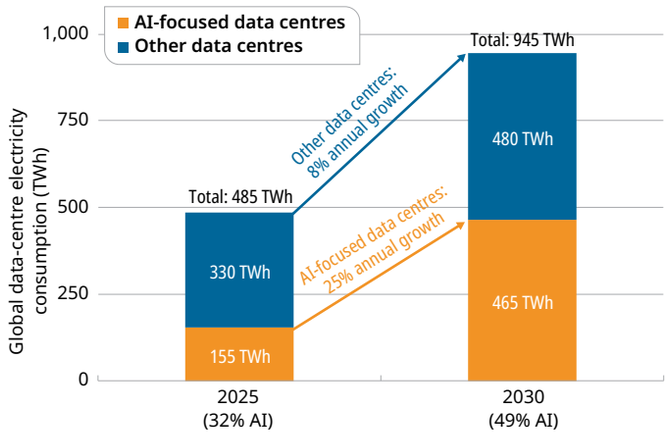
Once AI chips have been manufactured, they are assembled into servers, networked and installed in data centres in large numbers, together with the power supply, cooling technology and connectivity needed to operate them. Most installed data-centre capacity serves general-purpose cloud computing, enterprise software, data storage and streaming, running general-purpose processors and typically drawing 10-25 megawatts (MW) of power.[15]

AI-focused facilities are built around accelerated servers and are much larger, drawing around 100 MW or more, with the largest sites exceeding 1 gigawatt (GW) of power.[16] A 1 GW facility running at full load for a

Data centres consumed an estimated 485 TWh of electricity in 2025, about **1.5%** of global electricity demand

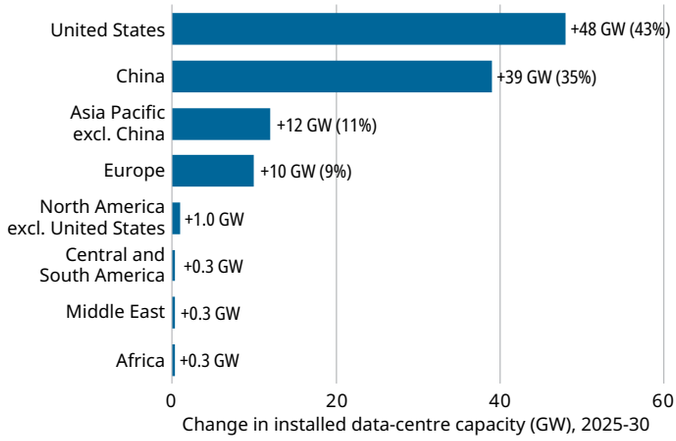
[14] See Lenovo (2022).
[15] See IEA (2025).
[16] See IEA (2025) and Epoch AI (2026d).

CHART 3.6 AI is projected to drive most of the increase in data-centre electricity demand to 2030



SOURCE: IEA (2026).
NOTE: "AI-focused data centres" refers to the electricity consumption of data centres running a large number of accelerated servers. Figures for 2030 reflect the base-case scenario of the International Energy Agency (IEA; see IEA, 2026).

CHART 3.7 Projected growth in data-centre capacity is concentrated in the United States and China



SOURCE: IEA (2026).
NOTE: This chart shows the change in total installed data-centre capacity (including cooling and auxiliary equipment) between 2025 and 2030 under the IEA's base-case scenario.

year would use more electricity than Armenia or Latvia consumes annually.[17] Training (building) AI models requires large accelerated server clusters running continuously for weeks or months without serving any users, so it can take place wherever power and land are available. In contrast, inference – where the trained AI model applies its learned patterns to new data – benefits from being near end users of the data. It can be run for smaller deployments with lower power requirements per site.[18]

Data centres consumed an estimated 485 terawatt-hours (TWh) of electricity in 2025, about 1.5 per cent of global electricity demand (see Chart 3.6). Consumption is expected to roughly double by 2030 to around 3 per cent of the global total. AI-focused facilities accounted for around a third of all 2025 data-centre demand, but are projected to drive two-thirds of the increase to 2030 as their share reaches about half of total data-centre consumption.

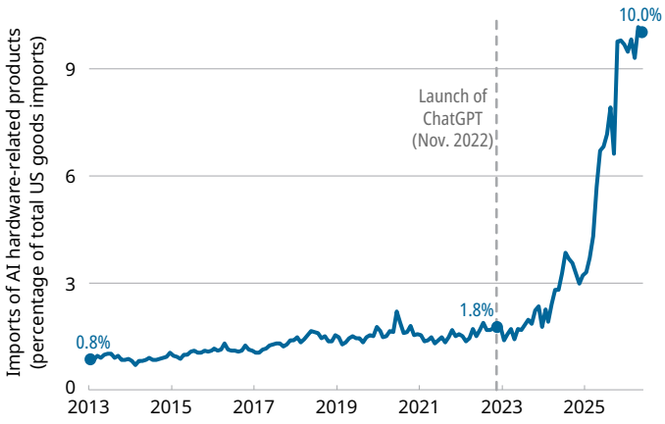
Projected growth in data-centre capacity is concentrated in the United States and China. Together, these two countries are expected to account for 78 per cent of the increase in global data-centre capacity between 2025 and 2030, while Africa, Central and South America and the Middle East are only projected to gain around 0.3 GW each over the five-year period (see Chart 3.7).[19]

The United States and China are expected to account for **78%** of the global increase in data-centre capacity

This large-scale AI build-out has been driving a rapid increase in trade in AI-related goods. Since 2018, world imports of servers and related data-processing equipment at the core of AI infrastructure have more than quadrupled.[20] In the United States, which is building more data-centre capacity than any other economy,

[17] Authors' calculations based on Ember (2026).
[18] See IEA (2025).
[19] See IEA (2026).
[20] Based on HS codes 847150, 847180 and 847330 and a balanced panel of 64 economies reporting to UN Comtrade in every quarter. See United Nations (2026).

CHART 3.8 AI hardware-related products now account for around 10 per cent of US goods imports



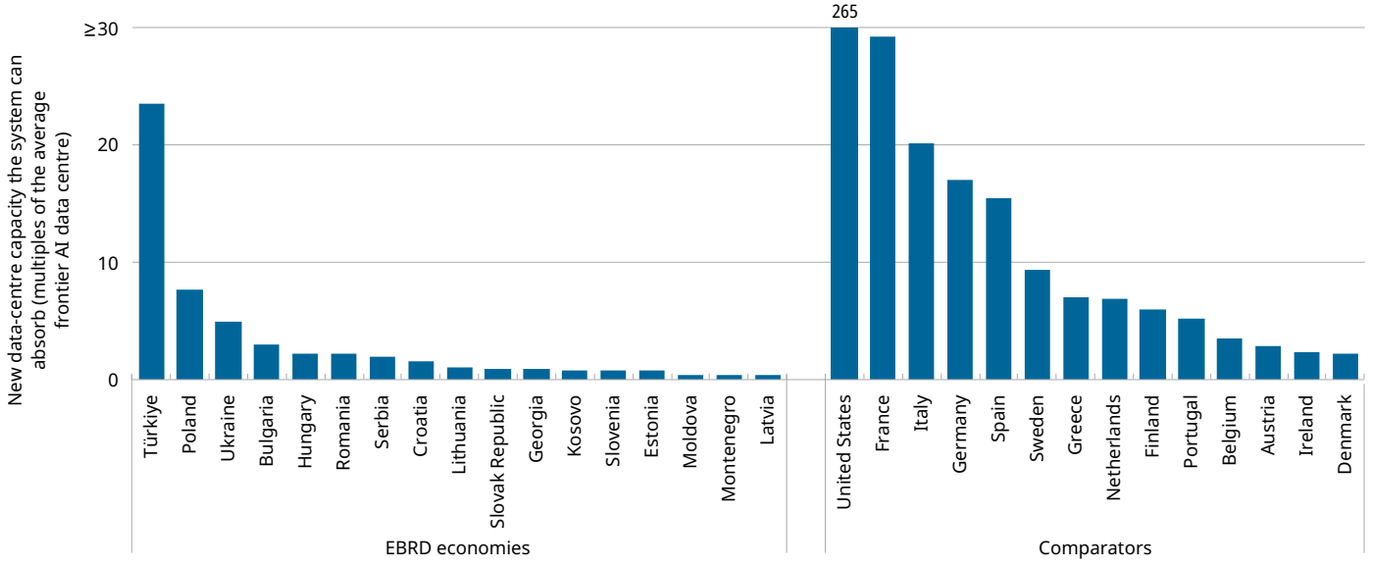
SOURCE: US Census Bureau (2026) and authors' calculations.
NOTE: Based on servers and processing units (8471.50.0150), server and GPU boards (8473.30.1180) and accelerator cards (8471.80.4000).

Close to 80% of European data-centre operators cite access to electricity as their biggest challenge over the next three years

imports of AI hardware-related products now account for around 10 per cent of total imports of goods, up from less than 2 per cent before the launch of ChatGPT (see Chart 3.8).[21]

Siting a large data centre involves balancing considerations related to energy supply, the local network, the availability of land and a skilled workforce, construction costs, environmental conditions and community relations.[22] Access to electricity is increasingly becoming the binding constraint: close to 80 per cent of European data-centre operators cite it as their biggest challenge over the next three years, with connection lead times running from a few years to more than a decade in congested markets.[23]

CHART 3.9 Most power systems in the EBRD regions have limited headroom for large AI data centres



SOURCE: EIA (n.d.), ENTSO-E (2026b), EPİAŞ (2026), IEA (2025), Epoch AI (2026d) and authors' calculations.
NOTE: This chart shows the number of average frontier data centres (262 MW) that a country's electricity system could accommodate without raising peak demand, provided the data centre pauses during the busiest 1 per cent of hours, based on hourly electricity demand over the 2019-25 period. Data start later for Georgia (December 2021), Kosovo (June 2021) and Moldova (January 2020). Ukraine data cover the period from 2019 to early 2022.

[21] See US Census Bureau (2026).
[22] See Arciniegas Rueda et al. (2026).
[23] See ENTSO-E (2026a).

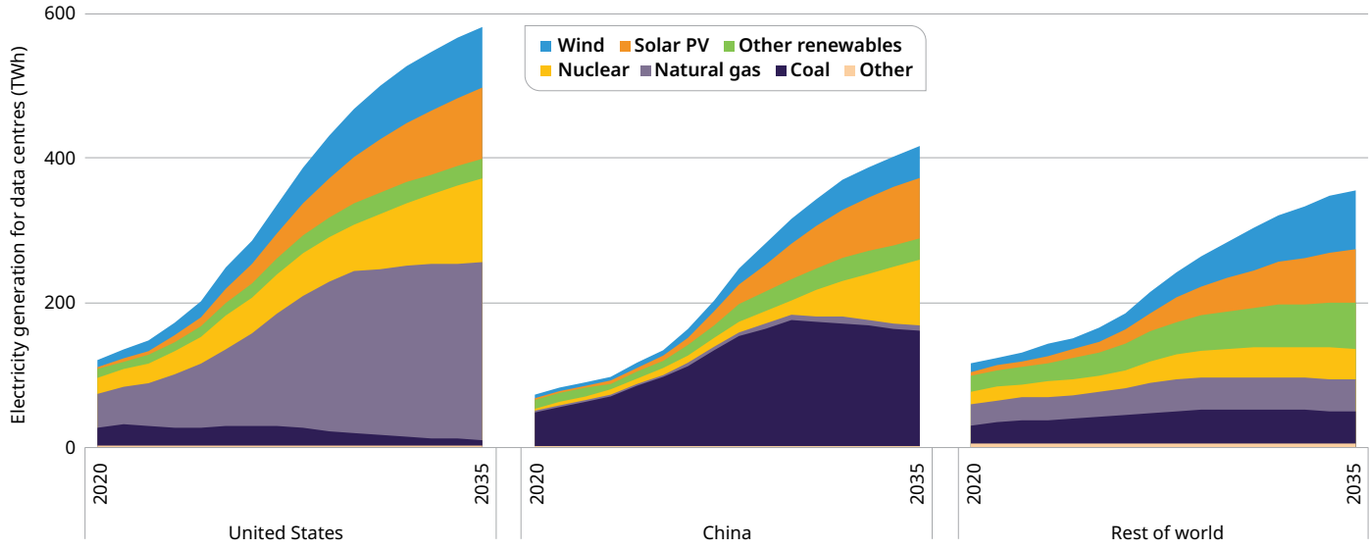
The following analysis estimates how much new data-centre load each economy's power system could take on today, based on hourly electricity demand over the period 2019-25. It assumes that the data-centre facility pauses during the busiest 1 per cent of hours (roughly 88 hours a year).[24] At these times, it could run on batteries or backup generation, or shift computing elsewhere. Otherwise, it is assumed not to raise peak demand (the 99.99th percentile of each country's hourly demand over the 2019-25 period). Estimates of spare capacity are expressed in multiples of the average frontier AI data centre (262 MW).[25] The analysis abstracts from additional bottlenecks that may arise in transmission and any future capacity additions.

The estimated power-supply headroom varies from economy to economy (see Chart 3.9). Türkiye could accommodate roughly 23 frontier AI data centres, comparable to spare capacity in the largest western European markets; Poland could take around eight. Nearly half of the EBRD economies covered could not accommodate a single frontier AI data centre without raising peak load. By comparison, headroom in the United States is around 69 GW, equivalent to around 265 such data centres.

Meeting the resulting electricity demand will require a broad mix of generation capacity. Renewables are expected to supply nearly half of the increase in global data-centre electricity demand to 2030, while natural gas and coal will account for over 40 per cent. The use of fossil fuels reflects the need for reliable round-the-clock power supply when wind and solar output is low and storage capacity remains limited. The mix differs sharply across markets: demand is predominantly gas powered in the United States and coal powered in China (see Chart 3.10).

Renewables are expected to supply nearly
HALF
of the increase in global data-centre electricity demand to 2030

CHART 3.10 Data-centre electricity is set to rely on a mix of gas, coal, renewables and nuclear-powered generation



SOURCE: IEA (2025) and authors' calculations.
NOTE: Electricity generation for data centres by fuel source is based on the IEA's base-case scenario. "Rest of world" is calculated as global generation net of the United States and China.

[24] See IEA (2025).
[25] Calculations are based on Epoch AI (2026d).

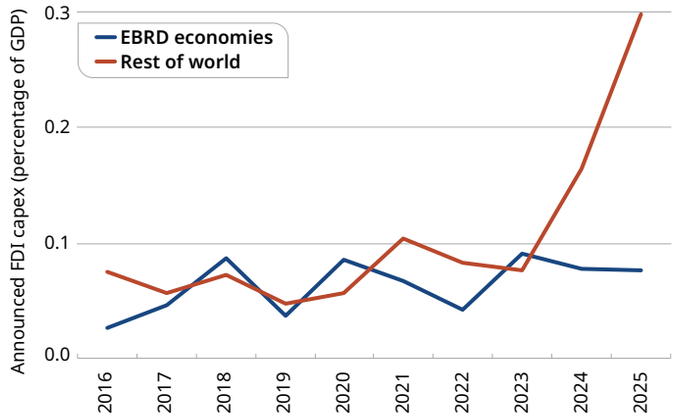
Grid constraints are also changing how that power is supplied. Data centres can be completed in two to three years, much faster than major transmission infrastructure, and estimates suggest that grid constraints could delay around 20 per cent of planned global capacity to 2030.[26] Developers are responding by locating data centres in places where power is readily available and pairing computing capacity with dedicated generation (including co-located renewables and, particularly in the United States, on-site gas). Technology companies are also securing nuclear and geothermal power through long-term agreements.[27] For instance, WBS Power plans to develop a 3.2 GW data-centre campus in Choczewo, Poland, in four phases, with the first part expected to begin operating in 2028-29. The proposed site is close to a major substation and the planned location for Poland's first nuclear power plant.[28]

Efficiency gains could ease grid constraints: faster progress on chips, software and data-centre design relative to AI demand could allow data centres to deliver the same services in 2035 using more than 15 per cent less electricity than is currently projected.[29] Well-integrated data centres can also support the wider energy system. Backup batteries can provide grid flexibility, while waste heat can be channelled to nearby buildings or district heating networks.[30]

At a global level, cross-border data-centre investment has accelerated sharply since 2023, to an average of 0.3 per cent of GDP per year based on data on the capital expenditure of announced projects (see Chart 3.11).[31] However, in the EBRD regions, announced cross-border capital expenditure has remained relatively stable since 2018, at 0.07 per cent of GDP.

Data centre-related FDI is unevenly distributed across the EBRD regions (see Chart 3.12). SSA is the largest recipient, at a cumulative US$ 9.7 billion (€8.6 billion) between 2019 and 2025, followed by EBRD economies in the EU (US$ 7.8 billion, or €6.9 billion) and SEMED (US$ 5.1 billion, or €4.5 billion). Over the same period, Türkiye, EEC and Central Asia each attracted between US$ 1.2 billion (€1.1 billion) and US$ 1.5 billion (€1.3 billion). North American investors supply roughly

CHART 3.11 Global investment in data centres has risen sharply, but EBRD economies have largely missed the surge



SOURCE: fDi Markets (2026), IMF (2026) and authors' calculations.
NOTE: Based on weighted averages across 41 economies in the EBRD regions and all other economies in the rest of the world.

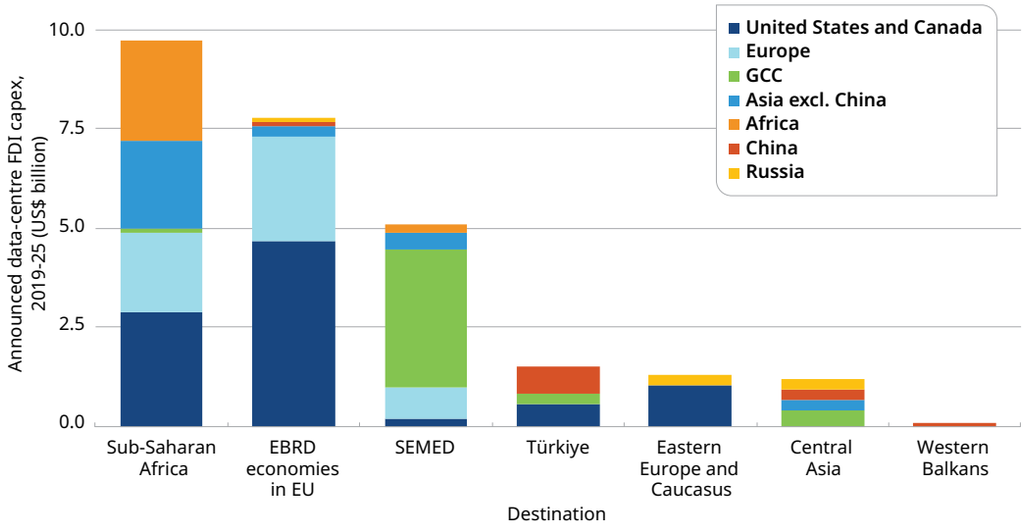
Among EBRD regions, SSA is the largest recipient of data-centre FDI, at a cumulative US$ 9.7 BILLION between 2019 and 2025

three-fifths of the capital directed to EBRD economies in the EU, while investors from Gulf Cooperation Council states provide the largest share in SEMED. Box 3.2 looks in more detail at the opportunities and challenges facing EBRD economies in SSA when it comes to the global AI economy.

Local economic gains from hosting data centres are estimated to be modest relative to the capital invested. Some studies identify employment and wage increases following data-centre expansion in the United States, concentrated in metropolitan areas and facilities owned by large technology firms.[32] Others find limited effects, with the creation of a typical data centre being associated with 100-200 additional local jobs and no significant effect on wages.[33] Greater data-centre capacity may

[26] See IEA (2025).
[27] See IEA (2025 and 2026).
[28] See WBS Power (2026).
[29] See IEA (2026).
[30] See Yuan et al. (2025).
[31] Authors' calculations based on fDi Markets (2026) and IMF (2026).
[32] See Alvarez et al. (2026) and Yue and Zeng (2026).
[33] See Bahar and Wright (2026a and 2026b).

CHART 3.12 Data-centre investment in the EBRD regions is concentrated in SSA and EBRD economies in the EU



SOURCE: fDi Markets (2026) and authors' calculations.
NOTE: Capital expenditure includes estimated values.

also support exports of cloud, hosting and data-processing services, although evidence on this channel's size remains limited. The computing capacity needed for AI can be provided as a cloud service and traded across borders, but competitiveness depends on connectivity, financing costs, reliable electricity, regulation and trust, as well as the scale and cost of the computing capacity itself.[34]

Domestic data-centre capacity can further reduce latency for applications requiring rapid response times, allow sensitive data to be stored or processed domestically[35] and enable hosting economies to retain some control over how AI is deployed.[36]

These potential economic and security gains must be weighed against the pressure on power systems and the environmental costs involved. The evidence on electricity prices is mixed: some studies find higher local costs after data-centre entry, while others show that historical data-centre growth has lowered average retail rates by spreading the system's fixed costs over a larger customer base.[37] One estimate puts the annual public-health and climate damage from air pollution and greenhouse gas emissions associated with US data-centre electricity use at around US$ 25 billion (€21.5 billion), varying by region according to the power source involved.[38] Water use is a further concern: by 2030, global AI data centres are projected to consume water equivalent to the basic annual domestic needs of all African countries south of the Sahara (1.3 billion people).[39]

PRODUCING AI KNOWLEDGE

Until the early 2010s, AI knowledge was generated mainly in universities by small research groups whose methods and results were published. Today, training a state-of-the-art model involves a single run costing hundreds of millions of US dollars and a limited pool of specialised researchers, placing it beyond the reach of universities and most firms.[40] Production of frontier AI

North American investors supply about **THREE-FIFTHS** of total data centre-related FDI in EBRD economies in the EU

[34] See Lokshin (2026).
[35] See Ferracane, González Ugarte and Rogaler (2025) and the "Policy and regulation" section of this chapter.
[36] See Meinhardt et al. (2026).
[37] See Alvarez et al. (2026), Yue and Zeng (2026) and Watten, Bistline and Blanford (2026).
[38] See Muller (2026).
[39] See Aczel et al. (2026).
[40] See Epoch AI (2026a).

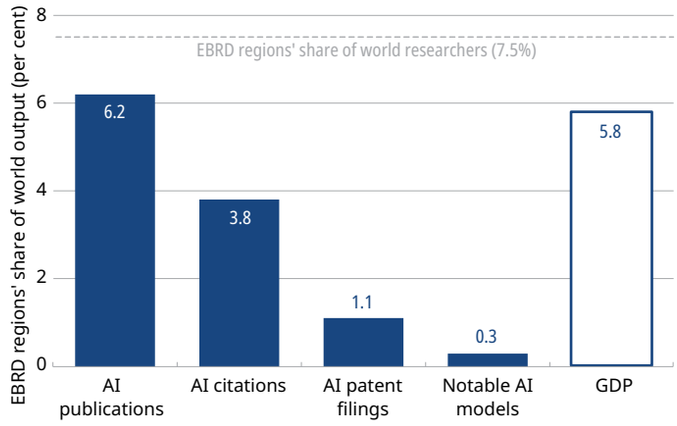
knowledge has become concentrated in a small number of corporate laboratories.[41]

EBRD economies' participation in AI knowledge production becomes more limited in areas where output is more capital intensive (see Chart 3.13). The EBRD regions' share of the world's AI research articles, at 6.2 per cent, falls short of their 7.5 per cent share of the world's researchers, and those articles' share of total citations is even smaller. The EBRD regions' share of AI patent filings is smaller still and their share of frontier AI models is almost zero: of 920 notable AI models released since 2010, only two involved a developer based in the EBRD regions, both at the Jagiellonian University in Poland. This concentration persisted in 2025, when 63 of 106 notable models came from US-based developers and 35 from China, against two from Europe. What is more, over 95 per cent came from industry rather than academia.[42]

The terms on which these models are made available to users in other economies may prove more favourable than the current concentration of production suggests. Open-weight models[43] have narrowed the performance gap to leading proprietary systems, driven most recently by Chinese developers such as Z.ai and Moonshot AI. Model capability may yet become a commodity (an input where suppliers compete on price because their products are close substitutes).[44] For instance, the chief executive of Mistral, Europe's largest AI model developer, has argued that the market is too large for any single provider to dominate.[45]

Should that view prove correct, competition would erode some of the rents currently earned in model production, with some of the surplus passing downstream to firms that apply models to products and services. Gains from AI would then depend primarily on the capacity of firms and workers to use AI rather than on economies' capacity to build frontier models.

CHART 3.13 EBRD economies are better represented in AI research than in AI patents and frontier models



SOURCE: CSET ETO (n.d.), Google Patents (n.d.), Epoch AI (2026a), UNESCO UIS (n.d.), IMF (2026), World Bank (n.d.a), OECD (2025b) and authors' calculations.
NOTE: AI publications are AI research articles attributed to economies through author affiliations. AI citations are the forward citations those articles receive. AI patent filings are Patent Cooperation Treaty applications, de-duplicated to one per patent family, with at least one inventor based in an EBRD economy and flagged as AI related in line with OECD (2025b). Notable AI models are landmark AI models with at least one developer organisation based in an EBRD economy. Publications, citations and notable AI models are summed over 2016-25 and patent filings over 2016-24, dated by the year of first filing. GDP is EBRD economies' share of world GDP in 2025 at market exchange rates in current US dollars. EBRD economies' share of the world's researchers compares the latest available figure for each EBRD economy with the sum of the latest available figures for all economies with data.

THE MARKET FOR END USER-FACING AI APPLICATIONS IS FLOURISHING

AI-based software and services sold to end users are the most downstream layer of the AI production chain. The analysis of that market segment in this section is based on July 2026 firm-level data from Dealroom, a data provider covering both listed and private startups and technology companies.[46] Firms are assigned to AI production stages using a large language model, with manual checks for big companies.[47]

Application-layer firms build products, tools or services powered by AI models, rather than a single upstream component. Because they depend heavily on the quality of models and infrastructure built upstream, their market entry was limited until 2022, but it rose sharply once commercial-grade generative AI became available.

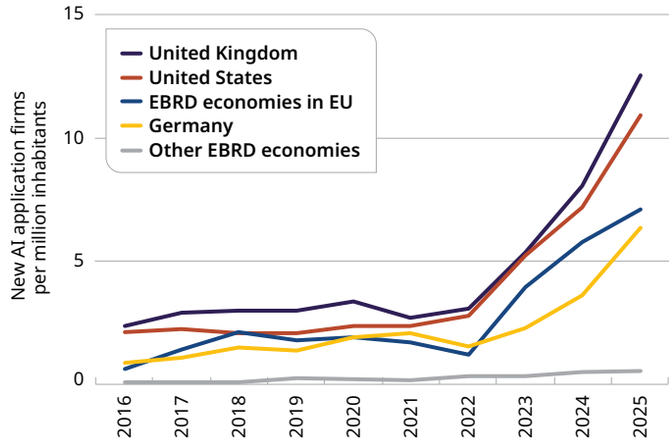
[41] See Ahmed, Wahed and Thompson (2023).
[42] See Epoch AI (2026a).
[43] Open-weight models are trained AI models whose parameters ("weights") are made publicly available, allowing third parties to run and often fine-tune the model on their own infrastructure, even though the training data, code or methodology may not be disclosed.
[44] See Demirer, Fradkin and Tadelis (2026).
[45] See The Economist (2026).
[46] See Dealroom (n.d.).
[47] The approach employed builds on Rishabh and Shreeti (2026); see Box 3.1 for methodological details.

In advanced comparators, such as Germany, the United Kingdom and the United States, the founding rate rose by around 70 per cent, on average, between 2022 and 2023 alone and roughly fourfold from 2021 to 2025.

Activity varies widely across the EBRD regions, broadly in line with income levels: in 2025, the average EBRD economy in the EU saw 7.1 new AI application firms per million inhabitants, roughly 13 times the average across other economies in the EBRD regions (see Chart 3.14). The Baltic states stand out: Estonia recorded roughly 40 new AI application firms per million people in 2025, surpassing the United Kingdom and the United States, while Lithuania (11) and Latvia (7) both placed above the 80th percentile of the cross-country distribution of newly founded AI application firms per capita.[48] This pattern mirrors the stronger startup ecosystems in those economies (see Chapter 4).[49]

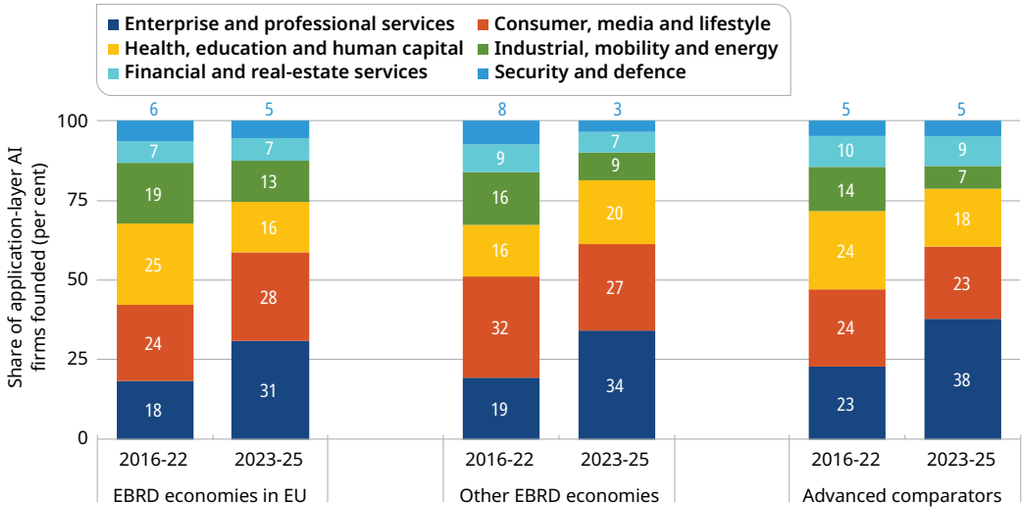
The sectoral mix of AI applications is broad (see Chart 3.15). The share of new firms targeting enterprise and professional services increased from about a fifth in 2016-22 to about a third in 2023-25. While many of these firms remain young and small, some have already scaled up, including Insider, a Turkish AI marketing platform, and Veriff, an Estonian identity verification company.

CHART 3.14 Firms building AI applications are proliferating, but most EBRD economies create few such firms



SOURCE: Dealroom (n.d.), World Bank (n.d.a) and authors' calculations.
NOTE: "EBRD economies in EU" comprises Bulgaria, Croatia, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, the Slovak Republic and Slovenia. Group averages are unweighted averages across economies. Application-layer AI firms are identified using a large language model-based classification (see Box 3.1).

CHART 3.15 For AI application firms, enterprise and professional services are the fastest-growing end market



SOURCE: Dealroom (n.d.) and authors' calculations.
NOTE: AI application firms with no Dealroom industry tag are omitted. "Advanced comparators" comprises Canada, France, Germany, the United Kingdom and the United States. AI application firms are identified using a large language model-based classification (see Box 3.1).

[48] Based on data for 98 economies with at least one AI application firm founded since 2016.
[49] See Rishabh and Shreeti (2026).

The combined valuation of AI application firms in the EBRD regions stood at around US$ 11 billion (€9.6 billion) in 2026, based on market capitalisation for publicly listed firms and the most recent post-money valuation for private firms. The largest and most valuable AI application firms are mostly US-based: the top 1 per cent globally by valuation account for around 90 per cent of the segment's total valuation.

AI FIRMS ACROSS THE SUPPLY CHAIN

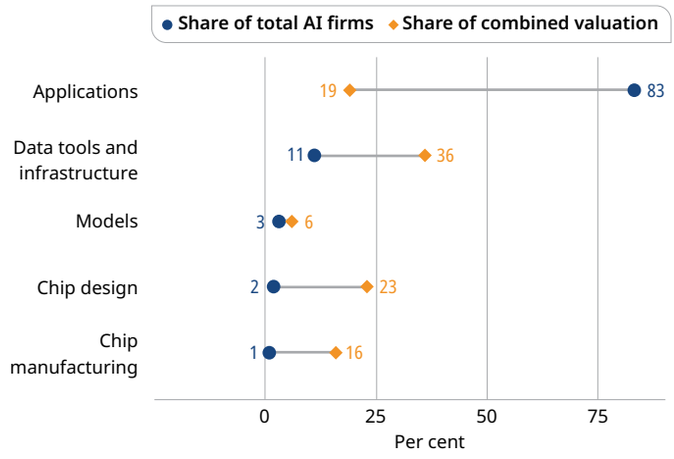
AI applications are a less concentrated market segment than AI-related hardware, with lower barriers to entry. Across the 91 economies covered in Dealroom, applications account for 83 per cent of firms, but only 19 per cent of their combined valuation (see Chart 3.16). In contrast, data tools and infrastructure providers account for 11 per cent of firms, but 36 per cent of valuation, while chip design and manufacturing account for a combined 39 per cent of valuation but only 3 per cent of firms – reflecting the high entry barriers, substantial fixed costs and economies of scale that characterise the upstream layers.[50]

The top
1%
of AI application firms globally by valuation account for around
90%
of the segment's total valuation

Advanced chip manufacturing or frontier-model training requires investment and capabilities that few economies can sustain. More realistic opportunities for new entrants lie in manufacturing niches and downstream activities: supporting application firms serving domestic and regional markets and supplying the skills, connectivity, data access and risk capital they need. Consequently, for most economies in the EBRD regions, larger gains from AI are likely to come from using the technology rather than producing it.

AI applications account for
83%
of firms, but only
19%
of their combined valuation

CHART 3.16 More than four-fifths of AI firms build applications, but value is concentrated upstream in infrastructure and chips



SOURCE: Dealroom (n.d.) and authors' calculations.
NOTE: The sample comprises AI supply-chain firms carrying a valuation in 91 economies (including 32 economies in the EBRD regions). See Box 3.1 for details of the methodology.

[50] See Gambacorta and Shreeti (2025) and Korinek and Vipra (2025).

AI ADOPTION

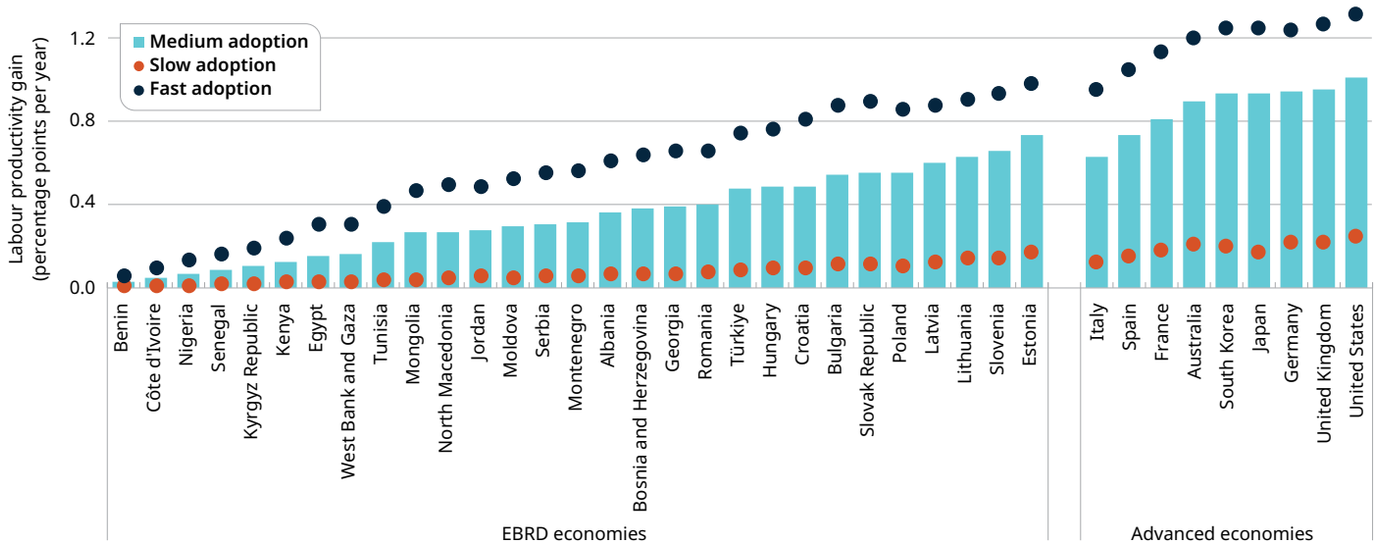
UNEVEN GAINS FROM AI

Experimental studies demonstrate sizeable productivity gains from using AI to complete specific tasks, such as professional writing, copy editing and software development. In customer support, productivity gains are estimated at around 15 per cent, with larger gains for less experienced workers.[51] Whether these translate into economy-wide gains depends on how many tasks AI can improve, how quickly and widely firms adopt it, and how much weight the benefiting activities carry in national output in the future.[52]

The following analysis combines three elements to estimate potential labour productivity gains from AI adoption in EBRD economies: a 30 per cent productivity gain when AI suits a task well (from experimental evidence); the share of each sector's tasks that AI can meaningfully accelerate; and a projected diffusion of intensive AI use over the next decade, following the adoption paths of earlier general-purpose technologies – slow, medium and fast scenarios benchmarked to electricity, the internet and mobile phones, respectively. Gains are weighted by sector value-added shares and converted into labour productivity effects (see Box 3.1).

Under the medium adoption scenario (modelled on the diffusion of the internet), AI could add around 0.03-0.7 percentage points (pp) to annual labour productivity growth across the EBRD regions over the coming decade (see Chart 3.17). Under the slow adoption scenario, gains remain below 0.2 pp a year in all EBRD economies, while under the fast adoption scenario (modelled on mobile phones), gains exceed 0.5 pp, on average, and approach 1 pp in the Baltic states and Slovenia. Estimated gains are much smaller in lower-income economies in Central Asia, SEMED and SSA.

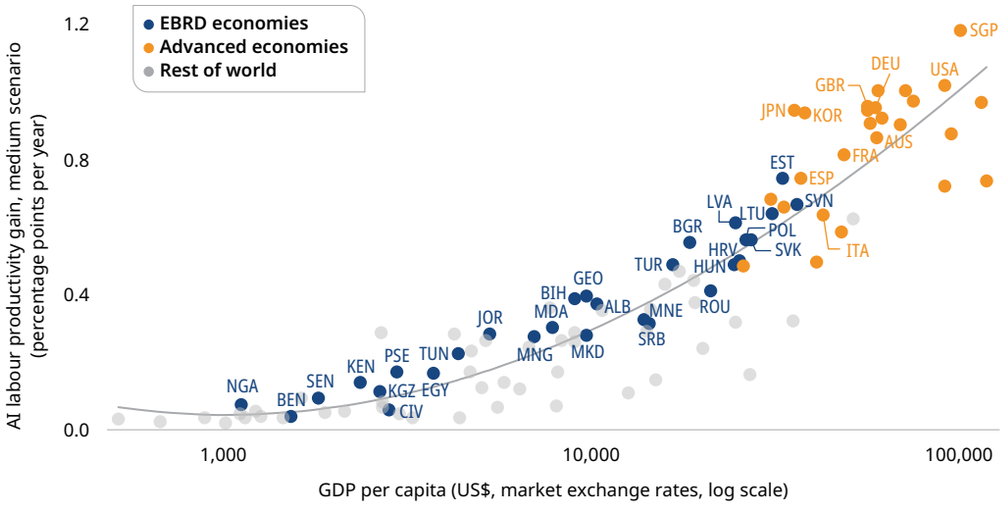
CHART 3.17 AI could add most to labour productivity in higher-income economies



SOURCE: Filippucci et al. (2025), OECD (2022), United Nations Statistics Division (n.d.), ILO (n.d.) and authors' calculations.
NOTE: This chart shows AI's contribution to annual labour productivity growth over a 10-year horizon. Adoption is assumed to follow an S-shaped path under each scenario. See Box 3.1 for details of the methodology.

[51] See Noy and Zhang (2023) and Brynjolfsson, Li and Raymond (2025).
[52] See Acemoglu (2025).

CHART 3.18 Estimated AI productivity gains rise with income



SOURCE: Filippucci et al. (2025), OECD (2022), United Nations Statistics Division (n.d.), ILO (n.d.), IMF (2026) and authors' calculations.
NOTE: Estimated under the medium adoption scenario (see Chart 3.17). The fitted line is a cubic polynomial in logged GDP per capita.

Globally, the estimated productivity gains from AI adoption rise strongly with income (see Chart 3.18), reaching around 0.6-1 pp a year in several advanced economies. Richer economies tend to have more employment in occupations and sectors such as professional services and finance, where generative AI can assist with a meaningful share of tasks.[53]

AI may, therefore, widen rather than narrow productivity differences. Without faster adoption and complementary investment, economies with the most ground to make up stand to gain least.

UNDERSTANDING AI ADOPTION

The effective rate of AI adoption depends on how many people or firms use AI, how often they use it and for what tasks, and how deeply the use of AI is integrated into workflows. Recent worker and firm surveys that shed light on these aspects are limited to the United States and selected European countries.[54] This section relies on usage data from AI model providers across the EBRD regions to shed light on various dimensions of AI adoption.

Intensive generative AI use is greater in economies where the conditions for AI adoption are assessed as being more favourable (see Chart 3.19). In this analysis, the intensity of AI adoption reflects each economy's share of global Claude.ai usage relative to its share of the global working-age population, while the AI Preparedness Index spans digital infrastructure, skills, innovation and regulation in the area of AI.[55]

Cross-country differences suggest comprehensive AI adoption does not materialise automatically as frontier AI capabilities improve. Most economies in the EBRD regions are assessed as having little AI preparedness and limited use of AI, with notable exceptions. In Estonia, for instance, usage is approaching advanced-economy levels.

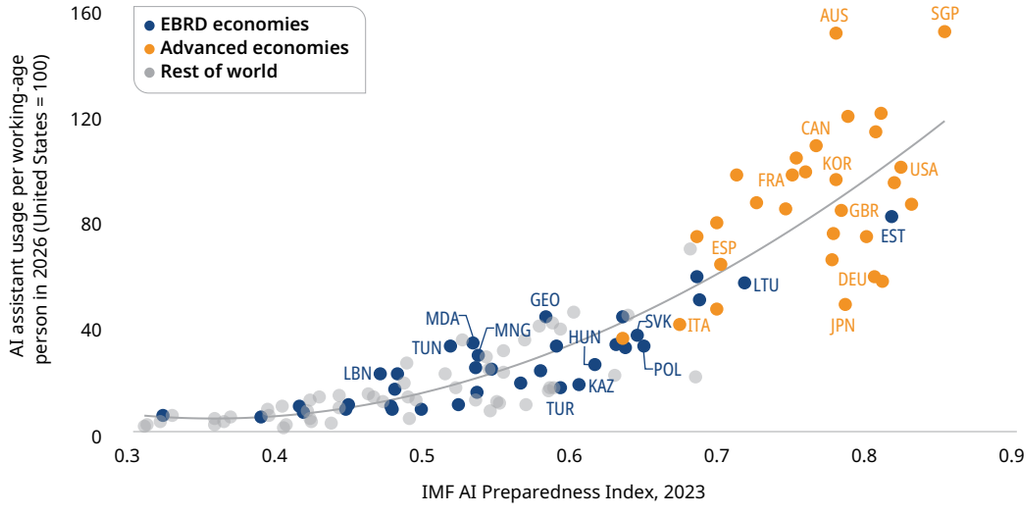
AI AND WORKERS: EARLY EVIDENCE

Technological advances have long raised concerns about worker displacement. The patterns of such displacement tend to be complex: technology automates some tasks while raising demand for others and creating new ones. Unlike industrial robots and earlier waves of IT automation, generative AI reaches directly into knowledge-intensive work – writing, coding and data analysis – and its rapidly improving capabilities may leave workers with less time to adjust to technological change.

So far, evidence does not point to widespread job losses, though studies remain concentrated in advanced economies, and AI's effects are difficult to separate from

[53] See Cazzaniga et al. (2024).
[54] See Bick et al. (2026) for international survey evidence on these countries.
[55] See Cazzaniga et al. (2024).

CHART 3.19 AI assistant usage and AI preparedness track each other closely



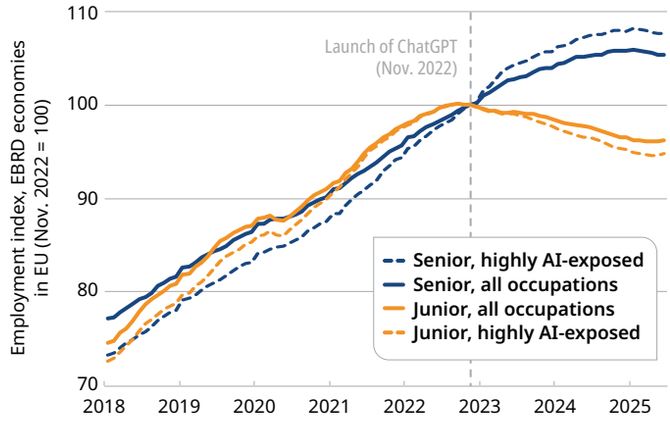
SOURCE: Anthropic (2026), Cazzaniga et al. (2024) and authors' calculations.
NOTE: AI assistant usage is each economy's share of global Claude.ai usage relative to its share of the global working-age population, rebased so that the United States equals 100. The fitted line is a cubic polynomial in the AI Preparedness Index.

other labour-market changes. US payroll data show no economy-wide displacement, but employment among 22- to 25-year-olds in highly AI-exposed occupations is now 19 per cent below where it would have been had it grown in line with employment in less exposed occupations. This gap largely reflects weaker hiring of junior staff once firms have integrated generative AI, detected in firm-level studies. Other studies, including from Norway, find little or no effect; remote working may also explain part of the decline in junior hiring.[56] The analysis that follows uses employment histories compiled by Revelio Labs from online professional profiles to examine whether similar patterns are emerging in EBRD economies in the EU, comparing employment trends among junior and senior workers.[57]

Since late 2022, junior employment in EU economies in the EBRD regions has lagged senior employment overall, more so among the most AI-exposed occupations (see Chart 3.20 and Box 3.1). However, the patterns are descriptive and factors other than AI may have contributed to this divergence.

It remains too early to assess AI's long-term impact on labour markets and hierarchies. Junior workers often perform the codified tasks that AI can most readily automate, and reducing new recruitment is easier than cutting existing jobs. At the same time, younger workers tend to learn faster; with the help of AI, they can learn

CHART 3.20 Since access to generative AI spread in 2022, junior employment has lagged senior employment, especially in AI-exposed occupations



SOURCE: Revelio Labs (2025), Eurostat (2026b), Eloundou et al. (2024) and authors' calculations.
NOTE: Unweighted average across the EBRD economies in the EU, adjusted for population growth. Solid lines cover all occupations, while dashed lines cover the top quintile of occupations by exposure to AI.

to perform more complex tasks.[58] Policy can steer AI development and adoption towards technologies that augment rather than replace workers, while supporting reskilling for those displaced by automation. In healthcare, for example, public procurement and training can encourage the use of AI tools that expand the range of tasks performed by nurses and technicians.

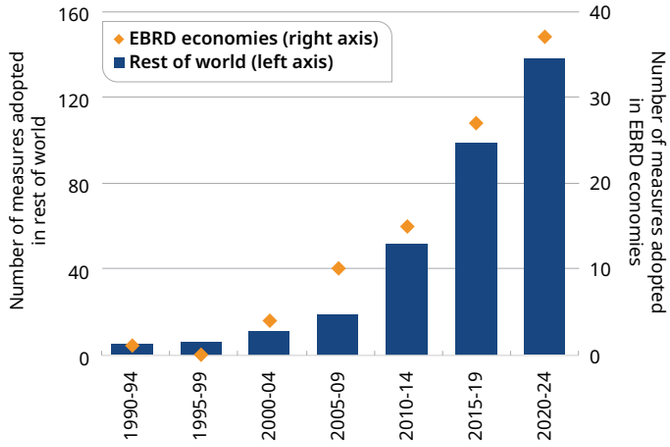
[56] See Brynjolfsson, Chandar and Chen (2026), Hosseini and Lichtinger (2026), Facius and Iacono (2026) and Lambert and Schindler (2026).
[57] See Revelio Labs (2025).
[58] See Acemoglu, Autor and Johnson (2026).

POLICY AND REGULATION

AI is a new general-purpose technology with far-reaching implications for data rights, labour markets and geopolitics. A country's influence over AI governance depends on the size of its market, its control over critical technologies and supply chains, its technological capabilities and its ability to enforce rules.[59]

Governments retain considerable authority over data governance, privacy and intellectual property, and over education and labour markets. Network connectivity and conventional data-centre siting remain largely within domestic control, while computing capacity is typically located outside an economy's borders and depends on concentrated global supply chains and large-scale investments. Governments also retain control over procurement of AI-based services domestically, while AI security and export controls are matters requiring international coordination.

CHART 3.21 The number of data localisation measures being adopted has increased dramatically since 2000



SOURCE: Ferracane, González Ugarte and Rogaler (2025) and authors' calculations.
NOTE: Countries adopting multiple measures are counted more than once. EU-wide measures are excluded. Data capture policy adoption, not the stringency or enforcement of measures.

DOMESTIC GUARDRAILS AND CAPACITY BUILDING

Governments are increasingly seeking more control over how data are collected, stored, processed and transferred. Data localisation measures – explicit requirements that data be stored or processed within a territory – have proliferated since the early 2000s, including in the EBRD regions (see Chart 3.21). Latvia was the first EBRD economy to require data to be stored locally, in 1992, followed by Estonia, Kazakhstan and Tunisia in 2004. Such measures can strengthen control over data handling, but may raise the cost of cloud access and AI adoption for domestic firms.

Safe cross-border data flows could be facilitated by interoperable privacy rules, secure transfer channels and safeguards tailored to sensitive sectors. Within economies, effective data use could be supported by AI-ready public datasets, data-sharing frameworks, controlled access for researchers and clear lines of responsibility for AI-assisted government decisions. Governments should also provide clear rules on copyright, data ownership and the status of AI-generated content, reducing uncertainty for both creators and adopters of AI.

Many AI models, however, are trained primarily on data from a small number of countries and in a limited set of languages, restricting their effectiveness in local contexts. Governments can help to close these gaps by supporting local-language datasets, sovereign AI infrastructure and open foundation models. Examples include Poland's PLLuM and Kazakhstan's KazLLM, which aim to improve AI performance in local languages and strengthen digital sovereignty.[60]

Better supporting infrastructure, including broadband internet, access to cloud services and data centres, reliable power grids and effective cybersecurity, can further help businesses, schools and governments to develop and use AI-based solutions. Transparency regarding available grid capacity can make the planning of data-centre projects more effective. Following a 2024 EU reform requiring the disclosure of available grid capacity, the European Network of Transmission System Operators for Electricity (ENTSO-E) and the EU

[59] See Bradford (2012) and Farrell and Newman (2019).

[60] See NASK NLP Research Group (n.d.) and Institute of Smart Systems and Artificial Intelligence (n.d.).

Distribution System Operator (DSO) Entity launched Capacitypedia in 2026 as a single access point for national hosting-capacity information.[61]

AI infrastructure can be coordinated across borders. For instance, the EU's InvestAI initiative aims to mobilise €200 billion for AI investment, including a €20 billion fund for large AI "gigafactories", alongside smaller AI "factories" where several countries pool computing power and expertise. Bulgaria, Lithuania, Poland, Romania and Slovenia have been selected to host AI factories, with smaller "antenna" sites planned for Hungary, Latvia, Moldova, North Macedonia, Serbia and the Slovak Republic.[62] In Africa, Cassava Technologies is partnering with NVIDIA to build similar AI factories in Egypt, Kenya, Morocco, Nigeria and South Africa.[63]

Human capital is equally important for the effective rollout of AI.[64] Analysis based on data from a recent representative household survey, the EBRD's Life in Transition Survey, suggests that basic digital proficiency remains lower in the EBRD regions than in Germany, even among young cohorts.[65] Training curricula and sectoral skills standards will need to be updated to reflect changing skills needs, complemented by on-the-job learning. Labour-market policies must also help workers adapt to changing occupational demand through retraining, job-search assistance and career guidance.

Several economies in the EBRD regions are piloting universal AI access. Estonia's AI Leap, combining student access with teacher training, is the most advanced example (see Box 3.3). However, returns to AI will depend less on access than on the capacity to use it effectively: schools need trained teachers, local-language content, data safeguards and evidence on what works.

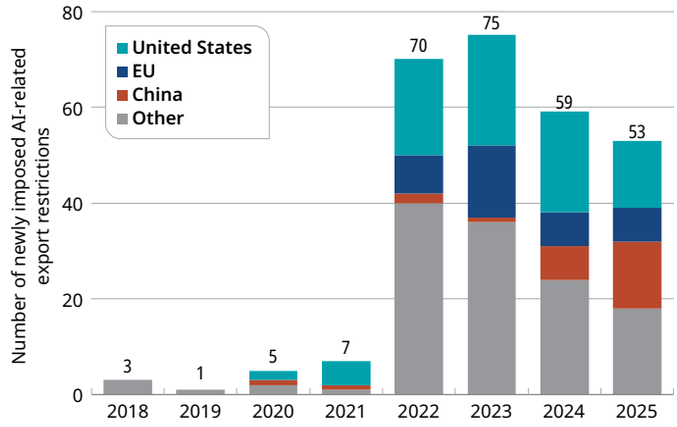
INTERNATIONAL COOPERATION AND GEOPOLITICS

As global AI governance takes shape, for most economies in the EBRD regions, market size may be too small for effective bespoke rules. However, those economies could exert influence through coalitions and joint procurement and, where appropriate, by aligning policy with the EU or another major market. For instance, the EU market is large enough that many firms find it cheaper to follow the bloc's rules everywhere rather than lose access to the single market – a phenomenon sometimes referred to as the "Brussels effect".[66]

Geopolitical alignment matters most where investment carries technology-transfer risk, as in semiconductor fabrication or battery production for electric vehicles. Investment-screening regimes have expanded in scope, and geopolitical alignment is increasingly shaping FDI in such strategic sectors.[67]

Export restrictions on AI-related goods have also surged since 2022 (see Chart 3.22). The United States, for instance, has limited access to advanced chips and semiconductor manufacturing equipment, targeting the production chain directly.

CHART 3.22 Export restrictions on AI-related goods have surged



SOURCE: Global Trade Alert (n.d.) and authors' calculations.
NOTE: This chart shows newly imposed export restrictions applicable to at least one AI-related HS6 product code by year of inception and implementing jurisdiction.

[61] See ENTSO-E (2026c).
[62] See European Commission (2025) and European High Performance Computing Joint Undertaking (2026).
[63] See Cassava Technologies (2025).
[64] See Cazzaniga et al. (2024).
[65] See EBRD (2025).
[66] See Bradford (2012).
[67] See Aiyar, Malacrino and Presbitero (2024) and Alfaro and Chor (2023).

The EU's AI Act, adopted in 2024, further regulates AI models and their deployment. Providers of general-purpose AI models face transparency and copyright-related obligations, while providers of models classified as posing a systemic risk face additional requirements for model evaluation, risk assessment and mitigation, serious-incident reporting and cybersecurity.[68]

Economies in the EBRD regions could seek to secure reliable access to AI technology and investment through credible cybersecurity rules, open procurement, data-centre security standards and compliance with relevant export controls. EU candidate economies in the Western Balkans and EEC could also benefit from early alignment with EU regulation. Other economies may find sector-specific rules and international standards better suited to their circumstances.

International banking regulation offers an example of such selective alignment. Basel banking standards are set by a small group of countries, while many other economies adopt and adapt those elements most relevant to their financial systems.[69]

Governments can also support AI adoption through sector-specific guidance on issues such as AI bias, accountability and data governance. Such guidance can reduce uncertainty and help unlock investment and domestic capabilities.

Effective regulation depends on regulatory expertise and enforcement capacity, including the ability to test AI systems and conduct risk-based procurement of AI tools. Regulatory expertise and enforcement capacity are particularly important, as AI is increasingly seen as a source of catastrophic risk, including potential human extinction. If the same willingness to reduce small mortality risks across large populations that underpins road safety and health policy were applied to AI in the United States, spending on AI risk mitigation equivalent to at least 1 per cent of GDP a year could be justified, even without accounting for future generations' well-being.[70]

CONCLUSIONS AND POLICY IMPLICATIONS

AI production is highly concentrated: advanced chips, semiconductor equipment, large data centres, frontier research and model development are dominated by a small number of economies and firms. EBRD economies' shares of global exports of AI-related goods are much smaller than their shares of other goods, and they remain marginal participants in frontier-model production.

Some, however, have strengths in electronics, software, precision equipment and application development that could support entry into new manufacturing niches. Developing and exporting AI-based applications, with their lower barriers to entry, may be within reach for a broader range of economies. Where power, connectivity and local conditions permit, investment in data centres can improve access to cloud-computing power and digital services, complemented by investment in reliable electricity supply, digital connectivity infrastructure and skills. Deeper local capital markets can further facilitate access to financing for this highly capital-intensive sector.

Measures to promote AI production and investment should be paired with policies that expand renewable energy generation or otherwise offset AI's environmental costs: US evidence suggests that localities more exposed to AI experience faster emissions growth, as nearby power plants shift to greater fossil-fuel use.[71]

[68] See US Department of Commerce, Bureau of Industry and Security (2022 and 2023) and European Union (2024).
[69] See Jones and Zeitz (2017).
[70] See Jones (2025).
[71] See Bonfiglioli et al. (2025).



For most economies in the EBRD regions, however, opportunities are greater in the area of adoption. Under the medium adoption scenario, AI could add around 0.03-0.7 pp to annual labour productivity growth over the next decade. Larger gains are expected in more advanced economies, reflecting their occupational mix, better digital infrastructure and stronger digital skills. Without large-scale investment and targeted policy action, AI could widen productivity gaps across economies. Early labour-market evidence does not point to widespread displacement of workers, but does indicate weaker hiring of junior workers in knowledge-intensive occupations exposed to AI automation.

Whether AI narrows or widens productivity gaps will depend on policy choices. Economies retain meaningful authority over how AI is used. Governments can act now by establishing domestic guardrails on data, privacy and intellectual property, and issuing sector-specific guidance on AI bias, accountability and data governance. They can also adopt transparent AI procurement rules, provide job-search assistance and retraining for workers displaced by automation, update training curricula, and align with EU or international standards where market access rewards it.

Other elements are capabilities that take time to build and cannot be fast-tracked by political will or funding alone: the credibility needed to attract AI technology, investment and partnerships, built through consistent cybersecurity practice and export control compliance; the regulatory expertise required to test AI systems and conduct risk-based procurement; and the broader digital skills base needed for AI to be used effectively. The sooner that work starts, the sooner these economies can put AI to its most productive use.

BOX 3.1 DATABASES AND DEFINITIONS

TRADE IN AI-RELATED PRODUCTS

The analysis of trade in AI-related products draws on the CEPII BACI database of reconciled bilateral trade flows, using the 2017 Harmonized System (HS) vintage for 2017-24 (unless stated otherwise).[72] AI-related goods comprise 24 six-digit (HS6) codes in three tiers: computing hardware (854231, 854232, 854239, 854290, 847150, 847180 and 847330); semiconductor manufacturing equipment (848610, 848620, 848640, 848690, 903082 and 903141); and semiconductor materials and inputs (381800, 280461, 280429, 281212, 285000, 811292, 811299, 370790, 370500, 281290 and 370199).

The relatedness of products A and B is measured as the minimum of (i) the probability of competitively exporting product A conditional on competitively exporting product B and (ii) the probability of competitively exporting product B conditional on competitively exporting product A.[73] Products are treated as "neighbours" or proximate only where links are statistically significant at the 1 per cent level.[74] For each AI-related product, coverage is the share of its neighbourhood that an economy already exports competitively, weighted by product relatedness. In Chart 3.4, neighbourhoods exclude other products in the AI basket.

REVELIO LABS AND ONLINE RÉSUMÉ WORKFORCE ANALYSIS

This analysis uses Revelio Labs data based on harmonised public LinkedIn profiles.[75] Employment spells contain profile-reported information – employer, job title, location and dates – alongside model-assigned information on occupations, seniority and countries. Revelio groups job titles into occupational clusters based on titles, descriptions and skills, mapped to O*NET-SOC occupations;[76] seniority is similarly predicted from titles, employers and job histories.

Employment spells at firms continuously active from January 2018 to June 2025 are aggregated into monthly economy-level counts of distinct workers by occupation and seniority. Counts for junior and senior employment are indexed to 100 in November 2022 and adjusted for population growth using populations aged 20-34 and 35-59, respectively. The resulting indices are then averaged across EBRD economies in the EU. Occupations highly exposed to AI are those in the top quintile of the Eloundou et al. (2024) task-level measure of exposure.

LinkedIn profiles overrepresent younger, urban, white-collar workers at larger firms and may be updated with a lag. Indexing reduces changes in coverage common to junior and senior workers, but not differential changes between these categories. The resulting patterns should, therefore, be viewed as suggestive rather than comprehensive or causal.

AI FIRMS ACROSS THE SUPPLY CHAIN

AI firms across the supply chain are identified using an extract from Dealroom,[77] a commercial database of private and listed technology companies compiled from filings, funding announcements, investor reporting and websites. Data were accessed in July 2026. Firms are assigned to economies based on their headquarters.

[72] See CEPII (2026).
[73] See Hidalgo et al. (2007).
[74] See Saracco et al. (2015).
[75] See Revelio Labs (2025).
[76] See O*NET (n.d.).
[77] See Dealroom (n.d.).

First, a broad filter on Dealroom's technology tags identifies firms that are potentially related to AI. A large language model then uses those tags and each firm's description to separate producers of AI from adopters and to assign producers to one of five supply-chain layers, building on Rishabh and Shreeti (2026). A firm is not counted as a producer of AI unless AI is central to what it sells; firms that merely embed third-party models or use AI internally are treated as adopters. Producers are separated into chip design, chip manufacturing, data tools and infrastructure, models, and applications. Assignments are individually reviewed for all firms valued at US$ 1 billion or more.

A MODEL OF PRODUCTIVITY GAINS FROM AI ADOPTION

Estimates of AI's potential contribution to labour productivity build on the methodology of Filippucci et al. (2025). Exposure to AI is measured at the level of work tasks using the Global Automation Atlas dataset.[78] The resulting exposure scores are economy-specific. A narrower measure of exposure counts tasks that a language model can perform alone, such as scoring, classification and the transformation of information. A broader measure of exposure adds tasks where automation requires AI to be combined with complementary software to a significant extent.

Task ratings are mapped to occupations using O*NET task statements, converted from the US occupational classification to the international standard (ISCO). Occupation-specific scores are, in turn, combined with each economy's occupation-by-industry employment structure from ILOSTAT,[79] yielding exposure scores for 18 broad sectors (the sections of ISIC Revision 4/NACE Revision 2). Economies without a recent occupation-by-industry employment survey are excluded; those covered by the employment data but absent from the AI exposure data receive their region's average occupation-level ratings (using the World Bank regional classification).[80] Sector-level gains are aggregated to the economy-wide gain using value-added shares from the OECD Inter-Country Input-Output tables[81] or, where unavailable, the latest available United Nations national accounts statistics,[82] adjusted by the inverse of the labour share (assumed to be 1.5). This analysis assumes unchanged sectoral employment shares.

The current AI adoption rate is anchored in the share of enterprises using AI in Eurostat's Community survey on ICT usage and e-commerce in enterprises,[83] supplemented by comparable rates that Filippucci et al. (2025) report for Canada and the United States. In line with that study, survey readings are averaged with an OLS prediction based on the IMF's AI Preparedness Index,[84] which reduces noise in individual surveys and extrapolates estimates to additional economies.

Within a scenario, economies differ in their starting levels of AI adoption and exposure. Moreover, the slow adoption scenario uses the narrower measure of task exposure to AI, covering only tasks a language model can perform alone, while the medium and fast adoption scenarios use the broader measure.

Adoption is then projected along a logistic curve to an 80 per cent ceiling over 10 years, its speed common to all economies within each scenario and set by analogy with earlier general-purpose technologies: electricity (slow), the internet (medium) and mobile phones (fast).

[78] See Garg, Crosta and Baier (2026).
[79] See ILO (n.d.).
[80] See World Bank (n.d.b).
[81] See OECD (2022).
[82] See United Nations Statistics Division (n.d.).
[83] See Eurostat (2026a).
[84] See Cazzaniga et al. (2024).

BOX 3.2 AI IN SSA

EBRD economies in SSA remain on the periphery of the global AI production chain. Their participation is concentrated in data services and application deployment, while weaknesses in terms of reliable electricity, network connectivity and computing capacity are limiting deeper AI rollout. The application layer is a source of significant near-term opportunity, provided these foundations can be strengthened.

Access to electricity ranges from relatively high in Ghana to low in Benin and Nigeria, and unreliable supply is limiting the expansion of digital infrastructure.[85] Africa accounted for only 0.4 per cent of global data-centre capacity in 2025[86] and most of the continent's data are hosted abroad, mainly in Europe and North America. Mobile broadband coverage has expanded rapidly, yet 60 per cent of people in African countries south of the Sahara live within reach of mobile internet services but do not use them, primarily due to affordability constraints.[87] Data centres are also energy and water intensive, which places a premium on siting decisions and on water-efficient cooling in locations where water resources are already under pressure.

SSA economies primarily contribute to global AI value chains through annotation and content moderation work. Nigeria and Kenya rank among the top global outsourcing destinations for AI data work, with several large annotation and content-moderation operations based in Nairobi.[88] These activities create employment, but independent labour assessments, as well as Kenya's own AI strategy, find this employment poorly paid and potentially exposed to automation as models improve, with workers stuck in entry-level roles, such as data annotation for foreign platforms, that do not necessarily meet basic standards of pay or conditions.[89]

More promising near-term opportunities lie further downstream in AI applications. For instance, AI-assisted agricultural advisory and health diagnostics applications have been deployed in Kenya and Nigeria.[90]

All six countries in the EBRD's SSA region have published national AI strategies: Benin and Senegal in 2023, Côte d'Ivoire, Kenya and Nigeria in 2025 and Ghana in 2026. However, implementation capacity varies across countries, with budget allocations, dedicated regulatory bodies and inter-ministerial coordination arrangements at different stages of development.[91]

Africa's mobile-first financial systems have generated structured, behaviourally rich data at scale: mobile money accounts processed transactions with a combined value of US$ 1.4 trillion (€1.2 trillion) across all African countries south of the Sahara in 2025,[92] and the resulting data are already being used to train credit-scoring models that extend financial access to borrowers without formal credit histories.[93] African languages, underrepresented in global foundation models, are another asset: Nigeria, Senegal and Kenya are making early investments in local-language AI.[94]

Where data are sourced from African users and workers, but models are owned and monetised elsewhere, the economic surplus largely accrues outside the continent.[95] Nigeria and Kenya have adopted data protection frameworks that put conditions on cross-border transfers of personal data; implementation and enforcement capacity is still being built.[96]

Africa's experience with mobile money demonstrates the potential of new technology to bypass legacy systems, but the analogy has limits when it comes to AI. Mobile money could operate on existing hardware with modest computing requirements, whereas frontier AI is highly capital and energy intensive. Technology adoption alone cannot act as a substitute for foundational investment in power, network connectivity, data governance and human capital.

[85] See Babayomi (2026).
[86] See IEA (2026).
[87] See GSM Association (2024).
[88] See Obia (2025) and Ndege (2026).
[89] See Du and Okolo (2025).
[90] See Begho, Daubry and Irabor (2025) on agricultural advisory and Obi et al. (2024) on health diagnostics.
[91] See OECD (2026).
[92] See GSM Association (2026).
[93] See Mwesigwa, Jackson and Csikszentmihalyi (2026).
[94] See Munga and Quansah (2025) and Mwangi (2024).
[95] See Du and Okolo (2025) and Melatagia Yonta (2025).
[96] See Federal Republic of Nigeria (2023) and Republic of Kenya (2019).

BOX 3.3 AI IN EDUCATION: A BICYCLE FOR THE MIND?

Steve Jobs, the founder of Apple, described the personal computer as a "bicycle for the mind" – a tool extending human capabilities. Generative AI, by offering low-cost personalised explanations and tailored advice, promises to provide cognitive assistance that surpasses past expectations. But when it comes to AI applications, education differs from most other goods and services in an important respect: it aims not just to complete tasks more efficiently, but to build the skills required to complete them independently.

Early evidence from the EBRD regions shows both the promise and risks of AI in education. In Nigeria, a randomised trial found that six weeks of AI-supported tutoring with teachers' guidance raised secondary-school students' test scores by 0.31 standard deviations.[97] In Türkiye, meanwhile, access to a standard AI assistant helped secondary-school students to solve mathematics problems while using it, but they subsequently performed 17 per cent worse than students who did not have access to an AI assistant when both groups were tested unaided. A tailored AI tutor that gave hints rather than answers substantially reduced the penalty associated with the use of AI assistance.[98] These results suggest that the ways in which AI is used may matter as much as its availability.

Governments in the EBRD regions have been moving towards system-wide adoption of AI in education. Estonia, Jordan, Kazakhstan and the Slovak Republic are among the first participants in OpenAI's Education for Countries initiative, pairing access to AI tools with teacher training and university-led evaluation of pilot programmes.

Estonia's AI Leap is one of the most ambitious system-wide initiatives, providing AI tools and training to around 20,000 upper-secondary students and more than 4,000 teachers while tracking learning outcomes. Its tailored Estonian-language tool is designed to prompt students with questions and hints rather than simply supply answers. Evidence from early implementation of the programme has been mixed: take-up has fallen short of universal use and no clear learning gains have yet emerged. Competition from general-purpose AI assistants that can provide answers immediately, without pedagogical guardrails, presents a notable challenge when it comes to rolling out AI tools for schools.

Early experience suggests that some learning tasks and assessments should remain unaided while foundational skills are acquired, and assessments should capture students' own reasoning. AI literacy is an essential new set of skills that goes beyond prompting and involves verifying, challenging and evaluating large language models' outputs. In fostering AI literacy, teachers need training and discretion over the use of AI to ensure that AI strengthens human learning and does not replace it. Independent evaluation of large-scale rollouts can help to fine-tune the use of AI in education.

As industry leaders offer free or discounted tools in a highly competitive market, public procurement systems can help to close gaps in access to AI while protecting student data, ensuring that products are sufficiently tailored to local languages and curricula, and avoiding excessive dependence on a single provider. The educational market also creates opportunities for firms in the EBRD regions, such as Poland's Brainly (providing AI tutoring with expert support) and Estonia's Lingvist (offering AI-based personalised language learning).

[97] See De Simone et al. (2025).
[98] See Bastani et al. (2025).

REFERENCES

D. Acemoglu (2025)
"The simple macroeconomics of AI", *Economic Policy*, 40(121): 13-58. Available at: https://doi.org/10.1093/epolic/eiae042.

D. Acemoglu, D. Autor and S. Johnson (2026)
"Building pro-worker artificial intelligence", The Hamilton Project, Washington, DC, Brookings Institution. Available at: https://www.hamiltonproject.org/publication/paper/building-pro-worker-ai.

M. Aczel, S. Chamanara, M. Matin, A. Farsi, T. Marwala and K. Madani (2026)
Environmental Cost of AI's Energy Use: Carbon, Water and Land Footprints, Richmond Hill, ON, Canada, United Nations University Institute for Water, Environment and Health (UNU-INWEH). Available at: https://doi.org/10.53328/INR26RMA002.

N. Ahmed, M. Wahed and N.C. Thompson (2023)
"The growing influence of industry in AI research", *Science*, 379(6635): 884-886. Available at: https://doi.org/10.1126/science.ade2420.

S. Aiyar, D. Malacrino and A.F. Presbitero (2024)
"Investing in friends: The role of geopolitical alignment in FDI flows", *European Journal of Political Economy*, 83: 102508. Available at: https://doi.org/10.1016/j.ejpoleco.2024.102508.

L. Alfaro and D. Chor (2023)
"Global supply chains: The looming 'Great Reallocation'", NBER Working Paper No. 31661, Cambridge, MA, National Bureau of Economic Research. Available at: https://doi.org/10.3386/w31661.

F.E. Alvarez, D. Argente, J. Chow and D. Van Patten (2026)
"Data centers and local economies in the age of AI: A shift-share approach", NBER Working Paper No. 35194, Cambridge, MA, National Bureau of Economic Research. Available at: https://doi.org/10.3386/w35194.

Anthropic (2026)
"Anthropic Economic Index: Understanding AI's effects on the economy", updated 26 June 2026, San Francisco, CA. Available at: https://www.anthropic.com/economic-index.

I. Arciniegas Rueda, A. Smidt, R. Wang, H.M. Park, D. Gill and H. van Soest (2026)
"Evaluating Potential Artificial Intelligence Energy Capacity at Different Data Center Sites", Research Report No. RR-A3845-3, Santa Monica, CA, RAND Corporation. Available at: https://www.rand.org/pubs/research_reports/RRA3845-3.html.

O.O. Babayomi (2026)
"How Africa Can Close the Infrastructure Gap Behind Its AI Ambitions", *Africa at LSE Blog*, 28 May. Available at: https://blogs.lse.ac.uk/africaatlse/2026/05/28/how-africa-can-close-the-infrastructure-gap-behind-its-ai-ambitions.

D. Bahar and G.C. Wright (2026a)
"The Local Economic Impact of Data Centers", working paper, August, Providence, RI, Brown University and Merced, CA, University of California. Available at: https://gregcwright-econ.github.io/files/DataCenters_LocalImpact_2026.pdf.

D. Bahar and G.C. Wright (2026b)
"New evidence on data center employment effects", Washington, DC, Brookings Institution. Available at: https://www.brookings.edu/articles/new-evidence-on-data-center-employment-effects.

H. Bastani, O. Bastani, A. Sungu, H. Ge, Ö. Kabakci and R. Mariman (2025)
"Generative AI without guardrails can harm learning: Evidence from high school mathematics", *Proceedings of the National Academy of Sciences*, 122(26): e2422633122. Available at: https://doi.org/10.1073/pnas.2422633122.

T. Begho, T.P. Daubry and A.E. Irabor (2025)
"A Scoping Review of Artificial Intelligence and the Future of African Agriculture: Opportunities, Challenges and the Path Forward", *Advances in Agriculture*, 1: 2862074. Available at: https://doi.org/10.1155/aia/2862074.

A. Bick, A. Blandin and D.J. Deming (2026)
"The rapid adoption of generative AI", *Management Science*. Available at: https://doi.org/10.1287/mnsc.2025.02523.

A. Bick, A. Blandin, D.J. Deming, N. Fuchs-Schündeln and J. Jessen (2026)
"Mind the gap: AI adoption in Europe and the U.S.", NBER Working Paper No. 34995, Cambridge, MA, National Bureau of Economic Research. Available at: https://doi.org/10.3386/w34995.

A. Bonfiglioli, R. Crinò, M. Filomena and G. Gancia (2025)
"Data, power and emissions: The environmental cost of AI", CEPR Discussion Paper No. 20686, London and Paris, Centre for Economic Policy Research. Available at: https://cepr.org/publications/dp20686.

A. Bradford (2012)
"The Brussels effect", *Northwestern University Law Review*, 107(1): 1-67. Available at: https://scholarlycommons.law.northwestern.edu/nulr/vol107/iss1/1.

E. Brynjolfsson, B. Chandar and R. Chen (2026)
"Canaries in the coal mine? Six facts about the recent employment effects of artificial intelligence", working paper, Stanford, CA, Stanford Digital Economy Lab. Available at: https://digitaleconomy.stanford.edu/publication/canaries-in-the-coal-mine-six-facts-about-the-recent-employment-effects-of-artificial-intelligence.

E. Brynjolfsson, D. Li and L. Raymond (2025)
"Generative AI at work", *The Quarterly Journal of Economics*, 140(2): 889-942. Available at: https://doi.org/10.1093/qje/qjae044.

Cassava Technologies (2025)
"Cassava to Upgrade its Data Centres with NVIDIA Supercomputers to Drive Africa's AI Future". Available at: https://www.cassavatechnologies.com/cassava-to-upgrade-its-data-centres-with-nvidia-supercomputers-to-drive-africas-ai-future.

M. Cazzaniga, F. Jaumotte, L. Li, G. Melina, A.J. Panton, C. Pizzinelli, E. Rockall and M.M. Tavares (2024)
"Gen-AI: Artificial intelligence and the future of work", IMF Staff Discussion Note SDN/2024/001, Washington, DC, International Monetary Fund. Available at: https://www.imf.org/en/publications/staff-discussion-notes/issues/2024/01/14/gen-ai-artificial-intelligence-and-the-future-of-work-542379.

CEPII (2026)
"BACI: International Trade Database at the Product-Level", Paris, Centre d'Études Prospectives et d'Informations Internationales. Available at: https://www.cepii.fr/CEPII/en/bdd_modele/bdd_modele_item.asp?id=37.

CSET ETO (n.d.)
"Country AI Activity Metrics", Washington, DC, Georgetown University, Centre for Security and Emerging Technology, Emerging Technology Observatory. Available at: https://eto.tech/dataset-docs/country-ai-activity-metrics.

Dealroom (n.d.)
"Dealroom.co", Amsterdam. Available at: https://dealroom.co.

M. Demirer, A. Fradkin and N. Tadelis (2026)
"The emerging market for intelligence: How firms buy and sell AI", *Journal of Economic Perspectives*, 40(3): 23-46. Available at: https://www.aeaweb.org/articles?id=10.1257/jep.20261506.

M.E. De Simone, F.H. Tiberti, M.R. Barron Rodriguez, F.A. Manolio, W. Mosuro and E.J. Dikoru (2025)
"From chalkboards to chatbots: Evaluating the impact of generative AI on learning outcomes in Nigeria", World Bank Policy Research Working Paper No. 11125, Washington, DC, World Bank. Available at: http://documents.worldbank.org/curated/en/099548105192529324.

M. Du and C.T. Okolo (2025)
"Reimagining the Future of Data and AI Labor in the Global South", Washington, DC, Brookings Institution, 7 October. Available at: https://www.brookings.edu/articles/reimagining-the-future-of-data-and-ai-labor-in-the-global-south.

EBRD (2025)
Transition Report 2025-26: Brave old world, London. Available at: https://www.ebrd.com/home/news-and-events/publications/economics/transition-reports/transition-report-2025-26.html.

EIA (n.d.)
"Hourly Electric Grid Monitor", Washington, DC, US Energy Information Administration. Available at: https://www.eia.gov/electricity/gridmonitor.

T. Eloundou, S. Manning, P. Mishkin and D. Rock (2024)
"GPTs are GPTs: Labor market impact potential of LLMs", *Science*, 384(6702): 1306-1308. Available at: https://doi.org/10.1126/science.adj0998.

Ember (2026)
"Yearly Electricity Data", London. Available at: https://ember-energy.org/data/yearly-electricity-data.

ENTSO-E (2026a)
"Data centres and the power system: expected trends, challenges and opportunities", 8 May, Brussels. Available at: https://eepublicdownloads.blob.core.windows.net/public-cdn-container/clean-documents/Reports/2026/ENTSO-E_Data_Centres_260520.pdf.

ENTSO-E (2026b)
"Actual total load", ENTSO-E Transparency Platform, Brussels. Available at: https://transparency.entsoe.eu.

ENTSO-E (2026c)
"ENTSO-E and DSO Entity launched Capacitypedia to improve access to grid hosting capacity information across Europe", 22 May, Brussels. Available at: https://www.entsoe.eu/news/2026/05/22/entso-e-and-dso-entity-launched-capacitypedia-to-improve-access-to-grid-hosting-capacity-information-across-europe.

EPİAŞ (2026)
"Real-time consumption", Şeffaflık Platformu, Istanbul, Enerji Piyasaları İşletme A.Ş. (Energy Exchange Istanbul). Available at: https://seffaflik.epias.com.tr.

Epoch AI (2026a)
"AI models", San Francisco, CA. Available at: https://epoch.ai/data/ai-models.

Epoch AI (2026b)
"What you need to know about AI chips", San Francisco, CA. Available at: https://epoch.ai/publications/chips-topic-overview.

Epoch AI (2026c)
"AI chip sales", San Francisco, CA. Available at: https://epoch.ai/data/ai-chip-sales.

Epoch AI (2026d)
"AI data centers", San Francisco, CA. Available at: https://epoch.ai/data/ai-data-centers.

European Commission (2025)
"EU launches InvestAI initiative to mobilise €200 billion of investment in artificial intelligence", press release, 11 February. Available at: https://digital-strategy.ec.europa.eu/en/news/eu-launches-investai-initiative-mobilise-eu200-billion-investment-artificial-intelligence.

European High Performance Computing Joint Undertaking (2026)
"AI Factories", Luxembourg. Available at: https://www.eurohpc-ju.europa.eu/ai-factories_en.

European Union (2024)
Regulation (EU) 2024/1689 of the European Parliament and of the Council of 13 June 2024 laying down harmonised rules on artificial intelligence, Official Journal of the European Union, L 2024/1689, Brussels. Available at: https://eur-lex.europa.eu/eli/reg/2024/1689/oj/eng.

Eurostat (2026a)
"Artificial intelligence by NACE Rev. 2 activity (isoc_eb_ain2)", Luxembourg. Available at: https://doi.org/10.2908/ISOC_EB_AIN2.

Eurostat (2026b)
"Population on 1 January by age group and sex (demo_pjangroup)", Luxembourg. Available at: https://doi.org/10.2908/DEMO_PJANGROUP.

D. Facius and R. Iacono (2026)
"Labor market consequences of generative AI: Early evidence from Norway", CESifo Working Paper No. 12752, Munich, CESifo. Available at: https://doi.org/10.65864/8a4auliirt.

REFERENCES

H. Farrell and A.L. Newman (2019)
"Weaponized interdependence: How global economic networks shape state coercion", *International Security*, 44(1): 42-79. Available at: https://doi.org/10.1162/ISEC_a_00351.

fDi Markets (2026)
"fDi Markets: cross-border greenfield investment data", London, fDi Intelligence, *Financial Times*. Available at: https://www.fdimarkets.com.

Federal Republic of Nigeria (2023)
Nigeria Data Protection Act, 2023, Official Gazette No. 119, Vol. 110, Government Notice No. 82, Lagos. Available at: https://ndpc.gov.ng/wp-content/uploads/2024/03/Nigeria_Data_Protection_Act_2023.pdf.

M.F. Ferracane, S. González Ugarte and T. Rogaler (eds.) (2025)
"DTI Database", Florence, Italy, Digital Trade Integration Project.
Available at: https://dti.eui.eu.

F. Filippucci, P. Gal, K. Laengle and M. Schief (2025)
"Macroeconomic productivity gains from artificial intelligence in G7 economies", OECD Artificial Intelligence Paper No. 41, Paris, OECD. Available at: https://doi.org/10.1787/a5319ab5-en.

L. Gambacorta and V. Shreeti (2025)
"The AI supply chain", BIS Paper No. 154, Basel, Switzerland, Bank for International Settlements. Available at: https://www.bis.org/publ/bppdf/bispap154.htm.

P. Garg, T. Crosta and J. Baier (2026)
"Global Automation Atlas", arXiv Working Paper No. 2605.17086. Available at: https://arxiv.org/abs/2605.17086.

Global Trade Alert (n.d.)
"Global Trade Alert", St. Gallen, Switzerland, St. Gallen Endowment for Prosperity through Trade. Available at: https://globaltradealert.org.

Google Patents (n.d.)
"Google Patents", San Francisco, CA.
Available at: https://patents.google.com.

GSM Association (2024)
The Mobile Economy: Sub-Saharan Africa 2024, London. Available at: https://www.gsma.com/solutions-and-impact/connectivity-for-good/mobile-economy/wp-content/uploads/2025/10/The-Mobile-Economy-Sub-Saharan-Africa-2024.pdf.

GSM Association (2026)
The State of the Industry Report on Mobile Money 2026, London. Available at: https://www.gsma.com/sotir.

C.A. Hidalgo, B. Klinger, A.-L. Barabási and R. Hausmann (2007)
"The product space conditions the development of nations", *Science*, 317(5837): 482-487. Available at: https://doi.org/10.1126/science.1144581.

S.M. Hosseini and G. Lichtinger (2026)
"Generative AI as seniority-biased technological change: Evidence from U.S. résumé and job posting data", working paper, Cambridge, MA, Harvard University. Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=5425555.

IEA (2025)
Energy and AI, World Energy Outlook Special Report, Paris. Available at: https://www.iea.org/reports/energy-and-ai.

IEA (2026)
Key Questions on Energy and AI, World Energy Outlook Special Report, Paris. Available at: https://www.iea.org/reports/key-questions-on-energy-and-ai.

ILO (n.d.)
"ILOSTAT", Geneva, Switzerland, International Labour Organization.
Available at: https://ilostat.ilo.org.

IMF (2026)
"World Economic Outlook (WEO)", April, Washington, DC. Available at: https://data.imf.org/en/datasets/IMF.RES:WEO.

Institute of Smart Systems and Artificial Intelligence (n.d.)
"Kazakh Large Language Model (ISSAI KAZ-LLM)", Astana, Nazarbayev University. Available at: https://issai.nu.edu.kz/kazllm.

Intel (n.d.)
"International expansion for assembly", Intel Virtual Vault, Santa Clara, CA. Available at: https://www.intel.com/content/www/us/en/history/virtual-vault/articles/intel-penang.html.

C.I. Jones (2025)
"How much should we spend to reduce A.I.'s existential risk?", NBER Working Paper No. 33602, Cambridge, MA, National Bureau of Economic Research. Available at: https://doi.org/10.3386/w33602.

E. Jones and A.O. Zeitz (2017)
"The limits of globalizing Basel banking standards", *Journal of Financial Regulation*, 3(1): 89-124. Available at: https://doi.org/10.1093/jfr/fjx001.

A. Korinek and J. Vipra (2025)
"Concentrating intelligence: Scaling and market structure in artificial intelligence", *Economic Policy*, 40(121): 225-256. Available at: https://doi.org/10.1093/epolic/eiae057.

P.J. Lambert and Y. Schindler (2026)
"The broken ladder: AI, remote work, and early-career hiring", CAGE Working Paper No. 808/2026, Warwick, United Kingdom, University of Warwick. Available at: https://warwick.ac.uk/fac/soc/economics/research/centres/cage/publications/workingpapers/2026/the_broken_ladder_ai_remote_work_and_early_career_hiring.

Lenovo (2022)
"Lenovo Officially Opens First European In-House Manufacturing Facility in Üllő, Hungary", press release, 14 June. Available at: https://news.lenovo.com/pressroom/press-releases/first-european-in-house-manufacturing-facility-ullo-hungary.

M. Lokshin (2026)
"Cheap Energy Might Not Be Enough: A Trade Model of AI Compute Services", World Bank Policy Research Working Paper No. 11426, Washington, DC, World Bank. Available at: https://documents.worldbank.org/en/publication/documents-reports/documentdetail/099327207202690992.

C. Meinhardt, J.N. Pava, C. Yee and J.A. Landy (2026)
"The commercial landscape of AI sovereignty offerings", Human-Centered Artificial Intelligence (HAI) Policy & Society Issue Brief, Stanford, CA, Stanford University. Available at: https://hai.stanford.edu/policy/the-commercial-landscape-of-ai-sovereignty-offerings.

P. Melatagia Yonta (2025)
"Intelligence artificielle et développement: enjeux et opportunités pour l'Afrique", in Agence française de développement (ed.), *L'économie africaine 2025*, Paris, La Découverte, pp. 93-108. Available at: https://www.afd.fr/fr/ressources/leconomie-africaine-2025.

N.Z. Muller (2026)
"Measuring the impact of data centres in the United States economy: Monetary damage from air pollution and greenhouse gas emissions", NBER Working Paper No. 35100, Cambridge, MA, National Bureau of Economic Research. Available at: https://doi.org/10.3386/w35100.

J. Munga and S. Quansah (2025)
"Understanding Africa's AI Governance Landscape: Insights from Policy Practice and Dialogue", 11 September, Washington, DC, Carnegie Endowment for International Peace. Available at: https://carnegieendowment.org/posts/2025/09/understanding-africas-ai-governance-landscape-insights-from-policy-practice-and-dialogue.

K. Mwangi (2024)
"On the cusp of a new dawn? Microsoft's Kiswahili AI model to bridge tech inclusivity gap", *Business Daily Africa*, 27 May. Available at: https://www.businessdailyafrica.com/bd/corporate/technology/microsoft-s-kiswahili-ai-model-to-bridge-tech-incusivity-gap-4636416.

D. Mwesigwa, S.J. Jackson and C. Csikszentmihalyi (2026)
"Risk, Data, Alignment: Making Credit Scoring Work in Kenya", *CHI '26: Proceedings of the 2026 CHI Conference on Human Factors in Computing Systems*, Barcelona, Spain, 13-17 April 2026, New York, ACM. Available at: https://doi.org/10.1145/3772318.3790924.

NASK NLP Research Group (n.d.)
"PLLuM: Polish Large Language Model". Available at: https://pllum.org.pl/en.

A. Ndege (2026)
"South Africa, Nigeria, Kenya emerge as Africa's top work outsourcing markets", *TechCabal*, 29 May. Available at: https://techcabal.com/2026/05/29/south-africa-nigeria-kenya-global-outsourcing.

S. Noy and W. Zhang (2023)
"Experimental evidence on the productivity effects of generative artificial intelligence", *Science*, 381(6654): 187-192. Available at: https://doi.org/10.1126/science.adh2586.

C.L. Obi, J.O. Olowoyo, T.D. Malevu, L.L. Mugivhisa, T. Hungwe, M.O. Ogunrombi and N.M. Mkolo (2024)
"Impact of artificial intelligence and digital technology-based diagnostic tools for communicable and non-communicable diseases in Africa", *African Journal of Laboratory Medicine*, 13(1): a2516. Available at: https://doi.org/10.4102/ajlm.v13i1.2516.

V. Obia (2025)
"Africa's AI Policy Ambitions Ignore Energy, Climate and Labor Concerns", *Tech Policy Press*, 21 October. Available at: https://www.techpolicy.press/africas-ai-policy-ambitions-ignore-energy-climate-and-labor-concerns.

OECD (2022)
"Inter-Country Input-Output tables", Paris. Available at: https://www.oecd.org/en/data/datasets/inter-country-input-output-tables.html.

OECD (2025a)
The chip landscape: Geographical distribution of wafer fabrication capacity, OECD Science, Technology and Industry Policy Paper No. 188, Paris. Available at: https://doi.org/10.1787/02dbd028-en.

OECD (2025b)
Identifying emerging AI technologies using patent data: A semi-automated approach, Paris. Available at: https://doi.org/10.1787/d17e9a1a-en.

OECD (2026)
AI Governance in Africa, OECD AI Case Studies, Paris. Available at: https://www.oecd.org/en/publications/oecd-artificial-intelligence-case-studies_c517fcf5-en/ai-governance-in-africa_1ff55135-en.html.

O*NET (n.d.)
"The O*NET-SOC Taxonomy", O*NET Resource Center. Available at: https://www.onetcenter.org/taxonomy.html.

Republic of Kenya (2019)
The Data Protection Act, No. 24 of 2019, Kenya Gazette Supplement No. 181 (Acts No. 24), Nairobi, Office of the Data Protection Commissioner. Available at: https://www.odpc.go.ke/wp-content/uploads/2024/02/TheDataProtectionAct__No24of2019.pdf.

Revelio Labs (2025)
"Workforce Data", New York. Available at: https://www.reveliolabs.com/data.

K. Rishabh and V. Shreeti (2026)
"The geography of AI firms", BIS Working Paper No. 1343, Basel, Switzerland, Bank for International Settlements. Available at: https://www.bis.org/publ/work1343.htm.

F. Saracco, R. Di Clemente, A. Gabrielli and T. Squartini (2015)
"Randomizing bipartite networks: the case of the World Trade Web", *Scientific Reports*, 5: 10595. Available at: https://doi.org/10.1038/srep10595.

SIA and BCG (2022)
The Growing Challenge of Semiconductor Design Leadership, Washington, DC, Semiconductor Industry Association, and Boston, MA, Boston Consulting Group. Available at: https://www.semiconductors.org/wp-content/uploads/2022/11/2022_The-Growing-Challenge-of-Semiconductor-Design-Leadership_FINAL.pdf.

Silicon Analysts (2026)
"AI chip cost bridge: manufacturing cost breakdown for 18 accelerators", online tool, updated August 2026. Available at: https://siliconanalysts.com/tools/cost-bridge.

REFERENCES

The Economist (2026)
"An interview with Arthur Mensch", *Inside Tech*, *The Economist Insider*, 14 June. Available at: https://www.economist.com/insider/inside-tech/an-interview-with-arthur-mensch.

TrendForce (2026)
"AI demand drives 4Q25 global top 10 foundries revenue up 2.6% QoQ; Samsung gains share and Tower moves up in rankings", press release, 12 March. Available at: https://www.trendforce.com/presscenter/news/20260312-12965.html.

UNESCO UIS (n.d.)
"Data for the Sustainable Development Goals", Paris, UNESCO Institute for Statistics. Available at: https://www.uis.unesco.org/en.

United Nations (2026)
"UN Comtrade Database", New York, United Nations Statistics Division. Available at: https://comtradeplus.un.org.

United Nations Statistics Division (n.d.)
"National Accounts", New York. Available at: https://unstats.un.org/unsd/nationalaccount.

US Census Bureau (2026)
"International Trade Data: Monthly Imports by Harmonized Tariff Schedule (HTS) Commodity", Washington, DC. Available at: https://www.census.gov/data/developers/data-sets/international-trade.html.

US Department of Commerce, Bureau of Industry and Security (2022)
"Commerce implements new export controls on advanced computing and semiconductor manufacturing items to the People's Republic of China (PRC)", press release, 7 October. Available at: https://www.bis.gov/press-release/commerce-implements-new-export-controls-advanced-computing-semiconductor-manufacturing-items-peoples.

US Department of Commerce, Bureau of Industry and Security (2023)
"Commerce strengthens restrictions on advanced computing semiconductors, semiconductor manufacturing equipment, and supercomputing items to countries of concern", press release, 17 October. Available at: https://www.bis.gov/press-release/commerce-strengthens-restrictions-advanced-computing-semiconductors-semiconductor-manufacturing-equipment.

A. Watten, J. Bistline and G. Blanford (2026)
"Have data centers raised your electric bill? Causal evidence from the United States", arXiv preprint 2606.19777. Available at: https://arxiv.org/abs/2606.19777.

WBS Power (2026)
"WBS Power Advances 3.2 GW Energy Infrastructure for Hyperscale Data Center Campus", press release, *PR Newswire*, 24 March. Available at: https://www.prnewswire.com/news-releases/wbs-power-advances-3-2-gw-energy-infrastructure-for-hyperscale-data-center-campus-302719788.html.

WCO (2022)
"Harmonized System", Brussels, World Customs Organization. Available at: https://www.wcotradetools.org/en/harmonized-system.

World Bank (n.d.a)
"World Development Indicators", Washington, DC. Available at: https://datatopics.worldbank.org/world-development-indicators.

World Bank (n.d.b)
"World Bank Country and Lending Groups", Washington, DC. Available at: https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups.

X. Yuan, J. Liu, S. Sun, X. Lin, X. Fan, W. Zhao and R. Kosonen (2025)
"Data center waste heat for district heating networks: A review", *Renewable and Sustainable Energy Reviews*, 219: 115863. Available at: https://doi.org/10.1016/j.rser.2025.115863.

D. Yue and Y. Zeng (2026)
"The local economic effects of data center entry", SSRN Working Paper No. 6497238. Available at: https://doi.org/10.2139/ssrn.6497238.

