Technology and Innovation Report 2025

Chapter III

Preparing to seize AI opportunities

Developing countries need to prepare themselves for a world that is rapidly being reshaped by AI and other frontier technologies. A useful measure in assessing national preparedness to use, adopt and adapt frontier technologies is the UNCTAD frontier technologies readiness index.

Developed countries lead the ranking, but some developing countries, notably Singapore, China, and India, hold prominent positions. Moreover, some countries perform better than their levels of income may suggest, demonstrating strong potential to seize opportunities offered by frontier technologies and boost economic development.

This chapter further examines the key factors in AI adoption and development, highlighting the urgent need for improved infrastructure, data and skills in developing countries. Assessing readiness and identifying relative strengths and weaknesses in AI can guide the development of strategic plans and catch-up pathways.

United Nations

Key policy takeaways

- **Governments should strategically position themselves to seize the opportunities offered by AI.** This involves assessing national AI capacities across the three leverage points of infrastructure, data and skills; and identifying gaps to pinpoint areas of action. Different catch-up trajectories can steer the transition from current technological and productive capacities towards desired targets.

- **Evaluating AI opportunities and challenges, through technology assessment and foresight exercises, helps identify actions to strengthen the innovation system.** UNCTAD assists developing countries in technology assessment, and its Science, Technology and Innovation (STI) Policy Review Programme supports the development of STI policies.

- **A successful structural transformation requires cooperation among public authorities and ministries, such as those for STI, industry and education.** Stakeholder engagement is crucial to identify AI solutions for sustainable development and to formulate STI plans that align with national objectives.

A. The frontier technologies readiness index

To offer a comprehensive measure of each country's preparedness for frontier technologies, UNCTAD has devised the frontier technologies readiness index (UNCTAD, 2021). This combines indicators for ICT deployment, skills, research and development (R&D) activity, industrial capacity and access to finance. First launched along with the *Technology and Innovation Report 2021*, the index covers 170 countries, including 124 developing countries (see annex III).

As in previous years, the index rankings are dominated by developed countries in Europe and North America (table III.1). Developing countries generally rank lower, but Singapore stands out in fifth position and performs well across all the index's dimensions. Some BRICS countries also have good ranking positions, notably China, at 21; the Russian Federation, at 33; India, at 36; Brazil, at 38; and South Africa, at 52.[1]

Table III.1 also shows the rankings for five subindices. Among developing countries,

Table III.1
Readiness for frontier technologies, selected countries

Country name	Rank in 2024	Rank in 2022	Movement in rank	ICT ranking	Skills ranking	R&D ranking	Industry ranking	Finance ranking
Top 10								
United States	1	1	=	4	17	2	17	2
Sweden	2	2	=	17	2	15	7	14
United Kingdom	3	3	=	18	12	6	14	17
Netherlands (Kingdom of the)	4	5	↑	3	6	13	11	31
Singapore	5	4	↓	12	5	20	4	11
Switzerland	6	6	=	25	14	11	3	7
Republic of Korea	7	9	↑	14	32	4	13	5
Germany	8	7	↓	26	18	5	12	34
Ireland	9	12	↑	27	11	28	1	116
France	10	14	↑	7	21	8	24	19
Selected economies								
China	21	28	↑	101	64	1	6	3
Russian Federation	33	33	=	41	29	17	72	63
India	36	48	↑	99	113	3	10	70
Brazil	38	40	↑	38	59	18	50	41
South Africa	52	51	↓	76	71	41	55	27

Source: UNCTAD.
Note: Due to data updates and changes in weighting factors and numbers of countries, the rankings should not be compared with those calculated in previous years (see annex III for the complete table).

[1] The BRICS group of countries has developed into an intergovernmental organization that includes Brazil, the Russian Federation, India, China, South Africa, Egypt, Ethiopia, Indonesia, the Islamic Republic of Iran and the United Arab Emirates.

China ranks first in R&D, third in finance and sixth in industry, and India ranks third in R&D. The countries least prepared for frontier technologies are predominantly in Africa and Latin America and the Caribbean.

Between 2022 and 2024, the index shows that many developing countries experienced notable improvements. Argentina, Chile, China, North Macedonia and Uruguay, for example, increased their positions in ICT, thanks to significant rises in mean download speeds. Meanwhile, Bhutan, India, Morocco, the Republic of Moldova and Timor-Leste improved their positions in human capital, due to more years of schooling and a greater share of high-skill employment in their working populations. Angola and Barbados made progress in the R&D subindex, with more scientific publications and patents filed on frontier technologies. Armenia, Bahamas, Chad and Maldives moved up in the industry subindex due to higher shares of high-technology manufacturing exports. Trade data fluctuate and short-term changes should therefore be interpreted with caution.

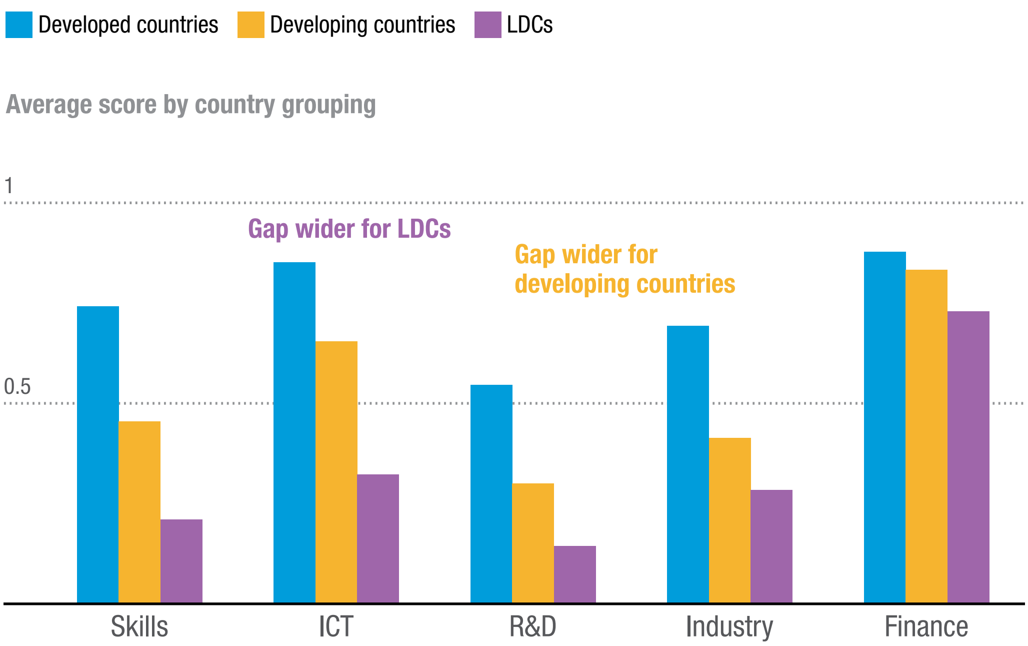
Burundi and Timor-Leste registered improvements in the finance subindex, with a higher share of domestic credit going to the private sector as a proportion of GDP that, if channelled toward productive investments, can support the adoption or development of frontier technologies.

The frontier technologies readiness index highlights areas for improvement, to enable the development, adoption and adaptation of these technologies. It also shows the strengths and weaknesses of country groups. It is important to emphasize that differences in rankings may not accurately reflect the disparities in underlying capacities. Actual levels of readiness are better indicated by countries' scores.

Figure III.1 presents the average scores across the subindices for developed countries, developing countries and least developed countries (LDCs). As expected, developed countries consistently outperform in all dimensions of the readiness index. However, differences vary across subindices.

Many developing countries have shown **improvements in the frontier technologies readiness index and subindices**

Figure III.1
Frontier technologies readiness subindices score, selected country groupings



Source: UNCTAD.

There are wide disparities between developed and developing countries in the R&D and industry subindices

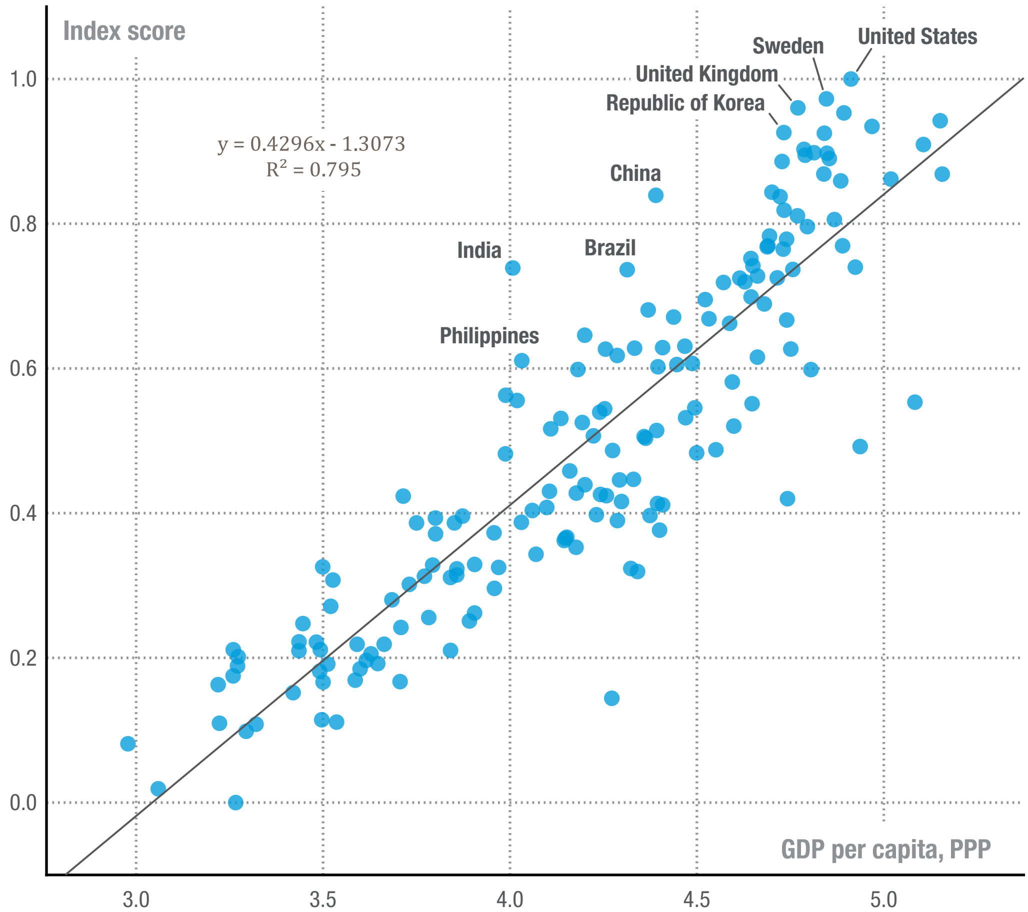
The skills subindex reveals significant differences between country groups. On average, LDCs register scores that are less than half of those of developing countries and less than one third of those of developed countries. The difference between developed and developing countries is narrower on the ICT subindex, although LDCs remain some way behind developing countries.

A similar pattern is observed in the R&D and industry subindices, with wide disparities between developed and developing countries, but narrower disparities between developing countries and LDCs. With regard to finance, differences among country groupings are less marked.

It might be expected that countries with higher per capita GDP are better prepared for frontier technologies. Overall this is true but, as shown in figure III.2, some countries perform far better than their levels of income may suggest, as indicated by their distance from the regression line of the index score on GDP per capita. Among developing countries, outperformers are Brazil, China, India and the Philippines; among developed countries, outperformers are the Republic of Korea, Sweden, the United Kingdom and the United States. There are correspondingly large differences in their rankings for GDP per capita and their rankings for the overall index; for India, 76 places; for China and the Philippines, 49 places; and for Brazil, 41 places.

Brazil, China, India and the Philippines are developing countries **outperforming in technology readiness**

Figure III.2
Brazil, China, India and the Philippines are developing countries outperforming in technology readiness
Correlation between index score and GDP per capita



Source: UNCTAD.
Note: GDP per capita is in current international dollars, purchasing power parity (logarithm)

These contrasts show that many countries have strong potential to seize the opportunities offered by frontier technologies and boost economic growth and overall development.

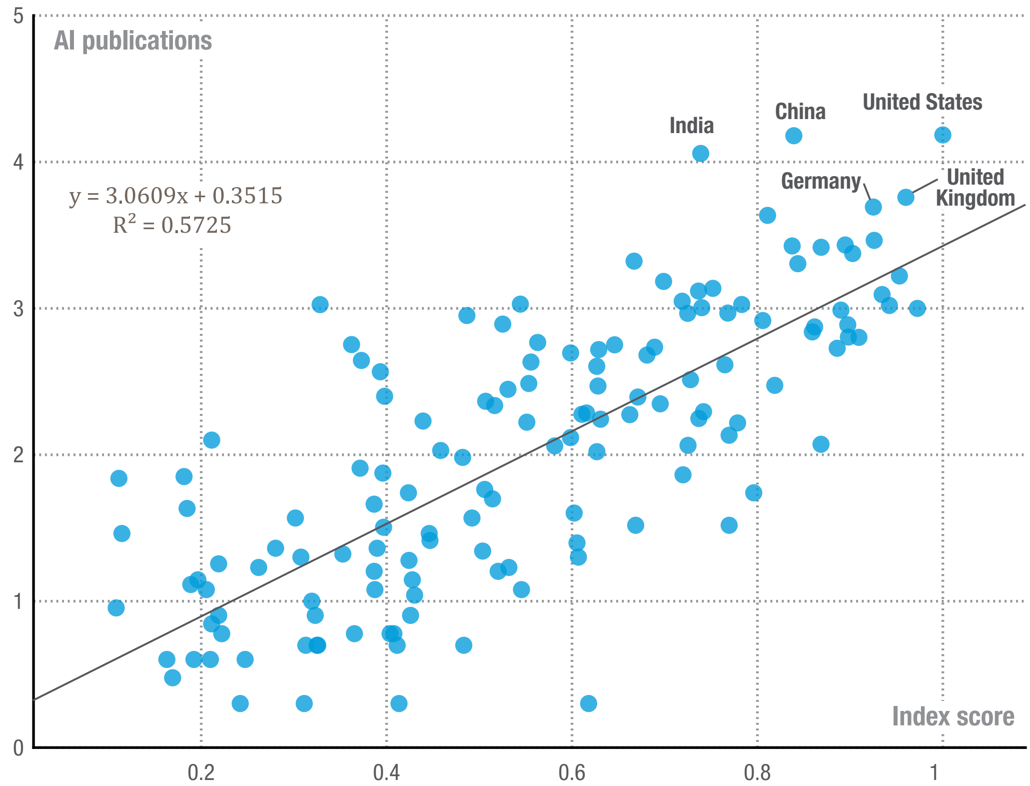
A common feature of the better performing countries is greater R&D activity and stronger industry capacities, which enable them to keep pace with technological development and eventually lead in some frontier technologies.[2] This highlights the importance of making efforts to improve a country's innovation ecosystem. Chapter IV discusses policy efforts that support the adoption and development of AI.

It is also notable that the readiness index correlates positively with the number of AI publications (figure III.3). AI publications are among the variables of the R&D subindex and some correlation is expected. Nevertheless, the components contributing the most to the index score are those related to skills and industry and all of the subindices correlate positively with AI publications even when controlling for GDP per capita, population size and regional factors.

Countries above the regression line produce more scientific knowledge than might be expected by their index score. For example, China, Germany, India, the United Kingdom and the United States show scientific strength in the field of AI.

The technology readiness index is strongly **associated with the generation of scientific knowledge in AI**

Figure III.3
Correlation between index score and knowledge generation in AI



Source: UNCTAD calculations, based on data from Scopus.
Note: Number of AI-related scientific articles in 2023 (logarithm).

[2] Outperformers compared to their economic performances show an average R&D score that is almost double with respect to other economies and an industry score that is about 50 per cent higher.

B. Key factors in the adoption and development of AI

It is important to identify areas in which AI can be **strategically deployed to make a real impact**

The information offered in the frontier technologies readiness index can be complemented by a detailed assessment of each country's strengths and weaknesses in the adoption and development of AI.

A technological wave unfolds in several phases. The initial development phase involving conceptualization or invention is often lengthy and costly. The adoption phase occurs when the technology begins to gain traction and early adopters start applying it to real-world problems. Finally, as the technology is diffused, it becomes more accessible and affordable and is more widely integrated into economies and societies. Widespread adoption often drives further innovation, which can lead to a renewed development phase.

The initial development of new technologies is typically driven by developed countries. Developing countries mostly only adopt frontier technologies, although some of the more technologically advanced developing countries may soon start adapting the technologies to their own conditions, which contributes to further development. This mirrors the classic company dilemma of whether to adopt innovations or to develop them, a choice that depends on contextual factors and own capabilities.

SMEs face limiting factors that hinder widespread AI adoption

Moving from AI proof-of-concept to large-scale roll-out may be more challenging than expected, and it is important to identify areas in which AI can be strategically deployed to make a real impact (Cohen and Levinthal, 1989; Teece, 1986; Teece et al., 1997). The rate of diffusion of AI among citizens and society depends on basic factors, including access to the Internet, electricity and digital devices, as well as basic and AI-relevant digital skills.

While adoption leverages those technologies that best align with existing socioeconomic structures and needs, development involves a more active role in shaping the direction of technological change.

Adoption

AI adoption involves using existing AI technologies to improve tasks and business processes, as well as adapting AI systems to particular sectoral needs. Most of the evidence on AI adoption comes from advanced economies in which large businesses are increasingly integrating AI into their practices and services. In 2024, a global survey showed that 72 per cent of large businesses used AI in some capacity. To date, they are largely using generative AI (GenAI) for the marketing and product development of information technology functions and less in manufacturing or supply-chain management (Singla et al., 2024).

Most of this activity is by larger firms that have the greatest resources, and the share of AI users in firms with more than 250 persons is generally double that of small and medium enterprises (SMEs) (OECD, 2023a). In some countries, differences may be even greater. In Italy, for example, one study showed that the probability of investing in AI could be more than five times higher for larger firms than smaller ones (Montresor and Vezzani, 2023).

It should be noted that a comprehensive understanding of AI adoption is generally hindered by a shortage of systematic evidence, particularly from developing countries, which may constrain the capacity to design effective policies and interventions.

Development

AI development includes all aspects related to the creation of new AI solutions, which includes the development of new models or algorithms and the improvement of existing ones, as well as all of the necessary resources and infrastructure to sustain the AI industry, such as computing power or the assembly of a cohort of developers trained to use new types of algorithms and data.

AI development is scaling up quickly. The number of AI publications and patents is growing exponentially (see chapter I). The number of English-language AI study programmes globally has almost tripled since 2017, and the proportion of computer science students specializing in AI has doubled since 2015 (Maslej et al., 2024).

In general, compared with adoption, development requires more advanced infrastructure, robust data systems and greater technological capabilities and skills, which are more likely to be found in developed countries. Developing countries may be able to take advantage of open-source models, which can help diffuse AI capacities worldwide. However, AI development requires building up robust infrastructure and innovation ecosystems and for some developing countries, it may be more viable to first prioritize adoption and adaptation.

Developing a domestic AI industry from scratch can be an expensive and lengthy endeavour. Creating AI models requires highly educated and skilled developers and engineers, who need professional and industrial opportunities to gain experience. Moreover, the AI industry is being driven by relatively young firms leveraging knowledge and software rather than physical assets, for whom attracting financing is based less on past performance and more on long-term market potential.

Lack of systematic evidence from developing countries limits their capacity to **design effective interventions**

C. Three critical leverage points for AI adoption and development

The adoption and development of AI critically depends on the three leverage points of infrastructure, data and skills.

Infrastructure refers to digital connectivity and computing power, and the associated networks, architecture and resources necessary to create, train and use AI solutions across a community or country.

Data are necessary for training AI models, with dedicated data for applying models to different use cases. Data are not only an input but are also generated through AI systems.

Skills include basic digital and advanced AI-specific skills, as well as the complementary skills needed for a cohesive workforce that can effectively create and use AI.

The elements of infrastructure, data and skills are needed in both adoption and development (table III.2). Although some elements may be relevant to both processes, it helps to identify particular AI requirements for more detailed analyses. Each element contributes to technological progress, but only together can they fully catalyse AI diffusion. Such interactions have led to breakthroughs such as deep learning and GenAI that have redefined the technology landscape. By supporting development in these critical leverage points, decision makers can trigger transformational economic cascades.

Developing countries can catalyze transformative changes by **focusing on the three key leverage points for AI**

Table III.2
Key elements of AI adoption and development

	Infrastructure	Data	Skills	Policy and governance
Adoption	Electricity ICT infrastructure Digital devices	Access to domain-specific data Data storage and processing power	Basic digital skills (e.g. data literacy) Awareness and understanding of AI Technical knowledge	Principles Governance Policies (e.g. industrial, innovation) Strategies
Development	International connectivity Data centres and high-speed networks	Large and diverse datasets High quality, standardized, and interoperable data Privacy, security and anonymization	Advanced digital skills (e.g. data science, machine learning) AI-specific skills and experiences Cognitive skills (e.g. problem solving)	

Source: UNCTAD.

Policy and governance for AI can serve to determine the overall direction, setting institutional or cultural guardrails, and creating a socioeconomic and structural context favourable to the development of AI ecosystems. Chapter IV further elaborates on domestic policies involving AI and chapter V reviews the state of global AI governance and how it can support efforts to guarantee that AI will benefit all.

Infrastructure

The adoption of AI relies on basic infrastructure such as electricity and the Internet. While over 90 per cent of the world's population has access to electricity (IEA et al., 2023), about 2.6 billion people are still offline and most of them are in rural areas (ITU, 2023).

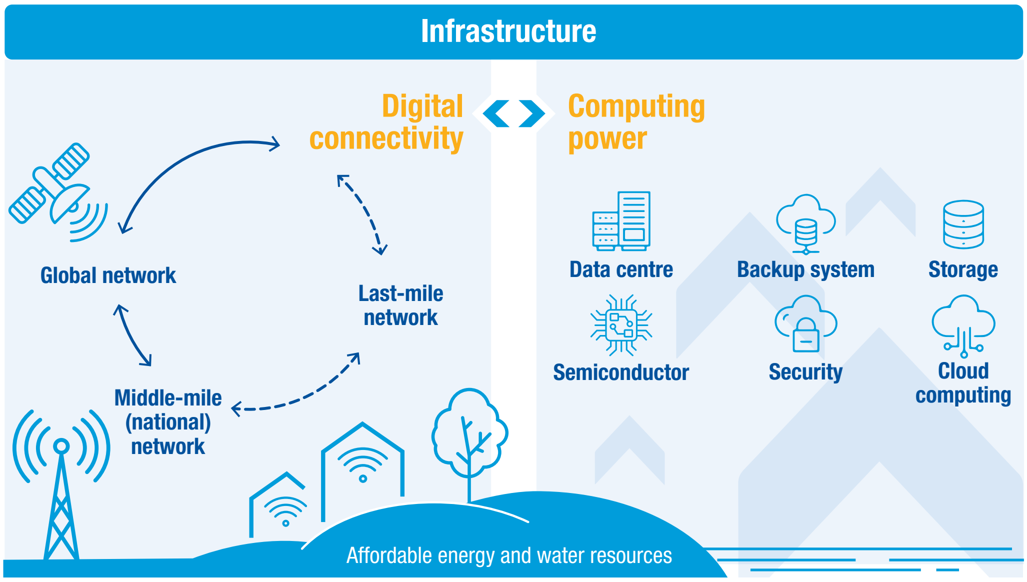
One third of the world's population is still offline and many lack last-mile infrastructure

AI infrastructure can be divided into two broad categories, namely, digital connectivity, which is largely related to information and communications technology (ICT); and computing power, often referred to as AI compute. They provide foundational support and linkages between actors and systems (figure III.4). Both require reliable and affordable energy and water resources.

Digital connectivity is often categorized into three segments. First, cross-border terrestrial and submarine cables and satellite linkages which provide access to global networks. Second, middle-mile networks are responsible for the distribution of traffic within countries, including content delivery networks and backbone networks. Third, last-mile or access networks are responsible for providing connectivity to individuals, households and businesses, typically consisting of fixed or mobile cellular networks. The increased use of AI systems and complementary technologies puts pressure on all digital connectivity segments (World Bank, 2021; ITU, 2022).

Although most countries have ICT networks, these often do not extend much beyond densely populated areas. They may be partially complemented by mobile connectivity for small-scale businesses and private users, but AI adoption is likely to be constrained, particularly for industrial uses (Bentley et al., 2024). As well as connections, end users also need affordable digital devices to connect to ICT networks and any associated hardware, as well as basic computing power. The last-mile limitations of telecommunications infrastructure in many developing countries indicate that, to close digital divides, one of the priorities should be universal digital connectivity.

Figure III.4
Key components of AI infrastructure



Source: UNCTAD.

The infrastructure demands are even greater for AI development, particularly for AI compute, that is, the computing power necessary to train and execute AI models. The increasing computational requirements for creating and training AI algorithms are being driven by an industry oriented towards multitasking and complex models. Handling large amounts of data and reducing operating times requires efficient data centres, high-speed networks and supercomputers.

AI compute requires increasingly complex semiconductors to address AI and big data requirements.[3] Most are produced by a handful of firms worldwide; when supplies are limited due to demand spikes or shocks, developing countries may therefore be last in line.[4] Computing resources and elements also include storage, security, backup systems, data centres and cloud computing. These core elements are often already available in many countries but need to be continuously upgraded or replaced to support the application and development of AI.[5]

Much of digital and cloud computing operates across national borders, relying on interoperable infrastructure and protocols. GenAI in particular requires accurate and increasing amounts of data, generally through large bandwidth and international connectivity. Efforts to reduce latency times and data transit costs have spurred the deployment of data centres closer to users (Richins et al., 2020). This trend can be accelerated by requirements to locate data in a particular territory or by setting standards for privacy or cybersecurity (UNCTAD, 2021).

[3] The electronics value chain begins with the extraction of raw minerals for the creation of computing hardware and semiconductors. The extraction of minerals takes place mainly in developing countries, for example, in 2023, Chile, the Democratic Republic of the Congo and Peru provided about half of the global output of copper, a key raw material in electronic devices (UNCTAD, 2024a).

[4] For instance, the COVID-19 pandemic resulted in a global chip shortage that was greater than the concomitant decrease in demand, negatively affecting several value chains, such as that of the automotive sector (Ramani et al., 2022; Burkacky et al., 2022).

[5] Advances in algorithms and architectures that have reduced computing power needs have not been able to compensate for the escalating computational requirements of modern machine-learning systems, which have grown by several orders of magnitude in the last decade (Sevilla et al., 2022; Thompson et al., 2022).

Data

The power of AI strongly relies on data quality, quantity and accessibility

Since 2010, the average size of training data sets for language models has tripled each year (Sevilla and Roldán, 2024). Too complex to be effectively processed by traditional processing approaches and platforms, huge and diverse data sets are better addressed by machine-learning and deep-learning algorithms, to produce new and transformative insights (Philip Chen and Zhang, 2014). The ability of AI models to analyse and learn from data is determined by their quantity, quality and accessibility (figure III.5).

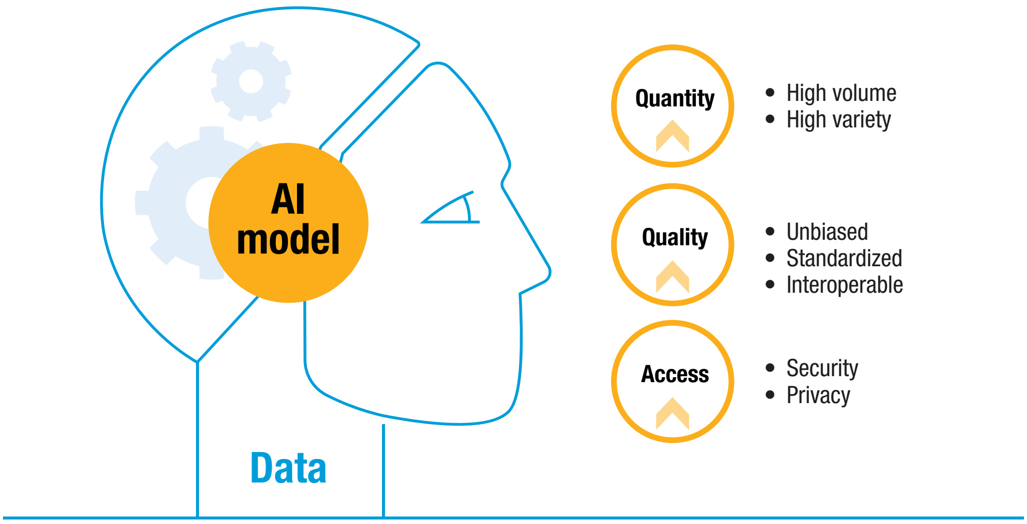
However, online data stocks are growing more slowly than the demands from AI, with the risk of shortages that can lead to data bottlenecks (Villalobos et al., 2024). An emerging challenge is how to train and operate AI models more efficiently, to produce trustworthy results from more limited data (Muennighoff et al., 2023).

AI adoption and customization require access to domain-specific data (e.g. geographical, industrial, cultural) that matches the use-case of AI models and solutions. Increasingly, data requirements overlap with infrastructure needs (e.g. data storage and processing), particularly for SMEs in traditional sectors, for which the costs of setting up and handling information technology systems can be prohibitive. The sectoral rollout of AI thus needs fine-tuning, with consideration given to field-specific needs.

Compared with adoption, AI development requires larger and more diverse data, to create, train and test foundation models that are generalizable and can be applied to a variety of use cases. Yet the concentration of control over large data sets by a few platform companies may limit opportunities for value generation based on data, including through AI development. This can hinder efforts to catch up, particularly for firms from developing countries.

Moreover, AI does not solve the "garbage in, garbage out" problem. If the data sets do not, for example, fully represent different groups or cultures, by gender, by underserved communities or by language, then algorithms are likely to produce biased, incomplete or misleading results. Biases, fabrications or hallucinations (i.e. incorrect or misleading results) can be exacerbated when data produced by AI are used as inputs to train other AI models.

Figure III.5
Data requirements for AI



Source: UNCTAD.

Data should be easily available and affordable for developers and users, and standardized and interoperable for quality assurance and efficient processing. At the same time, it is important to respect property rights, as well as privacy and security. The acquisition, processing and use of data should comply with legal and ethical norms and requirements with regard to privacy and data ownership, with security and anonymization procedures used to protect personal information. The importance of global data governance is discussed in chapter V.

Skills

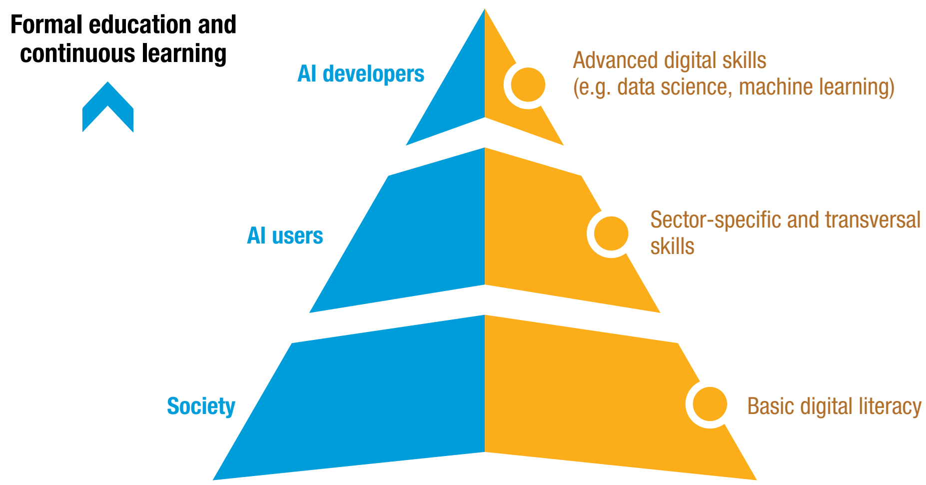
The adoption and development of AI depends on human efforts and skills. Engineers and computer scientists are needed in designing and producing computer chips and coding algorithms. At the same time, end-users require both digital skills and industry-specific knowledge to adopt and adapt AI.

Even if an economy has access, awareness and sufficient funds to adopt AI, this may still not suffice unless there are skilled workers who can use AI or identify opportunities for its use throughout the economy (Chui and Malhotra, 2018). Universal digital literacy provides a foundation for the inclusive use of frontier technologies and AI systems (figure III.6). However, adopting AI also requires the applied technical knowledge of AI in practice and transversal supporting skills (El-Adaileh and Foster, 2019). Furthermore, the adoption and development of AI requires constant flows of data from different industries and domains, along with experts on particular subjects, who can integrate AI systems with their domains.

Workers and the public need to learn how to participate in the AI ecosystem and develop their skill sets, for which reskilling is as important as formal education. For example, to employ GenAI effectively, users need to learn how to structure instructions that can be understood by GenAI, called prompt engineering. One study shows that many AI users enjoy using AI in the workplace and elsewhere but are concerned about potential job losses and that AI will decrease wages (Lane et al., 2023).

With AI advancing rapidly, **reskilling is just as crucial as formal education**

Figure III.6
Skills for adopting and developing AI



Source: UNCTAD.

Creating and training new AI models requires developers who are highly skilled and have acquired technical knowledge, often through tertiary education in mathematics and computer science. The foundation for this is formal education, followed by regular training. All developers need foundational data science and computing skills, as well as AI-specific training, and research and development opportunities across industry and academia. The development of AI also requires non-technical cognitive skills for creative problem-solving (OECD, 2023b).

D. Assessing preparedness for AI adoption and development

With regard to national preparedness for AI, countries may be considered under the following four categories according to adoption and development capacities, as shown in figure III.7:

a) Leaders – High capacities for both AI adoption and development.

b) Creators – High capacity for AI development, but relatively low capacity for adoption.

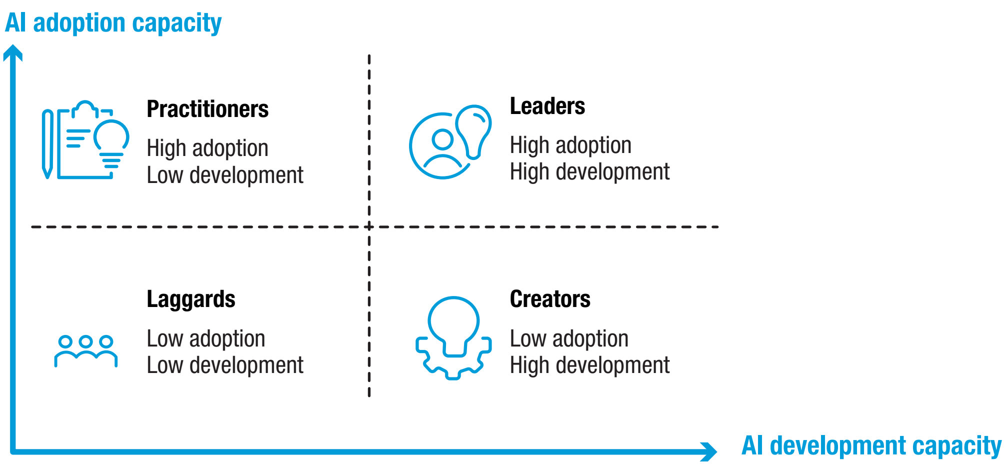
c) Practitioners – Low capacity for AI development but high capacity for adoption.

d) Laggards – Low capacities for both AI adoption and development.

The four categories of AI preparedness help assess a country's current position, illustrating its relative strengths and weaknesses as well as its potential catch-up trajectories (e.g. from laggards to practitioners, then to leaders). The following overview of country preparedness uses proxy indicators that have wide country coverage for infrastructure, data and skills. These can be complemented by insights from the frontier technologies readiness index and refined through detailed reviews of STI ecosystems.

The analysis uses indicators for intensity and level, to capture different mechanisms influencing AI adoption and development.

Figure III.7
Classification of countries according to capacity for AI adoption and development



Source: UNCTAD.

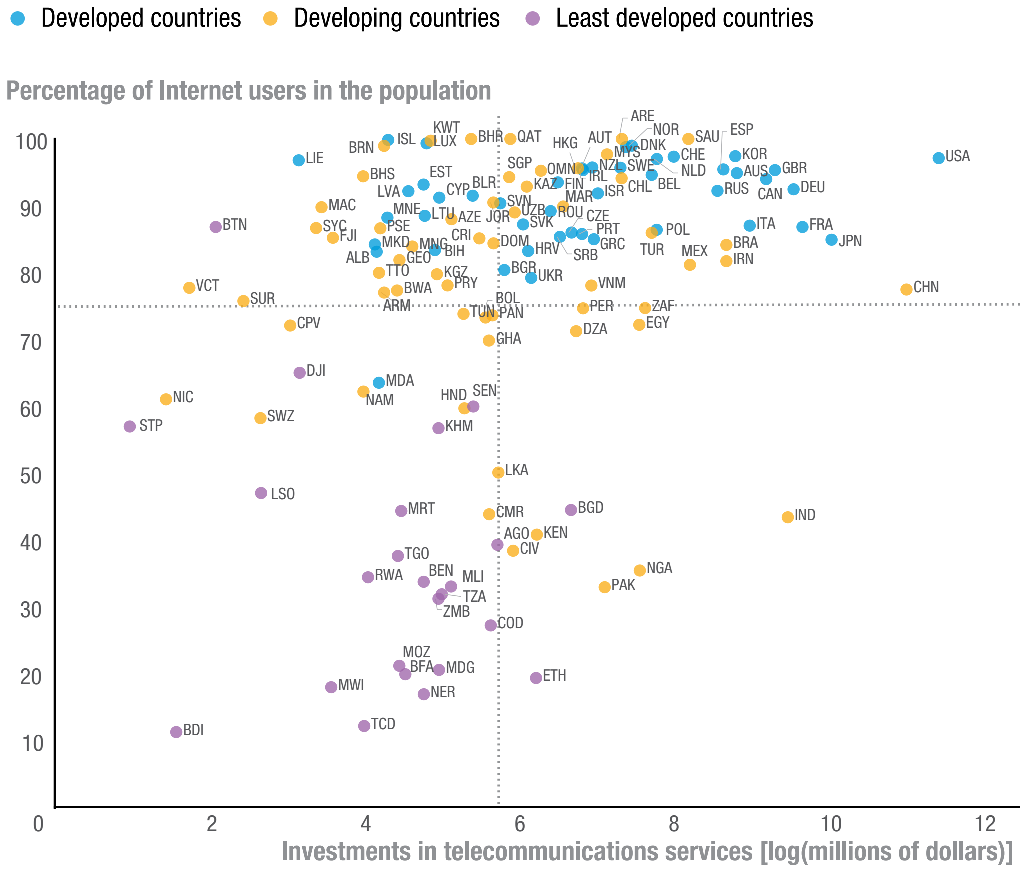
For instance, the proportion of the population with Internet access reflects the potential extent of AI adoption within an economy. Higher levels of data creation and transmission proxy instead a country's potential for AI development. In assessing national preparedness, comparisons of intensity and level illustrate how the strategic options for AI can be determined by country size.

AI infrastructure preparedness

On average, developed countries have the highest incidence of Internet penetration and LDCs have less than half of the incidence in developing countries (figure III.8). Similarly, investments in telecommunications services are the lowest among LDCs. Both developing countries and LDCs show high variability in the two indicators.

In the top right quadrant, the leaders are largely developed countries in Europe and North America, but also some middle- and high-income economies in Asia. In the bottom right, the creators include India and Nigeria, which have high levels of investments in telecommunications services, although less than half their populations have stable Internet access.

Figure III.8
AI infrastructure preparedness



Source: UNCTAD calculations, based on data from the ITU DataHub.
Notes: The proportion of the population using the Internet is a proxy for capacity to adopt AI and investments in telecommunications services is a proxy for AI development capacity. The dotted lines, at the global averages of the two indicators, divide the countries into four groups. Data labels use International Organization for Standardization economy codes. Data are for 2023 or the latest available year. Log transformation is used for investments in telecommunications services, to minimize the effect of outliers and smooth the effect of country size. An average from 2020 to 2023 is used in order to reduce fluctuation.

In the top left quadrant, the practitioners have a high capacity for adoption but low capacity for development, and include small upper middle-income and high-income countries such as Seychelles. In the bottom left quadrant, the laggards include several countries in Africa, such as Burundi and Chad, which have low levels of Internet penetration and investments in telecommunications services, and risk being excluded from the development opportunities offered by AI.

Countries can leverage private companies to **improve their digital infrastructure**

Some middle-income developing countries show high capacities for both AI adoption and development. In Africa, for instance, Egypt and Morocco exceed the global averages in both indicators. This is partly due to the submarine cables under the Mediterranean that connect them to the European continent and beyond. Egypt, for example, due to its geographical position, and links to more than 160 global submarine cable operators, can become a hub connecting three continents. Between 2009 and 2020, the number of submarine cables to Egypt increased from 6 to 13 and after 2025, is expected to exceed 18 (Telecom Egypt, 2024).

In Asia, the better performers include Malaysia, Singapore and Viet Nam, which have been improving their digital infrastructure. In Malaysia, for example, the Ministry of Digital created the Malaysia Digital Economy Corporation in 1996, aiming to establish the country as a digital hub in the Association of Southeast Asian Nations (Malaysia Digital Economy Corporation, 2022). In 2023, the Government introduced the digital ecosystem acceleration scheme, to further strengthen digital infrastructure through a series of incentives, such as investment tax credits on capital expenditure (Malaysian Investment Development Authority, 2023).

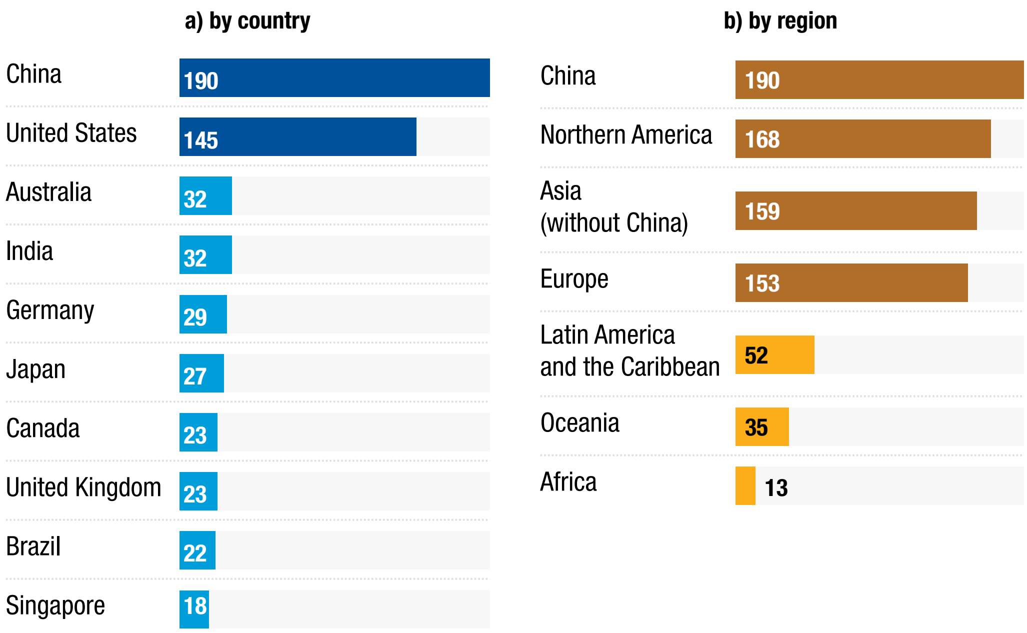
Countries in South-East Asia have generally attracted significant investment from major technology companies. In 2024, to advance new cloud and AI infrastructure, Microsoft announced an investment of $1.7 billion in Indonesia and $2.2 billion in Malaysia (Microsoft, 2024a, 2024b). In 2024, Google planned to invest $2 billion in Malaysia, to develop a data centre and cloud hub (Cyrill, 2024). In 2025, Amazon Web Services aims to launch a new hub in Thailand and invest $5 billion by 2037 (Amazon, 2024).

A core element of such investment is cloud infrastructure, which offers computing capabilities and storage with flexible access and at a relatively low cost, thereby supporting AI diffusion among SMEs. Cross-country comparisons are hindered by a lack of internationally comparable statistics, yet it may be noted that cloud computing is strongly concentrated among a few large providers; an indicator of availability is therefore the number of services (UNCTAD, 2024a). With regard to the top 10 economies in terms of cloud infrastructure services from major providers, China and the United States have more services than the rest of the world combined; India and Brazil are two developing countries on the list along with Singapore, and four of the top 10 countries in terms of cloud infrastructure are thus from the Global South (figure III.9).

With regard to cloud services by region, it may be noted that even if China is not included, Asia stands out. In addition to China, Japan, the Republic of Korea and Singapore, there are several cloud infrastructure services in South-East Asia. Africa is some way behind.

At the end of 2023, eight companies controlled about 80 per cent of the worldwide market share, led by Amazon, Microsoft and Google (Synergy, 2024). These companies may have limited interest in countries that do not generate enough data traffic and profits, which could contribute to deepening digital and AI divides between countries.

Figure III.9
Number of cloud infrastructure services, mid-2024



Source: UNCTAD calculations, based on data from Cloud Infrastructure Map.
Note: Figures based on Amazon Web Services, Google Cloud, IBM Cloud, Microsoft Azure, Oracle Cloud, Alibaba Cloud, Tencent Cloud, and Huawei Cloud.

AI data preparedness

ITU has set the affordability target for fixed broadband at 2 per cent of gross national income per capita. On average, developed countries score better in data affordability, with many developing countries and LDCs still far from the ITU target (figure III.10). The gap between developed and developing countries for data traffic is narrower, with LDCs lagging behind.[6]

Among the leaders, China performs well in both affordability and data quantity. A number of high-income economies, such as Hong Kong (China), Germany, the Russian Federation, the United Kingdom and the United States, also have a wealth of data that can be used to train and develop AI systems. Creators include Pakistan and the Bolivarian Republic of Venezuela, which have low levels of adoption but a high development potential.

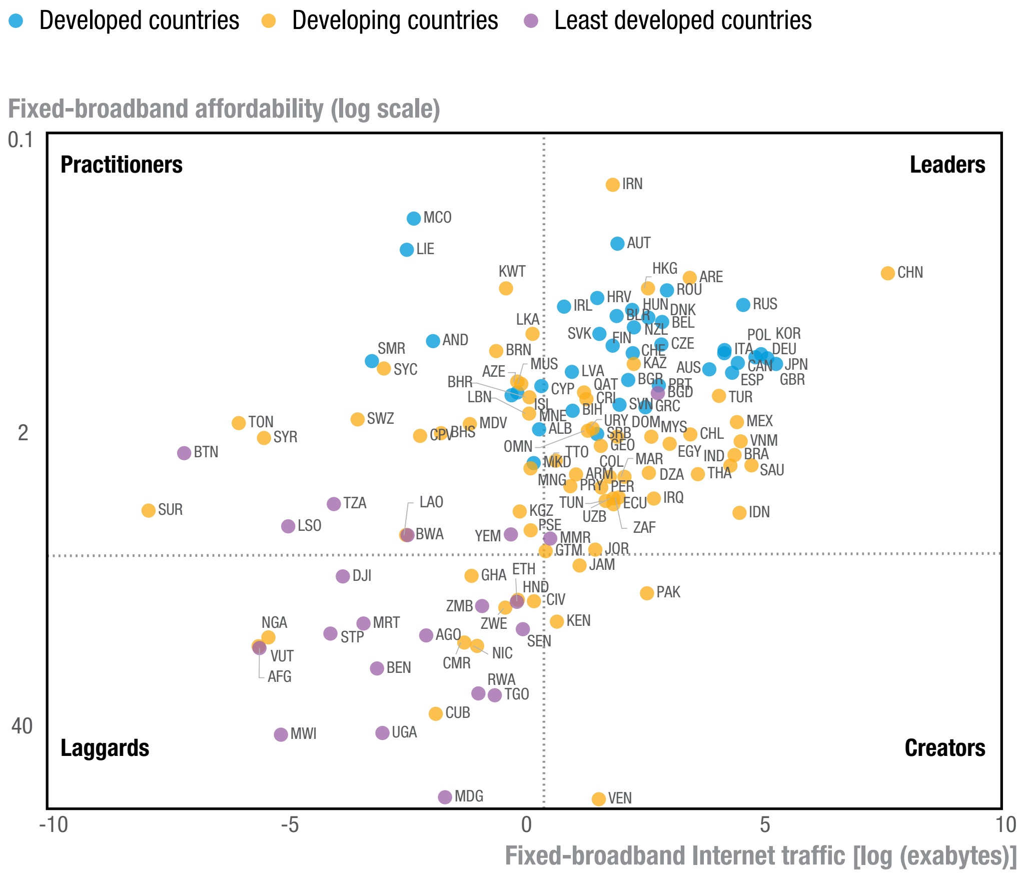
Practitioners include smaller economies such as Eswatini, Kuwait and Monaco that have high levels of AI adoption but a relatively low development potential; their small populations limit the data available for local AI models. Laggards, which show low potential in both AI adoption and development, are mostly developing countries in Africa and Latin America and the Caribbean.

China has the world's greatest fixed-broadband traffic, due to its large population and because it has significantly reduced fixed-broadband prices, from around 5 per cent of gross national income a decade prior to 0.5 per cent at present, which is about one sixth of the global median (ITU, 2024). The Government has put in place regulatory reforms to increase competition among Internet service providers while encouraging new market entrants. The fibre-optic network has been upgraded and expanded to enhance connectivity in rural and underserved areas.

China has reduced fixed broadband prices, **to favour digital uptake**

[6] Although mobile networks record a higher number of subscriptions, 83 per cent of world data traffic takes place through fixed networks (ITU, 2024).

Figure III.10
AI data preparedness



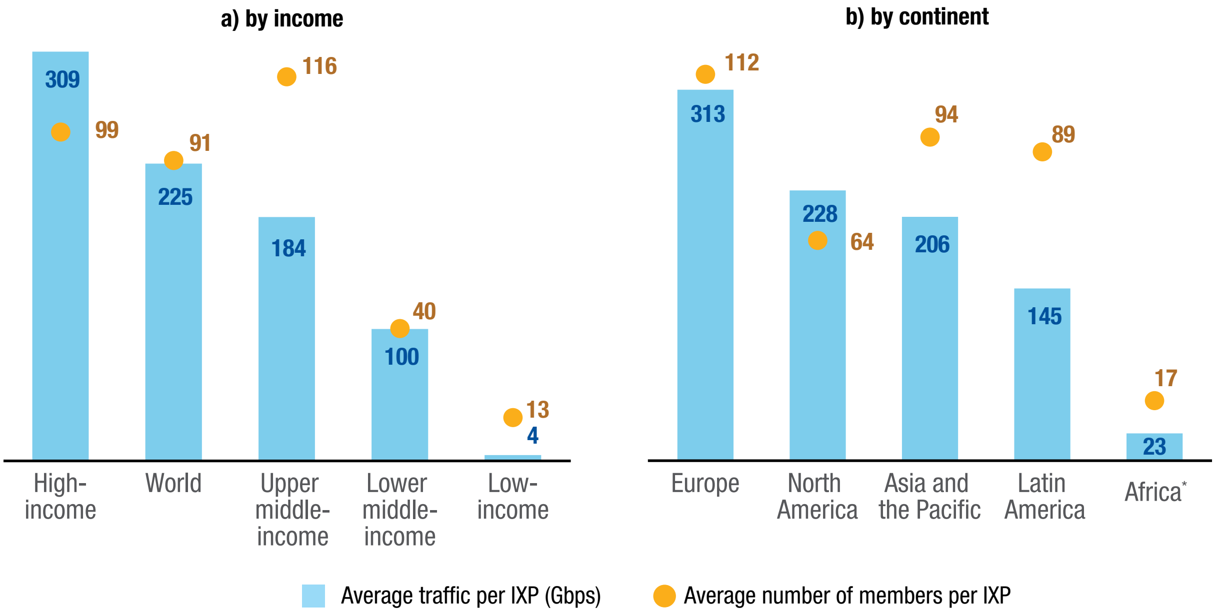
Source: UNCTAD calculations, based on data from the ITU DataHub.
Notes: The average cost of fixed broadband connection as a proportion of gross national income per capita and the fixed broadband internet traffic are proxies for data preparedness. The dotted lines, at the global averages of the two indicators, divide the countries into four groups. Data labels use International Organization for Standardization economy codes. Data are for 2023 or the latest available year. Log transformation is used for fixed-broadband Internet traffic, to minimize the effect of outliers and smooth the effect of country size. An inverted scale is used in the y-axis, as lower values mean better affordability. Comparable data on fixed-broadband Internet traffic are not available for the United States in recent years.

Financial incentives to Internet service providers have lowered costs for consumers, and fair pricing has been promoted by consumer protection measures and price caps (China, State Council, 2013, 2017).

Additional information on data preparedness is available by analysing the number of Internet exchange points. These are physical locations where Internet service providers connect and exchange traffic between their networks and are a crucial element of middle-mile digital connectivity.

Traffic per Internet exchange point is highest in high-income countries, although the average number of members per point is highest in upper middle-income economies, partly because they host some of the world's largest Internet exchange points, such as Ponto de Troca de Tráfego Metro São Paulo in Brazil, Qianhai New-Type Internet Exchange in China and Moscow Internet Exchange in the Russian Federation. Low middle income and low-income economies show low values for both Internet exchange point traffic and membership (figure III.11).

Figure III.11
Internet exchange point traffic and membership, mid-2024



Source: UNCTAD calculations, based on data from Packet Clearing House.
Notes: Gbps, gigabits per second; IXP, Internet exchange point. Data for Africa excludes South Africa because it has almost as many members (about 1,300) as all of the other Internet exchange points in the rest of Africa combined, which distorts the regional figure.

European Internet exchange points are well-established with many years of experience; they generate the highest traffic volume and have the highest number of members per Internet exchange points. In contrast, Africa is far behind, with limited participation and data flows.

AI skills preparedness

GitHub is a major platform through which developers can collaborate, and hosts a large number of open-source projects.[7] Country groupings illustrate the differences in AI skills preparedness, with LDCs scoring rather low in both GitHub developers as a share of the working-age population and the proportion of the working-age population with tertiary education. With some noticeable exceptions, developed countries rank better than developing countries in both indicators (figure III.12).

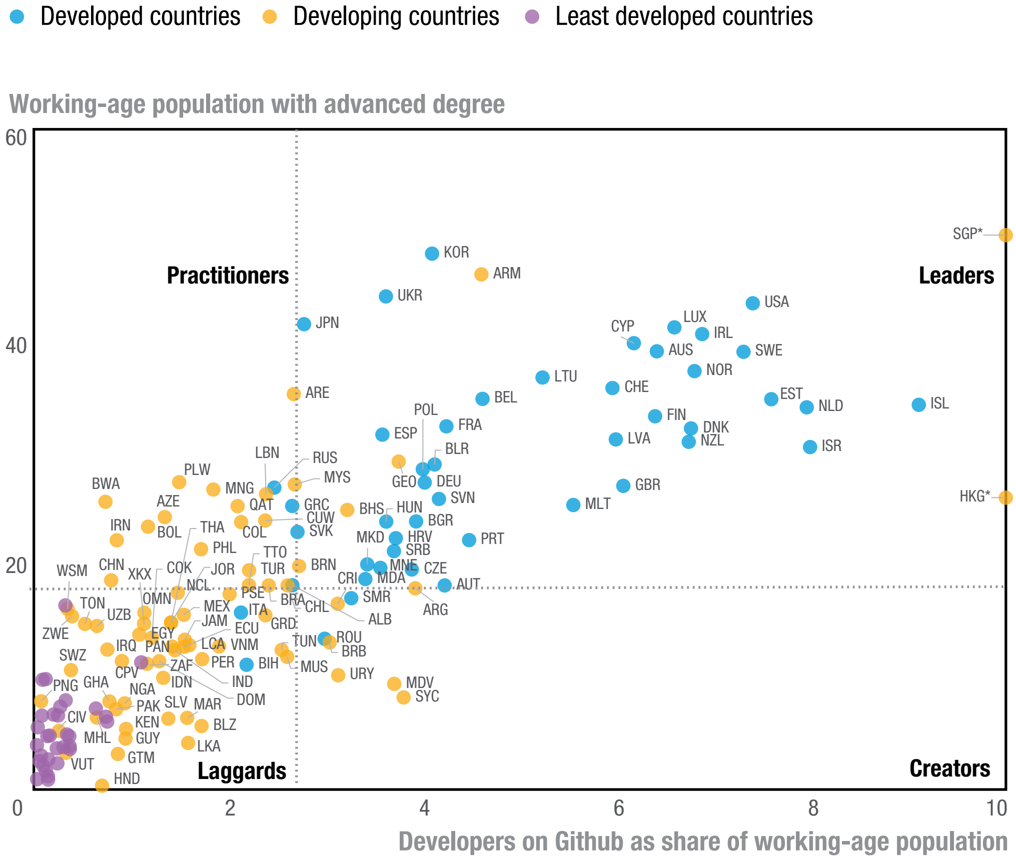
The leaders in the top-right quadrant are mainly developed economies, such as Canada, Ireland, the Republic of Korea, and the United States. Hong Kong (China) and Singapore have particularly high numbers of GitHub developers. Countries in the bottom-right quadrant have low AI adoption but high development potential and include developed economies in Europe, such as Romania, and some island countries such as Maldives and Seychelles.

There are relatively few economies with high potential in AI adoption but low development capacity. In fact, most developing economies display relatively low skills capacity for both adoption and development.

The proportion of developers in the population does not tell the whole story. Large countries may have a low proportion of developers, but this could still represent a substantial body of developers on which to build AI development advantages.

[7] GitHub is the most widely used developers' platform in the world to create, manage and share code. Due to its open approach, the platform is largely used by developers from both the public and private sectors, as well as from industry and academia, making it a reasonable proxy indicator for AI development capacity.

Figure III.12
AI skills preparedness
(Percentages)



Source: UNCTAD calculations, based on data from GitHub and the International Labour Organization.
Notes: The share of the working-age population with an advanced degree is a proxy for AI adoption capacity and developers on GitHub as a share of the working-age population is a proxy for AI development capacity. Dotted lines at the global averages of the two indicators, divide the countries into four groups. Data labels use International Organization for Standardization economy codes. Data from GitHub are for 2023 and data from the International Labour Organization are for 2023 or the latest available year. * Hong Kong (China) and Singapore have high shares of GitHub developers with respect to working-age population, at 25 and 27 per cent respectively; values have been truncated at 10 per cent, to clarify the presentation.

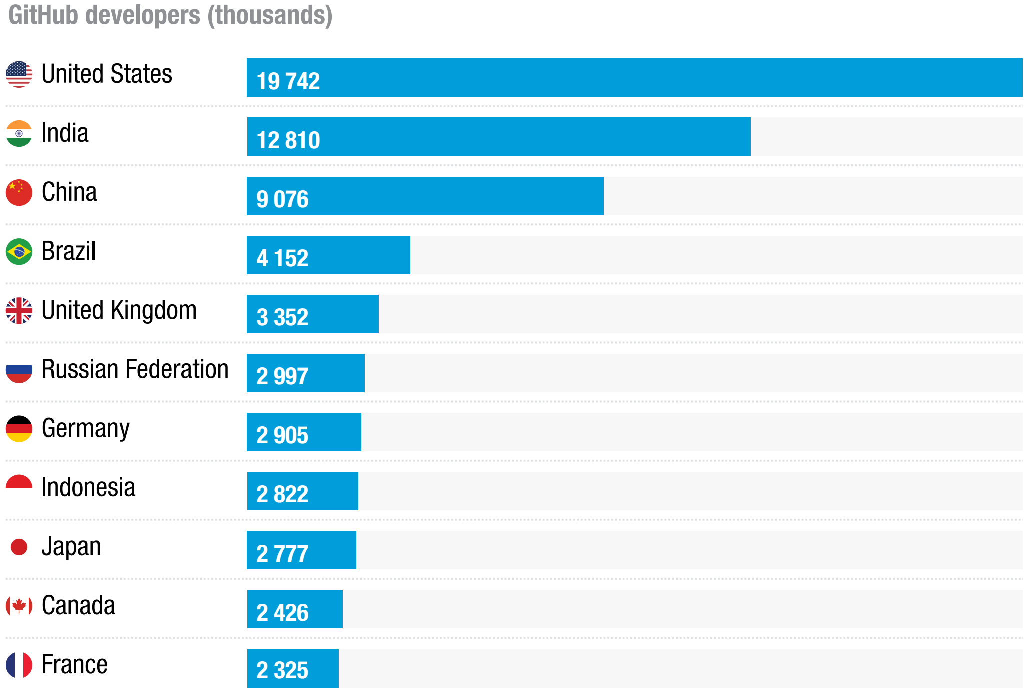
Many developing countries are experiencing **rapid growth in developer numbers**

The United States has the most GitHub developers, followed by India and China (figure III.13). China and India have the world's largest populations and, despite relatively low shares, can leverage a significant mass of AI developers, which puts them in favourable positions with respect to AI development and the production of AI-related scientific knowledge.

Many developing countries have achieved rapid growth in the number of developers (figure III.14).

The fastest increase, at 40 per cent, was in Nigeria, Ghana and Kenya, which have become promising hubs for technology companies (Daigle, 2023). The growth in developer numbers is also notable in Latin America and the Caribbean, for example in Argentina, the Plurinational State of Bolivia, Colombia and Brazil. In Asia and the Pacific, India, Viet Nam, Indonesia and the Philippines already had a significant number of developers but had increases of more than 30 per cent.

Figure III.13
Economies with at least 2 million GitHub developers, 2023

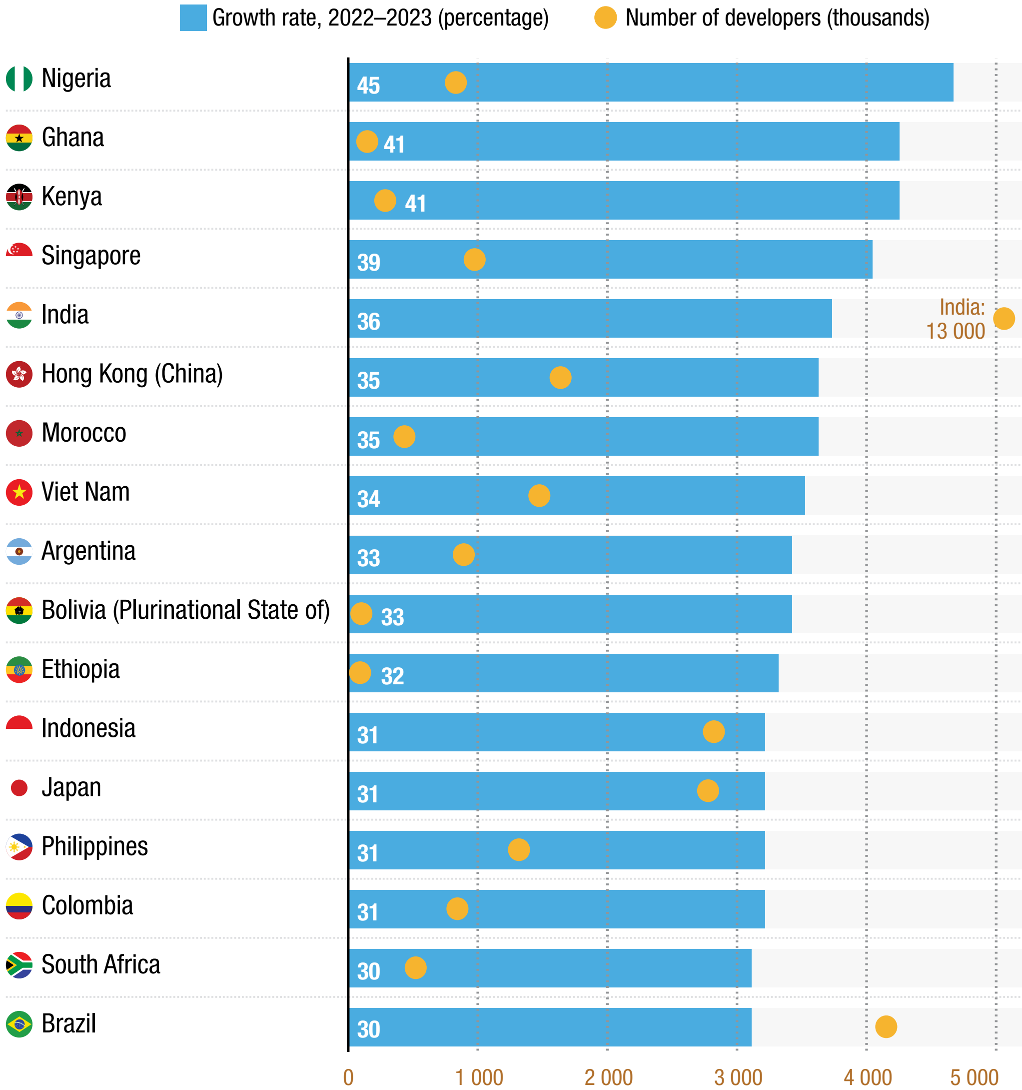


Source: UNCTAD calculations, based on data from GitHub.
Note: The figure shows the number of developer accounts located in a given economy based on mode daily location, excluding users that are bots or otherwise flagged as spam within internal systems. Yearly figures are obtained by averaging quarterly data.

Many students in Asia perform well in the Programme for International Student Assessment, particularly in science and mathematics, signifying a strong potential for both AI adoption and development (OECD, 2024).

There are large talent pools in India, with around 13 million developers, and in Brazil, with 4 million. These two countries are also among the leading countries in creating GenAI projects on GitHub, and are significant contributors to advances in AI. The lead of India partly reflects government policy. The Government has closely collaborated over the years with the private sector and academia to build centres of excellence, such as the Indian Institute of Technology Hyderabad and the Indian Institute of Technology Kharagpur in AI, the Kotak Indian Institute of Science Artificial Intelligence–Machine Learning Centre and the National Association of Software and Service Companies centre of excellence in data science and AI. In 2024, the Cabinet approved the India AI mission to strengthen the AI innovation ecosystem, aimed at, for example, reducing barriers to entry into AI programmes and increasing the number of AI courses in tertiary education, focusing on small and medium-sized cities (India, Competition Commission, 2024).

Figure III.14
Economies with the fastest growth in number of developers



Source: UNCTAD calculations, based on data from GitHub.

Brazil has also been cultivating AI talent, at both the federal and state levels. For example, through strategic partnerships between public and private institutions, the Research Foundation of the state of São Paulo has created a network of applied research centres (Brazil, Ministry of Science, Technology and Innovations, 2021).

The initiative is also aimed at creating scholarships to attract researchers and further boost performance in terms of AI publications (Brandão, 2024).

These approaches highlight the importance of training AI specialists to sustain the development of a strong and diffused AI ecosystem and attract and cultivate AI talent.

E. Strategic positioning for AI

To seize the opportunities offered by AI, developing countries need to strategically position themselves for structural transformation and provide a fertile environment in which AI-empowered businesses can thrive. Key to this is close cooperation among public authorities and ministries, such as those for STI, industry and education. These ministries can also work with stakeholders to identify and sustain AI applications for sustainable development, particularly those that incorporate social, economic and environmental considerations, such as creating and augmenting jobs and encouraging the green transition.

Strategic positioning to leverage AI for sustainable development can be coupled with a gap analysis to link the vision with actual actions, to make it a reality. The frontier technologies readiness index helps identify areas in which countries need to improve. This chapter offers country snapshots and Governments should carry out more comprehensive assessments of strengths and weaknesses and of capabilities and gaps along the three critical leverage points of infrastructure, data and skills. The key elements shown in table III.2 can be used as starting points for actions to empower agents, who can operate along the five As framework (box III.1).

In addition, a thorough assessment of AI-related opportunities and challenges, along with foresight exercises on longer-term science and technology scenarios, can help identify actions to direct an economy towards preferred futures.

Technology assessment should include stakeholder engagements to map the STI ecosystem and formulate STI plans that align with national objectives and the opportunities and challenges posed by frontier technologies. UNCTAD helps developing countries in technology assessment and its STI Policy Review programme supports STI system policies and plans (UNCTAD, 2019).[8]

Based on a gap analysis, countries can establish their own catch-up trajectories, to move from current technological and productive capacities to the desired targets. Some developing countries in Africa and South-East Asia have strengthened their infrastructure to support Internet usage and cross-border connectivity. China has established a strong advantage in data affordability and quantity. China, Brazil and India have produced a large pool of AI developers. These illustrate different catch-up trajectories and highlight the importance of policy efforts in order to enhance preparedness in the light of the rapid evolution of AI.

Technological catch-up is closely tied to a country's readiness to embrace new technological waves. The adoption and development of AI hinge on the necessary digital infrastructure, capacity for data collection and transmission and a mix of sector-specific and digital skills, which can be strengthened by dynamic interactions between users and producers.

Close cooperation across public bodies is key in triggering a **technology-led structural transformation**

Strategic positioning starts with a thorough **assessment of the AI opportunities and challenges**

[8] For example, UNCTAD supports STI policymakers and other stakeholders in target countries in Africa in designing and implementing a technology assessment exercise in the energy and agricultural sectors and in taking action to utilize technologies as catalysts for sustainable development (UNCTAD, 2024b).

Box III.1
The five As framework for AI adoption and development

The diffusion of technologies and innovations is shaped by communications and interaction among economic agents and the way the innovation system works. Frontier technologies need to be taken up by agents – entrepreneurs, citizens and policymakers – who can be empowered through a combination of the 5 As, namely, availability, affordability, awareness, ability and agency.

Source: UNCTAD.

Availability and affordability are critical in the widespread adoption of AI, providing equitable opportunities across diverse groups and communities. Limited digital infrastructure and data, combined with challenges in affordability, risk widening the gap between leading and lagging countries.

Awareness about frontier technologies and successful implementation examples empowers agents to leverage AI for economic progress. Understanding AI applications, potential uses, risks and limitations is key in their beneficial diffusion, as well as for policymakers facing different options to guide progress and development.

Ability and agency drive meaningful change. Laggard countries may lack the scientific and technological expertise of countries leading in AI but should aim to customize technology to local needs while addressing potential social, cultural and institutional barriers. Achieving inclusive and equitable AI development hinges on fostering knowledge, active engagement and the power to direct AI towards serving human development.

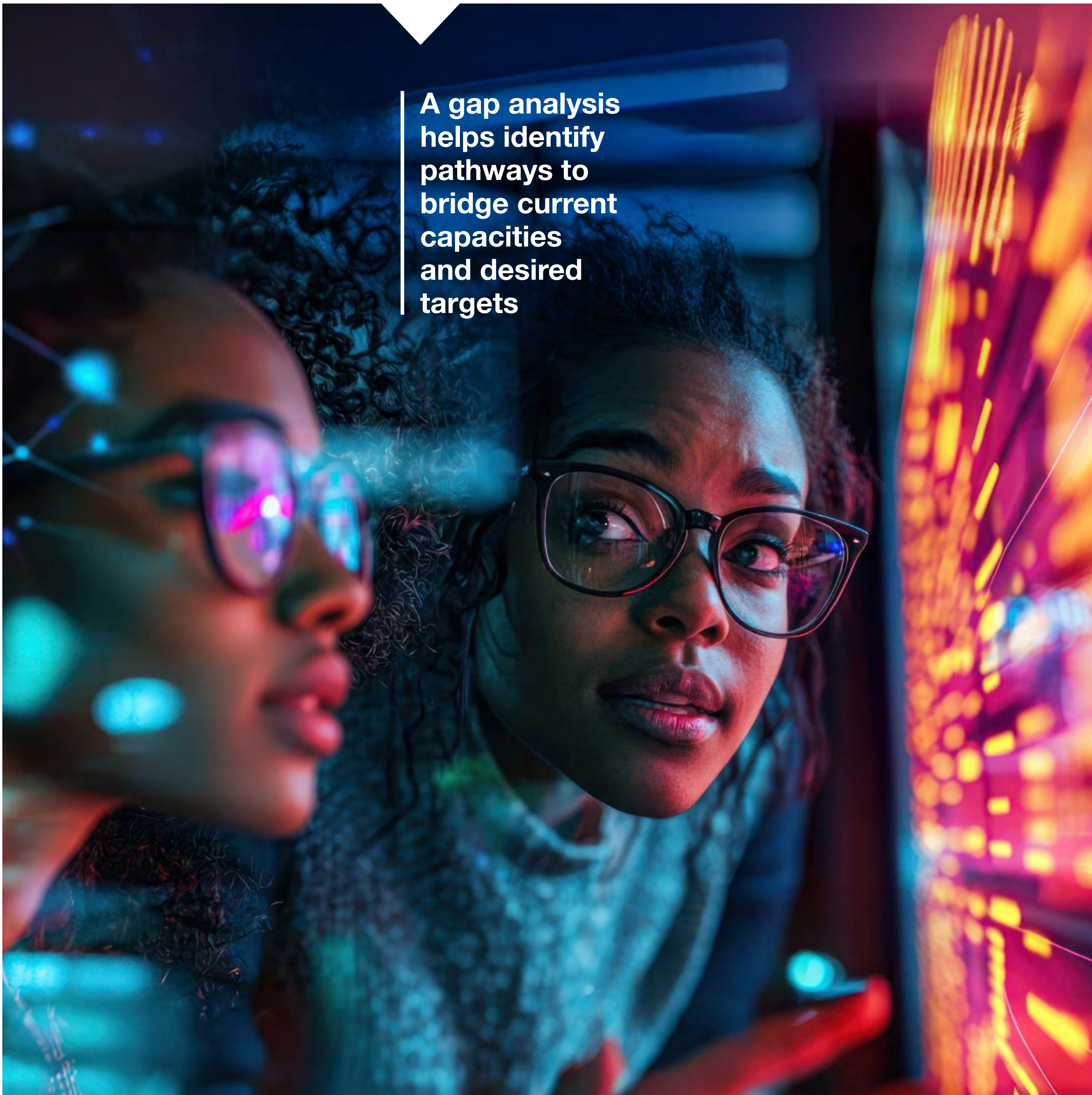
For instance, computing power is central to both AI adoption and development. Its availability enables users to implement and scale AI solutions and to experiment with new algorithms and applications. Affordable computing power can reduce barriers to AI research and development and deployment. Key factors such as data storage capacities, processing speeds and cloud computing capacities determine the performance and efficiency of AI algorithms and models.

Public awareness, ability and agency are essential in seizing business opportunities and addressing potential concerns while fostering the societal acceptance of AI. The benefits of computing power can be fully realized by users equipped with strong technical knowledge and digital skills, while agency over computing power allows them to customize digital environments for AI, to meet particular requirements, optimize performance and ensure efficiency.

Source: UNCTAD.

Currently, AI technology development is largely controlled by a handful of companies and countries. Yet smaller firms in other countries can adopt and adapt the technologies, fostering market niches in different industries and enhancing their competitiveness in both domestic and international markets (Lee and Malerba, 2017).

Cumulative effects play an important role in the AI innovation ecosystem, making it difficult for latecomers to catch up in innovation capacities. This requires a careful consideration of the characteristics of new digital technologies. In general, hardware development is associated with product innovation and is typically organized along with formal R&D and strong industry and university linkages (Lema et al., 2021). The software segment is linked to processes and service innovations, which rely on widely dispersed informal activities and interactions among developers, users and global actors. Such interactions require a rethinking of industrial and innovation policies that is discussed in the next chapter.



Annex III

Frontier technologies readiness index

A. Frontier technologies readiness index results

The index is calculated using the methodology in Technology and Innovation Report 2021 (see section C). The index gives results for 170 economies, with the United States, Sweden and the United Kingdom receiving the highest scores in 2024 on a scale of 0 to 1 (table 1). Based on their rankings, economies are placed within one of the following four 25-percentile score groups: low; lower middle; upper middle; and high.

Table 1
Frontier technologies readiness index score ranking

Economy	Total score	2024 rank	2022 rank	Change in rank	Score group	ICT rank	Skills rank	R&D rank	Industry rank	Finance rank
United States	1.00	1	1	=	High	4	17	2	17	2
Sweden	0.97	2	2	=	High	17	2	15	7	14
United Kingdom	0.96	3	3	=	High	18	12	6	14	17
Netherlands (Kingdom of the)	0.95	4	5	↑	High	3	6	13	11	31
Singapore	0.94	5	4	↓	High	12	5	20	4	11
Switzerland	0.93	6	6	=	High	25	14	11	3	7
Republic of Korea	0.93	7	9	↑	High	14	32	4	13	5
Germany	0.93	8	7	↓	High	26	18	5	12	34
Ireland	0.91	9	12	↑	High	27	11	28	1	116
France	0.90	10	14	↑	High	7	21	8	24	19
Finland	0.90	11	8	↓	High	33	8	23	16	29
Belgium	0.90	12	11	↓	High	11	9	24	22	42
Canada	0.89	13	13	=	High	6	24	9	32	16
Hong Kong, China	0.89	14	10	↓	High	22	20	29	2	1
Israel	0.89	15	18	↑	High	31	16	21	5	43
Australia	0.87	16	15	↓	High	44	1	12	70	12
Luxembourg	0.87	17	19	↑	High	2	13	47	29	25
Norway	0.86	18	16	↓	High	10	7	27	54	13
Denmark	0.86	19	17	↓	High	42	10	22	30	9
Japan	0.84	20	20	=	High	16	62	7	19	4
China	0.84	21	28	↑	High	101	64	1	6	3

Economy	Total score	2024 rank	2022 rank	Change in rank	Score group	ICT rank	Skills rank	R&D rank	Industry rank	Finance rank
Spain	0.84	22	22	=	High	5	30	14	41	37
New Zealand	0.82	23	21	↓	High	15	3	43	61	10
Italy	0.81	24	24	=	High	46	39	10	27	50
Austria	0.81	25	23	↓	High	39	26	25	28	32
Malta	0.80	26	26	=	High	8	28	73	8	44
Poland	0.78	27	27	=	High	28	34	26	33	97
Slovenia	0.78	28	30	↑	High	20	15	64	18	92
Iceland	0.77	29	25	↓	High	1	4	75	85	30
Estonia	0.77	30	29	↓	High	24	25	59	25	57
Portugal	0.77	31	32	↑	High	21	27	32	51	36
Czechia	0.76	32	31	↓	High	55	33	33	20	71
Russian Federation	0.75	33	33	=	High	41	29	17	72	63
Slovakia	0.74	34	39	↑	High	9	49	53	26	53
United Arab Emirates	0.74	35	34	↓	High	45	35	31	42	51
India	0.74	36	48	↑	High	99	113	3	10	70
Cyprus	0.74	37	37	=	High	53	36	52	36	49
Brazil	0.74	38	40	↑	High	38	59	18	50	41
Hungary	0.73	39	36	↓	High	35	42	46	21	99
Lithuania	0.73	40	42	↑	High	30	22	66	43	96
Greece	0.72	41	41	=	High	50	19	36	59	69
Latvia	0.72	42	38	↓	High	32	23	69	39	113
Malaysia	0.72	43	35	↓	Upper middle	49	74	30	15	18
Türkiye	0.70	44	46	↑	Upper middle	79	31	16	73	68
Chile	0.70	45	50	↑	Upper middle	23	40	40	105	21
Romania	0.69	46	47	↑	Upper middle	19	66	38	38	122
Thailand	0.68	47	43	↓	Upper middle	40	77	37	40	8
Serbia	0.67	48	52	↑	Upper middle	47	60	65	31	95
Uruguay	0.67	49	56	↑	Upper middle	13	47	77	45	112
Saudi Arabia	0.67	50	45	↓	Upper middle	58	38	19	120	66
Bulgaria	0.66	51	44	↓	Upper middle	67	57	50	35	79
South Africa	0.65	52	51	↓	Upper middle	76	71	41	55	27
Argentina	0.63	53	61	↑	Upper middle	57	37	60	79	152
Mexico	0.63	54	54	=	Upper middle	73	75	34	37	98
Colombia	0.63	55	60	↑	Upper middle	72	48	39	92	82
Kuwait	0.63	56	63	↑	Upper middle	48	54	84	49	26
Ukraine	0.63	57	55	↓	Upper middle	71	52	48	60	120
Barbados	0.62	58	62	↑	Upper middle	34	41	79	80	47
Croatia	0.62	59	49	↓	Upper middle	80	43	70	52	77

Economy	Total score	2024 rank	2022 rank	Change in rank	Score group	ICT rank	Skills rank	R&D rank	Industry rank	Finance rank
Philippines	0.61	60	58	↓	Upper middle	69	107	68	9	75
Belarus	0.61	61	59	↓	Upper middle	65	46	81	46	110
Costa Rica	0.61	62	57	↓	Upper middle	61	55	98	34	67
North Macedonia	0.60	63	75	↑	Upper middle	29	67	99	44	59
Viet Nam	0.60	64	53	↓	Upper middle	81	120	51	23	15
Bahrain	0.60	65	64	↓	Upper middle	43	53	87	63	40
Kazakhstan	0.58	66	71	↑	Upper middle	91	44	72	53	117
Morocco	0.56	67	67	=	Upper middle	88	111	42	58	33
Jordan	0.56	68	77	↑	Upper middle	66	95	56	74	35
Qatar	0.55	69	69	=	Upper middle	37	91	63	124	23
Oman	0.55	70	68	↓	Upper middle	64	99	55	90	58
Montenegro	0.55	71	65	↓	Upper middle	51	45	127	82	81
Iran (Islamic Republic of)	0.54	72	73	↑	Upper middle	94	82	35	94	56
Republic of Moldova	0.54	73	76	↑	Upper middle	52	76	80	69	118
Mauritius	0.53	74	66	↓	Upper middle	84	70	82	83	45
Tunisia	0.53	75	70	↓	Upper middle	113	72	67	56	52
Indonesia	0.53	76	72	↓	Upper middle	104	109	49	48	93
Panama	0.52	77	74	↓	Upper middle	63	87	89	86	24
Lebanon	0.52	78	80	↑	Upper middle	112	88	71	64	22
Georgia	0.51	79	78	↓	Upper middle	89	51	103	91	48
Peru	0.51	80	89	↑	Upper middle	75	90	58	140	80
Bosnia and Herzegovina	0.51	81	79	↓	Upper middle	62	78	96	77	76
Armenia	0.50	82	84	↑	Upper middle	77	81	112	57	61
Brunei Darussalam	0.49	83	83	=	Upper middle	60	58	91	126	91
Bahamas	0.49	84	86	↑	Upper middle	36	61	129	119	83
Egypt	0.49	85	82	↓	Upper middle	115	92	45	89	109
Trinidad and Tobago	0.48	86	81	↓	Lower middle	54	56	130	122	84
Uzbekistan	0.48	87	90	↑	Lower middle	83	106	74	95	88
Sri Lanka	0.46	88	85	↓	Lower middle	114	83	83	84	78
Albania	0.45	89	88	↓	Lower middle	82	80	108	97	104
Libya	0.45	90	96	↑	Lower middle	116	68	97	110	156
Ecuador	0.44	91	94	↑	Lower middle	87	94	78	138	60
Namibia	0.43	92	92	=	Lower middle	120	114	111	47	55
Fiji	0.43	93	87	↓	Lower middle	93	84	114	117	20
Paraguay	0.43	94	95	↑	Lower middle	68	85	133	131	65
Mongolia	0.42	95	91	↓	Lower middle	90	65	106	146	86
Nepal	0.42	96	105	↑	Lower middle	117	116	92	98	28
Guyana	0.42	97	104	↑	Lower middle	74	102	153	111	131

Economy	Total score	2024 rank	2022 rank	Change in rank	Score group	ICT rank	Skills rank	R&D rank	Industry rank	Finance rank
Saint Vincent and the Grenadines	0.42	98	97	↓	Lower middle	56	50	166	165	85
Maldives	0.41	99	114	↑	Lower middle	97	63	147	100	94
Dominican Republic	0.41	100	93	↓	Lower middle	86	105	136	75	105
El Salvador	0.41	101	103	↑	Lower middle	96	123	131	66	54
Jamaica	0.40	102	99	↓	Lower middle	59	98	138	156	72
Algeria	0.40	103	111	↑	Lower middle	122	69	76	149	132
Azerbaijan	0.40	104	101	↓	Lower middle	100	93	88	135	121
Ghana	0.40	105	102	↓	Lower middle	107	128	85	93	157
Nigeria	0.39	106	116	↑	Lower middle	126	101	54	158	149
Botswana	0.39	107	108	↑	Lower middle	111	110	104	104	106
Bolivia (Plurinational State of)	0.39	108	107	↓	Lower middle	98	89	124	152	39
Kyrgyzstan	0.39	109	110	↑	Lower middle	92	104	122	107	127
Cambodia	0.39	110	106	↓	Lower middle	118	143	106	67	6
Saint Lucia	0.38	111	109	↓	Lower middle	70	100	166	123	73
Bangladesh	0.37	112	121	↑	Lower middle	140	132	61	108	90
Kenya	0.37	113	113	=	Lower middle	129	130	86	71	101
Belize	0.37	114	98	↓	Lower middle	78	108	158	139	87
Guatemala	0.37	115	118	↑	Lower middle	105	140	133	78	89
Iraq	0.36	116	115	↓	Lower middle	109	103	62	169	146
Bhutan	0.35	117	100	↓	Lower middle	85	96	143	170	46
Venezuela (Bolivarian Republic of)	0.35	118	122	↑	Lower middle	121	79	109	157	108
Eswatini	0.34	119	112	↓	Lower middle	131	73	156	96	128
Nicaragua	0.33	120	123	↑	Lower middle	95	117	166	113	107
Pakistan	0.33	121	130	↑	Lower middle	153	164	44	76	153
Togo	0.33	122	129	↑	Lower middle	142	112	134	99	114
Lao People's Democratic Republic	0.33	123	117	↓	Lower middle	102	137	150	81	129
Suriname	0.32	124	119	↓	Lower middle	103	97	166	121	140
Honduras	0.32	125	126	↑	Lower middle	110	145	117	133	38
Gabon	0.32	126	128	↑	Lower middle	106	119	125	130	147
Djibouti	0.31	127	134	↑	Lower middle	130	126	143	65	130
Myanmar	0.31	128	125	↓	Lower middle	135	138	119	68	111
Congo	0.31	129	127	↓	Low	133	125	143	88	145
Rwanda	0.31	130	137	↑	Low	119	144	100	115	123
Cameroon	0.30	131	131	=	Low	151	115	90	102	144
Cabo Verde	0.30	132	120	↓	Low	108	122	158	160	62
Senegal	0.28	133	132	↓	Low	123	163	101	125	103

Economy	Total score	2024 rank	2022 rank	Change in rank	Score group	ICT rank	Skills rank	R&D rank	Industry rank	Finance rank
Vanuatu	0.27	134	124	↓	Low	124	121	166	147	64
Angola	0.26	135	139	↑	Low	137	133	120	128	161
Sao Tome and Principe	0.26	136	135	↓	Low	128	118	166	101	150
Côte d'Ivoire	0.25	137	136	↓	Low	127	152	119	142	125
Lesotho	0.25	138	133	↓	Low	125	134	150	153	119
Timor-Leste	0.24	139	146	↑	Low	157	86	154	132	126
Burkina Faso	0.22	140	150	↑	Low	139	168	114	127	102
Solomon Islands	0.22	141	138	↓	Low	132	135	166	143	100
Papua New Guinea	0.22	142	140	↓	Low	152	131	127	144	138
Zimbabwe	0.22	143	142	↓	Low	146	139	107	148	160
Ethiopia	0.21	144	148	↑	Low	164	157	57	129	136
Liberia	0.21	145	145	-	Low	155	141	135	150	141
Mauritania	0.21	146	156	↑	Low	134	159	146	136	124
Mali	0.21	147	147	=	Low	147	169	141	87	115
Benin	0.21	148	155	↑	Low	144	153	115	151	134
Madagascar	0.20	149	141	↓	Low	148	165	141	112	137
Zambia	0.20	150	149	↓	Low	150	136	110	161	148
Guinea	0.19	151	160	↑	Low	145	150	138	145	158
Haiti	0.19	152	143	↓	Low	136	142	160	118	168
Malawi	0.19	153	144	↓	Low	162	146	123	109	162
United Republic of Tanzania	0.18	154	151	↓	Low	143	166	94	162	139
Uganda	0.18	155	152	↓	Low	165	147	93	114	143
Niger	0.18	156	158	↑	Low	163	162	146	62	155
Comoros	0.17	157	154	↓	Low	161	124	156	159	135
Tajikistan	0.17	158	159	↑	Low	159	127	148	164	151
Gambia	0.17	159	161	↑	Low	138	156	150	141	159
Mozambique	0.16	160	157	↓	Low	156	154	128	163	133
Guinea-Bissau	0.15	161	162	↑	Low	154	149	166	155	142
Equatorial Guinea	0.14	162	153	↓	Low	141	129	166	168	164
Sudan	0.11	163	165	↑	Low	158	155	102	166	165
Yemen	0.11	164	166	↑	Low	168	161	95	116	166
Democratic Republic of the Congo	0.11	165	163	↓	Low	160	151	122	167	163
Afghanistan	0.11	166	164	↓	Low	167	148	116	134	169
Chad	0.10	167	168	↑	Low	166	167	139	106	154
Burundi	0.08	168	167	↓	Low	170	160	160	154	74
South Sudan	0.02	169	169	=	Low	169	170	166	137	167
Sierra Leone	0.00	170	170	=	Low	149	158	153	103	170

Source: UNCTAD.

B. Frontier technologies readiness index results for selected groupings

Table 2
Small island developing states

Economy	Total score	2022 rank	2021 rank	Change in rank	Score group	ICT rank	Skills rank	R&D rank	Industry rank	Finance rank
Bahamas	0.49	84	86	↑	Upper middle	36	61	129	119	83
Bahrain	0.60	65	64	↓	Upper middle	43	53	87	63	40
Barbados	0.62	58	62	↑	Upper middle	34	41	79	80	47
Belize	0.37	114	98	↓	Lower middle	78	108	158	139	87
Cabo Verde	0.30	132	120	↓	Low	108	122	158	160	62
Comoros	0.17	157	154	↓	Low	161	124	156	159	135
Dominican Republic	0.41	100	93	↓	Lower middle	86	105	136	75	105
Fiji	0.43	93	87	↓	Lower middle	93	84	114	117	20
Guinea-Bissau	0.15	161	162	↑	Low	154	149	166	155	142
Guyana	0.42	97	104	↑	Lower middle	74	102	153	111	131
Haiti	0.19	152	143	↓	Low	136	142	160	118	168
Jamaica	0.40	102	99	↓	Lower middle	59	98	138	156	72
Maldives	0.41	99	114	↑	Lower middle	97	63	147	100	94
Mauritius	0.53	74	66	↓	Upper middle	84	70	82	83	45
Papua New Guinea	0.22	142	140	↓	Low	152	131	127	144	138
Saint Lucia	0.38	111	109	↓	Lower middle	70	100	166	123	73
Saint Vincent and the Grenadines	0.42	98	97	↓	Lower middle	56	50	166	165	85
Sao Tome and Principe	0.26	136	135	↓	Low	128	118	166	101	150
Singapore	0.94	5	4	↓	High	12	5	20	4	11
Solomon Islands	0.22	141	138	↓	Low	132	135	166	143	100
Suriname	0.32	124	119	↓	Lower middle	103	97	166	121	140
Timor-Leste	0.24	139	146	↑	Low	157	86	154	132	126
Trinidad and Tobago	0.48	86	81	↓	Lower middle	54	56	130	122	84
Vanuatu	0.27	134	124	↓	Low	124	121	166	147	64
Average score	**0.38**	**109**	**106**			**93**	**93**	**137**	**118**	**92**

Source: UNCTAD.

Table 3
Least developed countries

Economy	Total score	2022 rank	2021 rank	Change in rank	Score group	ICT rank	Skills rank	R&D rank	Industry rank	Finance rank
Afghanistan	0.11	166	164	↓	Low	167	148	116	134	169
Angola	0.26	135	139	↑	Low	137	133	120	128	161
Bangladesh	0.37	112	121	↑	Lower middle	140	132	61	108	90
Benin	0.21	148	155	↑	Low	144	153	115	151	134
Burkina Faso	0.22	140	150	↑	Low	139	168	114	127	102
Burundi	0.08	168	167	↓	Low	170	160	160	154	74
Cambodia	0.39	110	106	↓	Lower middle	118	143	106	67	6
Chad	0.10	167	168	↑	Low	166	167	139	106	154
Comoros	0.17	157	154	↓	Low	161	124	156	159	135
Democratic Republic of the Congo	0.11	165	163	↓	Low	160	151	122	167	163
Djibouti	0.31	127	134	↑	Lower middle	130	126	143	65	130
Ethiopia	0.21	144	148	↑	Low	164	157	57	129	136
Gambia	0.17	159	161	↑	Low	138	156	150	141	159
Guinea	0.19	151	160	↑	Low	145	150	138	145	158
Guinea-Bissau	0.15	161	162	↑	Low	154	149	166	155	142
Haiti	0.19	152	143	↓	Low	136	142	160	118	168
Lao People's Democratic Republic	0.33	123	117	↓	Lower middle	102	137	150	81	129
Lesotho	0.25	138	133	↓	Low	125	134	150	153	119
Liberia	0.21	145	145	=	Low	155	141	135	150	141
Madagascar	0.20	149	141	↓	Low	148	165	141	112	137
Malawi	0.19	153	144	↓	Low	162	146	123	109	162
Mali	0.21	147	147	=	Low	147	169	141	87	115
Mauritania	0.21	146	156	↑	Low	134	159	146	136	124
Mozambique	0.16	160	157	↓	Low	156	154	128	163	133
Myanmar	0.31	128	125	↓	Lower middle	135	138	119	68	111
Nepal	0.42	96	105	↑	Lower middle	117	116	92	98	28
Niger	0.18	156	158	↑	Low	163	162	146	62	155
Rwanda	0.31	130	137	↑	Low	119	144	100	115	123
Senegal	0.28	133	132	↓	Low	123	163	101	125	103
Sierra Leone	0.00	170	170	=	Low	149	158	153	103	170
Solomon Islands	0.22	141	138	↓	Low	132	135	166	143	100
South Sudan	0.02	169	169	=	Low	169	170	166	137	167
Sudan	0.11	163	165	↑	Low	158	155	102	166	165
Timor-Leste	0.24	139	146	↑	Low	157	86	154	132	126

Economy	Total score	2022 rank	2021 rank	Change in rank	Score group	ICT rank	Skills rank	R&D rank	Industry rank	Finance rank
Togo	0.33	122	129	↑	Lower middle	142	112	134	99	114
Uganda	0.18	155	152	↓	Low	165	147	93	114	143
United Republic of Tanzania	0.18	154	151	↓	Low	143	166	94	162	139
Yemen	0.11	164	166	↑	Low	168	161	95	116	166
Zambia	0.20	150	149	↓	Low	150	136	110	161	148
Average score	**0.21**	**146**	**147**			**146**	**146**	**127**	**124**	**131**

Source: UNCTAD.

Table 4
Landlocked developing countries

Economy	Total score	2022 rank	2021 rank	Change in rank	Score group	ICT rank	Skills rank	R&D rank	Industry rank	Finance rank
Afghanistan	0.11	166	164	↓	Low	167	148	116	134	169
Armenia	0.50	82	84	↑	Upper middle	77	81	112	57	61
Azerbaijan	0.40	104	101	↓	Lower middle	100	93	88	135	121
Bhutan	0.35	117	100	↓	Lower middle	85	96	143	170	46
Bolivia (Plurinational State of)	0.39	108	107	↓	Lower middle	98	89	124	152	39
Botswana	0.39	107	108	↑	Lower middle	111	110	104	104	106
Burkina Faso	0.22	140	150	↑	Low	139	168	114	127	102
Burundi	0.08	168	167	↓	Low	170	160	160	154	74
Chad	0.10	167	168	↑	Low	166	167	139	106	154
Eswatini	0.34	119	112	↓	Lower middle	131	73	156	96	128
Ethiopia	0.21	144	148	↑	Low	164	157	57	129	136
Kazakhstan	0.58	66	71	↑	Upper middle	91	44	72	53	117
Kyrgyzstan	0.39	109	110	↑	Lower middle	92	104	122	107	127
Lao People's Democratic Republic	0.33	123	117	↓	Lower middle	102	137	150	81	129
Lesotho	0.25	138	133	↓	Low	125	134	150	153	119
Malawi	0.19	153	144	↓	Low	162	146	123	109	162
Mali	0.21	147	147	=	Low	147	169	141	87	115
Mongolia	0.42	95	91	↓	Lower middle	90	65	106	146	86
Nepal	0.42	96	105	↑	Lower middle	117	116	92	98	28
Niger	0.18	156	158	↑	Low	163	162	146	62	155
North Macedonia	0.60	63	75	↑	Upper middle	29	67	99	44	59
Paraguay	0.43	94	95	↑	Lower middle	68	85	133	131	65
Republic of Moldova	0.54	73	76	↑	Upper middle	52	76	80	69	118

Economy	Total score	2022 rank	2021 rank	Change in rank	Score group	ICT rank	Skills rank	R&D rank	Industry rank	Finance rank
Rwanda	0.31	130	137	↑	Low	119	144	100	115	123
South Sudan	0.02	169	169	=	Low	169	170	166	137	167
Tajikistan	0.17	158	159	↑	Low	159	127	148	164	151
Uganda	0.18	155	152	↓	Low	165	147	93	114	143
Uzbekistan	0.48	87	90	↑	Lower middle	83	106	74	95	88
Zambia	0.20	150	149	↓	Low	150	136	110	161	148
Zimbabwe	0.22	143	142	↓	Low	146	139	107	148	160
Average score	**0.31**	**124**	**124**			**121**	**121**	**118**	**115**	**113**

Source: UNCTAD.

Table 5
Sub-Saharan Africa

Economy	Total score	2022 rank	2021 rank	Change in rank	Score group	ICT rank	Skills rank	R&D rank	Industry rank	Finance rank
Angola	0.26	135	139	↑	Low	137	133	120	128	161
Benin	0.21	148	155	↑	Low	144	153	115	151	134
Botswana	0.39	107	108	↑	Lower middle	111	110	104	104	106
Burkina Faso	0.22	140	150	↑	Low	139	168	114	127	102
Burundi	0.08	168	167	↓	Low	170	160	160	154	74
Cabo Verde	0.30	132	120	↓	Low	108	122	158	160	62
Cameroon	0.30	131	131	=	Low	151	115	90	102	144
Chad	0.10	167	168	↑	Low	166	167	139	106	154
Comoros	0.17	157	154	↓	Low	161	124	156	159	135
Congo	0.31	129	127	↓	Low	133	125	143	88	145
Côte d’Ivoire	0.25	137	136	↓	Low	127	152	119	142	125
Democratic Republic of the Congo	0.11	165	163	↓	Low	160	151	122	167	163
Djibouti	0.31	127	134	↑	Lower middle	130	126	143	65	130
Equatorial Guinea	0.14	162	153	↓	Low	141	129	166	168	164
Eswatini	0.34	119	112	↓	Lower middle	131	73	156	96	128
Ethiopia	0.21	144	148	↑	Low	164	157	57	129	136
Gabon	0.32	126	128	↑	Lower middle	106	119	125	130	147
Gambia	0.17	159	161	↑	Low	138	156	150	141	159
Ghana	0.40	105	102	↓	Lower middle	107	128	85	93	157
Guinea	0.19	151	160	↑	Low	145	150	138	145	158
Guinea-Bissau	0.15	161	162	↑	Low	154	149	166	155	142
Kenya	0.37	113	113	=	Lower middle	129	130	86	71	101
Lesotho	0.25	138	133	↓	Low	125	134	150	153	119

Economy	Total score	2022 rank	2021 rank	Change in rank	Score group	ICT rank	Skills rank	R&D rank	Industry rank	Finance rank
Liberia	0.21	145	145	=	Low	155	141	135	150	141
Madagascar	0.20	149	141	↓	Low	148	165	141	112	137
Malawi	0.19	153	144	↓	Low	162	146	123	109	162
Mali	0.21	147	147	=	Low	147	169	141	87	115
Mauritania	0.21	146	156	↑	Low	134	159	146	136	124
Mauritius	0.53	74	66	↓	Upper middle	84	70	82	83	45
Mozambique	0.16	160	157	↓	Low	156	154	128	163	133
Namibia	0.43	92	92	=	Lower middle	120	114	111	47	55
Niger	0.18	156	158	↑	Low	163	162	146	62	155
Nigeria	0.39	106	116	↑	Lower middle	126	101	54	158	149
Rwanda	0.31	130	137	↑	Low	119	144	100	115	123
Sao Tome and Principe	0.26	136	135	↓	Low	128	118	166	101	150
Senegal	0.28	133	132	↓	Low	123	163	101	125	103
Sierra Leone	0.00	170	170	=	Low	149	158	153	103	170
South Africa	0.65	52	51	↓	Upper middle	76	71	41	55	27
South Sudan	0.02	169	169	=	Low	169	170	166	137	167
Togo	0.33	122	129	↑	Lower middle	142	112	134	99	114
Uganda	0.18	155	152	↓	Low	165	147	93	114	143
United Republic of Tanzania	0.18	154	151	↓	Low	143	166	94	162	139
Zambia	0.20	150	149	↓	Low	150	136	110	161	148
Zimbabwe	0.22	143	142	↓	Low	146	139	107	148	160
Average score	**0.25**	**138**	**138**			**138**	**137**	**124**	**122**	**130**

Source: UNCTAD.

C. Technical note on methodology

The frontier technologies readiness index is calculated following the methodology in *Technology and Innovation Report 2021*. The indicators that compose the index are listed in table 6.

Table 6
Frontier technologies readiness index: Indicators

Category	Indicator (measure)	Source of data
ICT deployment	Internet users (share of population)	ITU
ICT deployment	Mean download speed (megabits per second)	M-Lab
Skills	Expected years of schooling	UNDP
Skills	High-skill employment (share of working population)	ILO
R&D activity	Number of scientific publications on frontier technologies	Scopus
R&D activity	Number of patents filed on frontier technologies	PatSeer
Industry activity	High-technology manufactures exports (share of total merchandise trade)	UNCTAD
Industry activity	Digitally deliverable services exports (share of total services trade)	UNCTAD
Access to finance	Domestic credit to private sector (share of GDP)	World Bank, IMF, OECD

Source: UNCTAD.

The underlying indicator data are statistically manipulated to form the index. First, the data are imputed using the cold deck imputation method, retroactively filling in the missing values with the latest values available from the same country. Second, the Z-score standardization is conducted, using the following formula:

$$X_{standardized} = (x - \mu)\,/\,\sigma$$

where x is a value to be standardized; μ is the mean of the population; and σ is the standard deviation of the population.

The standardized value of each indicator is then normalized to fall between the range of 0 to 1 using the following formula:

$$X_{normalized} = (x - Min)\,/\,(Max - Min)$$

where x is a Z-score standardized score to be normalized; Max is the largest score in the population; and Min is the smallest score in the population.

A principal component analysis (PCA) is then conducted, to remove correlated features among indicators and reduce overfitting. Based on the variance explained criteria method, the PCA finds that three principal components can retain over 80 per cent of the variation. The final index is therefore derived by assigning the weights generated by PCA with varimax rotation to the three principal components, then standardized and normalized to fall within the range of 0 to 1.

Frontier technologies readiness index =
$((0.4/0.8)*(PC1)+(0.28/0.8)*(PC2)+(0.12/0.8)*(PC3))_{\text{standarized \& normalized}}$

Separately, PCA is conducted on each building block of the index, to derive the score and country ranking. The minimum number of principal components that could retain over 80 per cent of the variation is used. The analysis is not conducted on "access to finance", since it has only one indicator.

ICT deployment = $(PC1)_{\text{standarized and normalized}}$

Skills = $(PC1)_{\text{standarized and normalized}}$

R&D activity = $(PC1)_{\text{standarized and normalized}}$

Industry activity = $((0.7)*(PC1)+(0.3)*(PC2))_{\text{standarized and normalized}}$

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