Technology and Innovation Report 2025

Chapter II

Leveraging AI for productivity and workers' empowerment

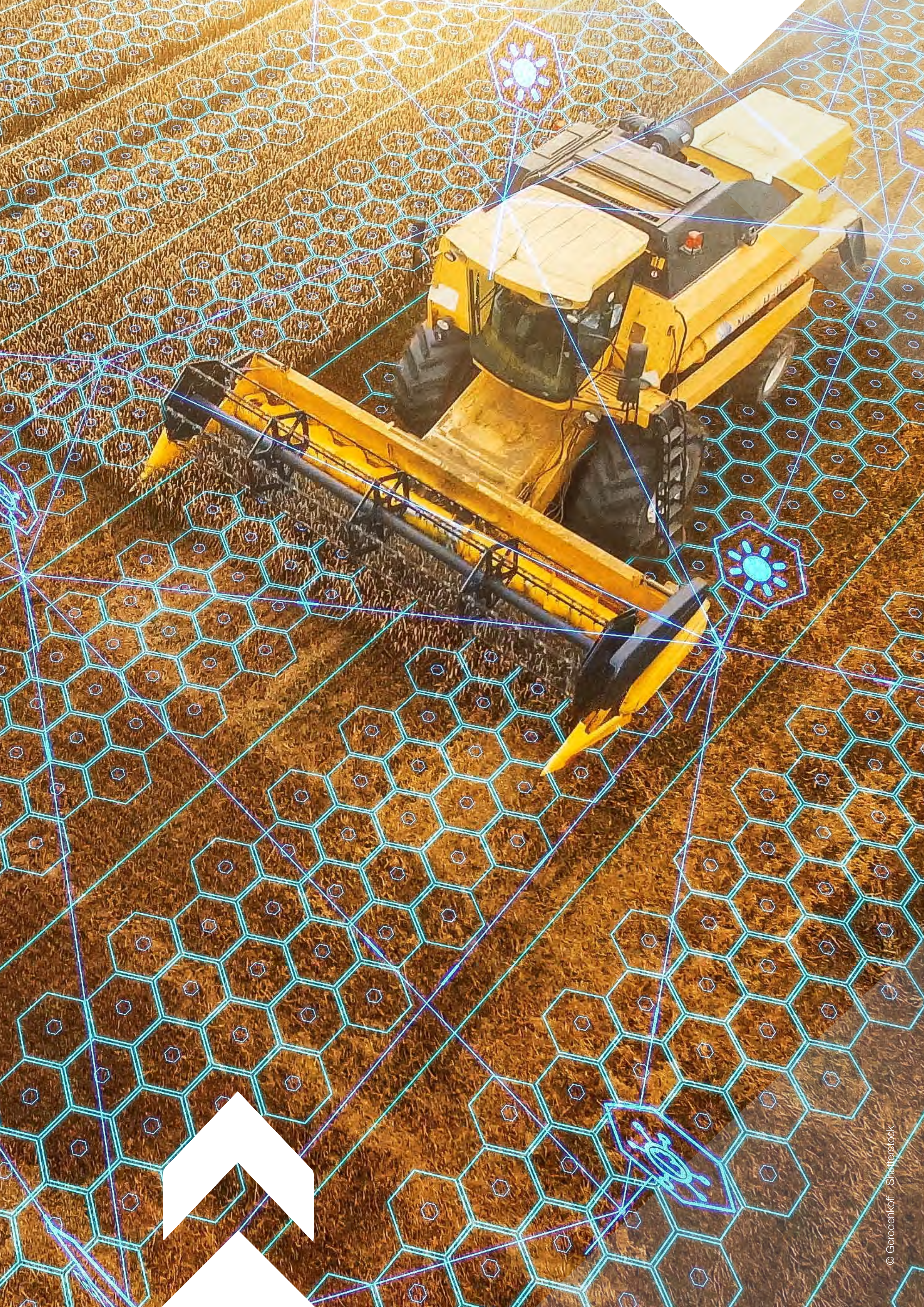
Compared with previous technological waves, AI can perform cognitive tasks and impact a far wider range of activities, conceivably affecting 40 per cent of global employment, transforming production processes and business operations.

AI can bring productivity gains and increase the income of some workers, but also cause others to lose their jobs, reshaping workplace dynamics and labour demand. Moreover, technological advancements are driving automation, shifting value towards capital.

However, the use of AI offers significant potential to augment worker capabilities, potentially reversing this trend and empowering workers, if supported by effective policies and strategic implementation.

Through case studies, this chapter illustrates how developing countries can overcome obstacles in AI adoption to reap its benefits. It also highlights the need to place workers at the centre of technological transformation, for the inclusive adoption of AI.

United Nations



Key policy takeaways

- **The impact of AI on work depends on a complex interplay of automation, augmentation and the creation of new roles.** Policymakers should understand these dynamics to ensure the equitable distribution of AI's benefits and to support smooth workforce transitions.
- **The adoption of AI in developing countries can be accelerated by redesigning AI solutions** around locally available infrastructure; utilizing and combining new sources of data; lowering skill barriers for AI with simple interfaces; and building strategic partnerships to access essential resources for AI.
- **Inclusive AI requires a strong emphasis on workers and their professional growth.** This includes empowering them with digital literacy, supporting those transiting to new jobs with reskilling training and enhancing overall capabilities through upskilling programmes. Workers should also be involved in the design and implementation of AI tools for an integration into workspaces that addresses their needs and preserves meaningful human roles.
- **Governments should promote human-complementary AI technologies through increased R&D funding, strategic public procurement and targeted tax incentives.** Improving labour market opportunities and establishing clear career development pathways can mitigate the risk of brain drain.

A. AI can transform production

AI can affect a wide range of tasks, **from physical to cognitive**

Previous automation technologies, including the introduction of computers and robotics, and early AI expert systems, relied on predefined conditional logic to guide them step-by-step from input to output. This limited them to routines and structured tasks that could readily be broken down and codified (Autor et al., 2003). AI technologies can go further by using machine learning to identify patterns and relationships from huge amounts of data, improve performance over time and adapt to changing circumstances without explicit reprogramming (Brynjolfsson et al., 2017).

The economic significance of this is twofold. First, AI can outperform conventional digital systems and in certain areas surpass human performance (Maslej et al., 2024). Second, unlike previous technological waves that mostly automated routine and low-skill functions, AI can take on tasks that were previously too expensive or difficult to automate, and can be extended to functions that require recognition, classification and prediction that once were thought to be exclusive to highly skilled workers (Brynjolfsson et al., 2017; 2018). In banking, for example, AI systems are being used to predict loan default rates (Turiel and Aste, 2020). In healthcare, AI image classifiers are being used to help doctors in interpreting scans and images, leading to faster and more reliable prognoses (Zhang et al., 2022).

AI primarily affects cognitive work, but when combined with other technologies, such as robotics or IoT sensors, it can also control physical production. In manufacturing, AI systems, through a network of smart sensors, can exercise real-time control of energy and water usage, for example (Henry Bristol et al., 2024). In agriculture, AI and machine vision can be paired with robots to automate crop harvesting.

The potential of AI applications has been further extended by generative AI (GenAI). In traditional machine learning, each model performs one specialized task, largely reproducing or representing existing knowledge. GenAI can be much more versatile, performing multiple tasks and adapting to the operating context and generating new content. GenAI can write texts, produce images and videos, write computer code and identify complex patterns in data, for knowledge-based services such as finance, education, law and healthcare (Bommasani et al., 2021). For example, GPT-4, the model that powers the chatbot ChatGPT, has been applied as a customer-support agent, a research assistant for lawyers and a medical research assistant for pharmaceutical discovery and development.[1]

As performance improves and costs decrease, AI can be integrated into many more production processes. In the best cases, this will augment human labour and improve the quality and speed of work. However, there is also the risk that it could replace workers altogether, increasing unemployment, depressing wages and degrading the work experience (Rotman, 2024). If AI is to bring about productive and inclusive economic transformations and reduce inequalities, Governments and companies need to put workers at the centre of AI adoption and development.

[1] For example, the electronic payment company Stripe uses GPT-4 to enhance their customer support chatbot. For a legal application of GPT-4, see Co Counsel, a legal research assistant, and for a medical research application, see Insight AI.

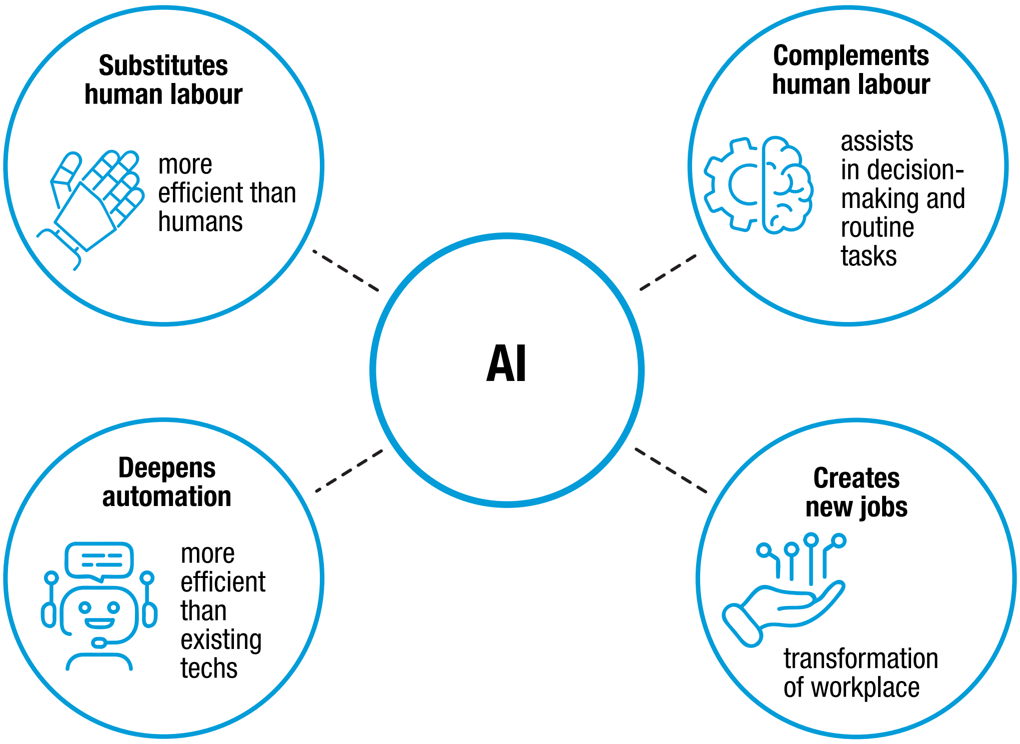
B. Key channels for impacting productivity and the workforce

AI can affect human labour and productivity in four main ways (figure II.1), often simultaneously (Acemoglu, 2024b; Acemoglu and Restrepo, 2019), through the following channels:

Substitute for human labour – AI can replace human workers in activities where machines are more efficient, extending the number of tasks in which machines have comparative advantages over humans and thereby displacing labour in favour of capital. For example, in the banking sector, instead of transactions being read manually, AI can monitor thousands of transactions simultaneously and detect anomalies and signs of fraud.

Complement human labour – AI can augment human skills, to improve quality, efficiency and productivity, and provide advanced data analysis to support decision-making. In day-to-day business, AI can automate routine tasks such as proofreading documents, scheduling meetings and suggesting replies to emails. This can free up workers for tasks that benefit more from human attention. In medicine, the use of AI can help diagnose cancers and other diseases by analysing electrocardiograms and computed radiography scans and finding abnormalities that might be undetectable by human staff. AI therefore serves as a useful tool that enhances human productivity while freeing workers to employ softer skills. Its use can also affect how people interact with and perceive one another, in both pro-social and anti-social ways (Hohenstein et al., 2023).

Figure II.1
Four channels through which AI impacts productivity and the workforce



Source: UNCTAD.

Deepen automation – AI can replace less-efficient technologies and deepen automation. For example, in customer service, GenAI chatbots can replace conventional rule-based chatbots, offering more personalized and accurate responses to inquiries, thereby improving a firm's overall operating efficiency – total factor productivity – without undermining the workforce.

Create new jobs – The use of AI can create new jobs, including roles in AI research and development, as well as in its deployment and maintenance. Its use can also create employment in emerging industries related to or created by AI. For example, one study identifies three emerging occupations, namely, AI trainers, who develop and upgrade AI models; AI explainers, who tailor AI models to particular use cases, such as AI-specific user experience designers; and AI sustainers, who monitor and refine AI uses, such as AI ethics experts (Shine, 2023).

C. Measuring the impacts

To assess the impact of AI on productivity and the workforce, economists generally use two metrics. One focuses on the associated increases in productivity, that is, the amount of goods and services produced for given inputs such as labour and capital. The other considers workforce exposure, that is, the degree to which their tasks can be performed by AI systems; the higher the exposure, the greater the potential for complementation or substitution.

Will AI increase productivity?

To date, research that employs systematic applied methods on data sets with good coverage and adequate scale is mostly based on micro-level studies on early adopters in developed countries. It is far from conclusive, yet suggests that firms using AI can make substantial productivity gains, particularly those employing skilled workers and those in service industries. A summary of recent firm-level studies indicates that AI can increase both labour productivity and total factor productivity, although the range of the estimates is wide, reflecting the differing capacities of firms to benefit from AI (figure II.2).

The use of AI can bring **substantial productivity gains**

For example, in some firms in Germany, sales achieved per worker increased substantially with higher levels of AI use (Czarnitzki et al., 2023). In some firms in Italy, total factor productivity increased by 2.2 per cent with the adoption of AI. A study of large firms from a range of countries showed that the accumulated stock of AI knowledge increased total factor productivity by 6.7 per cent (Benassi et al., 2022).

The impact may also depend on firm characteristics, such as size, although the evidence is mixed (see annex II). Some studies showed higher productivity gains in larger firms that could benefit from scale effects and greater financial resources (Zhai and Liu, 2023; Yang, 2022). Other studies showed advantages for smaller firms that could integrate new technologies more rapidly within existing production systems (Nucci et al., 2023; Damioli et al., 2021).

Most of the literature concentrates on developed countries, for which there is more detailed firm-level data. However, similar benefits could also arise in developing countries, as indicated by an analysis of listed firms in China (Zhai and Liu, 2023).

The early evidence thus suggests that the use of AI can enhance productivity, yet does not clarify the exact drivers.

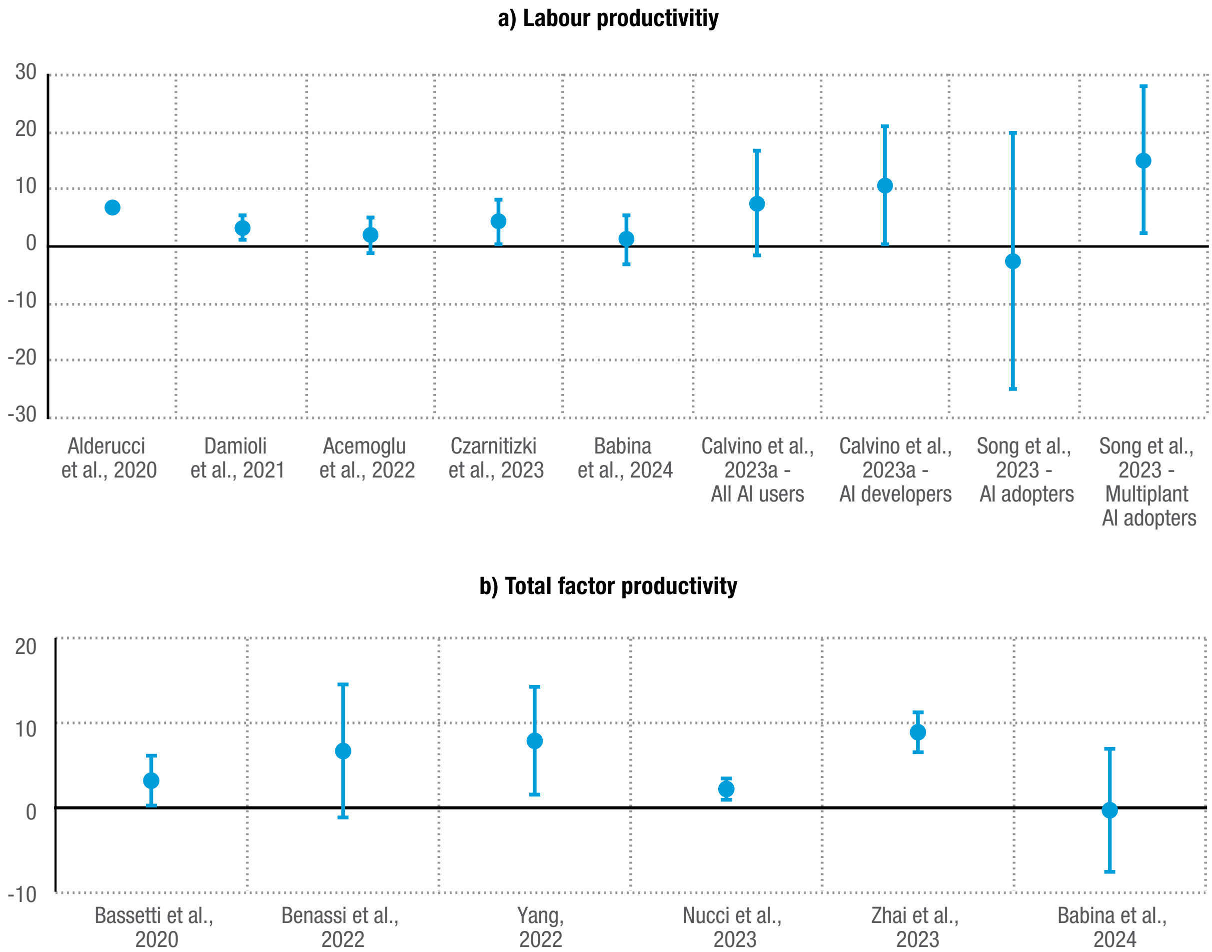
The ambiguities may be clarified once AI has been more widely adopted and there are more firm-level data, particularly from developing countries. Nevertheless, many companies have yet to implement AI on a significant scale, and it may be too early to draw definitive conclusions.

A new strand of research has emerged on the impact of GenAI tools, focused on particular tasks performed by workers within firms, to assess the impact of such tools on high-skill–related tasks.

While not directly comparable with studies that consider impacts at the firm level, these studies offer a glimpse of how the new technology may impact the workplace.[2]

Some studies indicate that GenAI is capable of markedly improving worker performance in a range of tasks (table II.1). For example, at a leading software company, when customer service staff used GenAI chat assistants, there was a 14 per cent increase in the number of issues resolved per hour (Brynjolfsson et al., 2023).

Figure II.2
Use of AI can improve a firm's productivity
Change in productivity, percentage



Source: UNCTAD, based on cited sources.
Note: Data points are the estimated average effects from listed articles, displayed as percentage changes through log-approximation; the tails represent the 95 per cent confidence intervals (see annex II).

2 Direct comparisons between these and earlier firm-level studies are not possible because higher productivity at the worker or task level does not necessarily translate to the same effect at the firm level.

GenAI has a significant **impact on cognitive and service-related tasks**

Similarly, at a business consultancy, consultants supported by ChatGPT were 12 per cent more efficient and had a 40 per cent increase in work quality (Dell'Acqua et al., 2023). Other studies demonstrate notable productivity enhancements in professional writing and computer coding (Noy and Zhang, 2023).

These micro-level studies used experimental or quasi-experimental designs to infer causal links between the use of GenAI tools and gains in labour productivity. They showed significant differences between workers at different skill levels, and it is therefore not clear from the studies whether the use of AI can reduce or increase inequality across workers.

For example, one study found that the largest productivity improvements in a customer service centre were from the least-skilled and least-experienced workers, who used an AI assistant to learn the good practices of the highest-skilled workers (Brynjolfsson et al., 2023). On the other hand, another study, on science material researchers, showed much higher productivity gains for leading researchers (Toner-Rodgers, 2024). This may be because the most experienced scientists were able to take advantage of their knowledge to prioritize the most promising AI suggestions, while the 30 per cent of least-productive researchers spent time on testing less promising options. Most of the evidence to date comes from early adopters, and whether similar productivity gains apply to latecomers, particularly from developing countries far from the technological frontier, remains to be ascertained.

Overall, the impact of AI, particularly the use of GenAI, tends to be greater for particular service-related tasks. Yet the benefits can also extend indirectly to other firms. Therefore, it is important to foster inter-industry synergies and complementarities between knowledge-based services and manufacturing and the primary sector in order to transmit productivity gains through the economy and drive an AI-powered industrial transformation.

More comprehensive studies that consider complex tasks that are more difficult for AI to learn can help better understand the impact of AI across the economy. Nonetheless, the early evidence on GenAI complements the findings from firm-level studies that show that the use of AI can increase productivity (box II.1).

Table II.1
Selected micro-level studies on GenAI productivity impacts

Study	Sample	GenAI used	Identification strategy	Measurement	Impact
Brynjolfsson et al., 2023	Call centre workers in a Fortune 500 company, 2020–2021	Customized ChatGPT	Difference-in-difference	Number of resolutions per hour	14 per cent increase
Dell'Acqua et al., 2023	Consultants in leading consulting firm, 2023	ChatGPT	Experiment	Number of tasks completed in given time	12.2 per cent increase
Noy et al., 2023	Working professionals, 2022	ChatGPT	Experiment	Completion time of writing tasks	37 per cent improvement
Peng et al., 2023	Professional freelance programmers, 2022	GitHub Copilot	Experiment	Completion time of programming tasks	55.8 per cent improvement

Source: UNCTAD, based on cited sources.

Box II.1
Using AI in business process outsourcing

One study examined the impact of GenAI on customer service agents at a United States-based business process outsourcing company, focused on the staggered deployment of a GPT-powered chat assistant firm serving SMEs, with some of the agents based in the Philippines and others in the United States and elsewhere.

The study showed that AI significantly improved worker productivity across three key metrics, namely, reduced handling time per chat, increased chats handled per hour and successful chat resolution rates. Yet these benefits were not uniformly distributed; the most significant improvements were among less-skilled and newer agents while highly skilled and experienced workers showed minimal gains. This finding is particularly significant given the steep learning curve and initial lower productivity often associated with newer hires in the business process outsourcing sector.

Interestingly, agents who adhered closely to AI recommendations demonstrated greater productivity gains, suggesting a link between AI engagement and learning. The agents sustained higher productivity even during software outages when AI assistance was unavailable, indicating a lasting impact on skill development.

The study also considered the impact of AI on workers. Contact centre work often involves demanding overnight shifts and challenging interactions with customers, but the study showed that, when the workers were supported by AI, customers were impressed, less likely to question their competence and generally treated them better. This helped reduce employee attrition, particularly among newer hires. The researchers attributed these positive effects in part to the ability of the AI system to capture and disseminate best practices from high-performing agents. However, customer satisfaction can also be reduced if using AI makes interactions feel overly scripted and inauthentic.

The study concluded that while AI assistance can enhance productivity and improve worker experience, it also creates incentives for firms to deskill positions and hire lower-skilled workers at lower wages. Companies could also eventually deploy even more advanced AI systems capable of entirely replacing human agents.

While offering significant potential for companies, the long-term implications for workers remain uncertain and may depend on the strength of workers' voices in workplace consultations or collective agreements. The findings are corroborated by another study involving 300 call-centre operators that showed that AI that automated repetitive tasks and provided real-time support could reduce stress levels among agents.

Source: Brynjolfsson et al., 2023; Abdikaparov, 2024; United Nations and ILO, 2024.

Many more occupations are exposed to AI

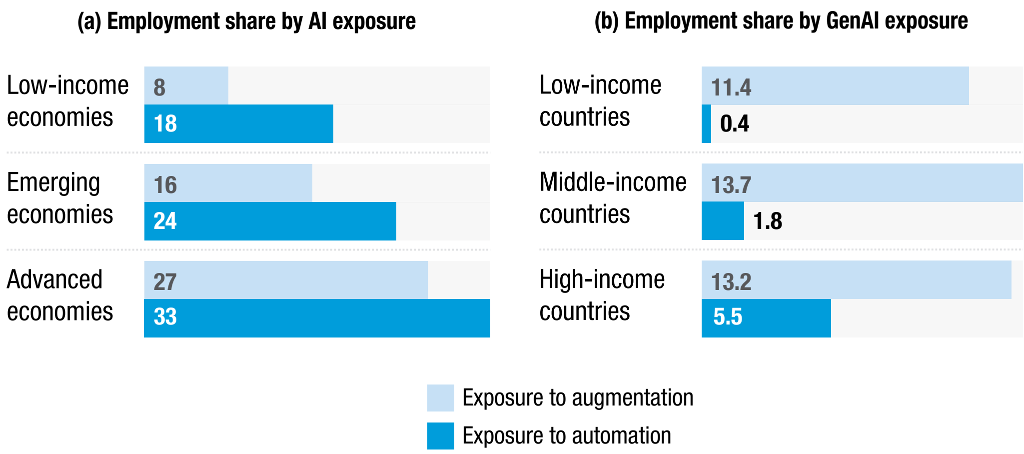
Developed countries face greater prospects of AI automation but also greater **opportunities for augmentation**

Previous waves of technology primarily impacted blue-collar occupations, but those most exposed by AI are in knowledge-intensive sectors (Nedelkoska and Quintini, 2018).[3] A recent OECD survey on job markets in Europe and North America listed the top industries prone to AI automation as those in finance, advertising, consulting and information technology (OECD, 2024). Similarly, a study in India based on online job postings between 2016 and 2019 found that AI-related skills requirements were concentrated in information technology, finance and professional services (Copestake et al., 2023). A recent global survey found that GenAI was being adopted least in manufacturing and more commonly in marketing and sales, product and services development and information technology functions (Singla et al., 2024).

One study estimated that AI would affect 40 per cent of global employment, showing that one third of jobs in developed countries had high potential for AI automation and around 27 per cent were exposed to AI augmentation (Cazzaniga et al., 2024; figure II.3). Workforces in advanced economies are at greater risk since more of their jobs involve cognitive tasks. However, these economies are also better positioned than emerging and low-income economies to capitalize on the benefits of AI.

For individual countries, the impacts depend on their occupational structures. For example, the United Kingdom has a significant share of employment in professional and managerial occupations that are highly exposed to AI augmentation, as well as in clerical support and technician occupations that could be exposed to AI-related automation (Cazzaniga et al., 2024). Developed countries are in general more likely than developing countries to face more immediate labour market adjustments and an increase in wage inequality.

Figure II.3
Developed countries have greater likelihoods of AI automation but also greater opportunities for augmentation
(Employment share exposed to AI, by country grouping; percentage)



Source: UNCTAD calculations, based on Cazzaniga et al., 2024 and Gymrek et al., 2024.
Note: Data from 125 countries in panel (a) and from 59 countries in panel (b); middle-income countries are the average of upper middle-income countries and lower middle-income countries, weighted by the number of countries in the sample.

[3] It should be noted, however, that even in non-knowledge intensive sectors, there are jobs highly exposed to AI (see, for example, Webb, 2020).

In contrast, in India, for example, most workers are agricultural workers and craftspeople, who are less exposed. Developing countries might, therefore, have time to gain insights from the experiences in developed countries.

A similar picture is seen when considering the impact of GenAI. Workers with higher levels of education are more exposed but also more likely to benefit. Overall, GenAI offers greater potential for labour augmentation than automation, particularly in low- and middle-income countries (figure II.3). Technicians and associate professionals can gain from augmentation while clerical support workers are highly exposed to automation. Exposure to GenAI within job categories is relatively balanced from a gender perspective (Gmyrek et al., 2024), but the over-representation of women among clerical support workers makes them more exposed to automation, particularly in the United States and Europe (United Nations and ILO, 2024).

A study in Latin America showed that GenAI was more likely to lead to augmentation than automation and to favour urban, educated and higher-income workers in formal occupations, with the benefits fairly evenly distributed across gender and age (Gmyrek et al., 2024). The study highlighted that nearly half of the occupations that could benefit from augmentation faced digital barriers. In addition, there is a significant gender-related imbalance in automation, largely because women are more likely to perform the most exposed jobs; the proportion of women-held jobs that are exposed to automation can be up to twice that of men. This, combined with the gender divide in digital skills and access to ICTs, can limit the benefits of AI adoption for women, thus widening existing inequalities (UNESCO et al., 2022).

It should be emphasized that the impact of AI on the labour market depends on the rate of technology adoption, as well as on other non-technological factors, such as the relative prices of capital and labour, economic structures and the social acceptance of new technology. These factors amplify or reduce expected AI-related impacts between sectors and countries (Brynjolfsson et al., 2017; Cazzaniga et al., 2024; UNCTAD, 2021).

GenAI offers greater potential for labour augmentation than automation

The use of AI **can magnify existing gender disparities**

Despite concerns about widespread job losses, the pace of automation has been slower than initially predicted (World Economic Forum, 2023a). In one survey conducted in 2020, employers expected that 42 per cent of their business tasks would be automated by 2027 but, subsequently, employers have reduced their estimates. As in previous waves of technological innovation, the use of AI has also created new jobs. One study of seven high-income countries found that while the use of AI had automated some tasks in finance and manufacturing, it had also introduced new tasks, and most employers reported higher productivity but no overall impact on employment (Lane et al., 2023). Box II.2 provides further discussion on the impact of AI in knowledge-intensive sectors.

Box II.2
Evidence from knowledge-intensive activities

The impact of AI in knowledge-intensive sectors varies by task. One study at a multinational energy firm, for example, found that while algorithms proved beneficial for tasks with clearly defined outcomes, they were less effective in areas requiring creativity, social intelligence or complex decision-making.

The study identified two distinct approaches to integrating algorithms. The first was task automation, replacing humans with algorithms on a task-by-task basis, and the second was process re-engineering, redesigning entire workflows around algorithmic solutions. The latter approach is potentially more transformative because it may require new skills in process-mapping, data analysis and software development. Making improvements and benefiting from AI therefore depends on the capacity of firms to adjust workplaces and job tasks. In this way, the use of AI can lead to structural changes; new teams can be dedicated to automation-as-a-service and new forms of hybrid workflows can blur traditional boundaries both within firms and with respect to external agents.

The introduction of algorithmic solutions in the firm also changed how knowledge was valued and acquired. Previously, the firm had greater regard for expert judgment, but the introduction of AI focused management more on quantifiable outputs, fostering a culture of metric-driven evaluation. This extended the use of AI beyond algorithmic recommendations, to encompass expert suggestions, leading some workers to question their own expertise.

The study also found a shift in learning practices. Faced with complex and often opaque algorithmic recommendations, knowledge workers prioritized the perceived safety and adequacy of these recommendations, even if they did not understand the underlying logic. They thus felt increasingly unfamiliar with their own area of expertise, also known as knowledge self-alienation.

Source: Amaya and Holweg, 2024.

Current evidence suggests that the future scenario is likely to be a complex interplay of automation, augmentation and the emergence of new roles. Automation is likely to reduce the labour share in value added in favour of capital, which will result in slower growth in wages than productivity and increasing wealth concentration. However, this tendency can be counterbalanced by the benefits of augmentation and of generating new tasks for workers (Acemoglu and Restrepo, 2019).

It is important to understand and plan for all eventualities. Increasing inequalities have already been stirring social discontent and weakening trust in public institutions, while increasing political polarization and undermining democratic governance (Qureshi, 2023). Policymakers and businesses need to understand these dynamics to ensure that the benefits of AI are distributed equitably and to facilitate smooth transitions.

Automation shifts value toward capital, but worker-augmenting technologies can reverse this trend

D. Working with uncertainties

If the history of past general-purpose technologies is any indication, it could take years or even decades for the full extent of the impacts of AI to materialize (Brynjolfsson et al., 2017). It will take time to acquire a substantial stock of AI technology across a wide range of industries and in firms of different sizes. It will also take time to build complementary assets in AI infrastructure, data and skills. In addition, firms need time to discover new productive uses for AI and integrate them within production activities. The aggregate economic outcome of AI in the long term is thus highly uncertain.

In advanced economies, such as Japan and the United States, optimistic projections place long-term annual productivity gains over a 10 to 20-year horizon at between 1 and 2 per cent (Hatzius et al., 2023). With less sectoral exposure to AI, most emerging economies are expected to experience lower levels but still substantial annual growth, at between 0.7 and 1.3 per cent (Hatzius et al., 2023). To put these numbers into perspective, in the past two decades, annual productivity growth in advanced economies has averaged at around 1 per cent and in emerging markets and developing economies, at around 4 per cent (Dieppe, 2021).

However, these expectations may be overstated. For instance, one estimate for the United States puts the annual AI-induced productivity boost over the next 10 years at less than 0.1 per cent. This is because AI systems may find it difficult to cope with certain tasks and, while the use of AI may generate new tasks that increase revenue, it may also generate others that are more malign, such as cyberattacks. Moreover, AI may harm consumers through manipulation or addiction. The impact of AI on welfare may be lower than its effect on productivity (Acemoglu, 2024b).

To shed light on the conditions needed for the use of AI to generate large and long-term aggregate benefits, three sources of uncertainty should be considered.

Uncertainty 1 – Easy and difficult tasks

Part of the disagreement over the long-term aggregate effects of AI originates from uncertainties about the rate of development of the technology and how well and quickly it can be integrated into future economic production. Optimistic observers state that AI will have ever-broadening applications and will spawn adjacent innovations, leading to major productivity improvements (Brynjolfsson et al., 2017).

The full impacts of AI **could take years to fully materialize**

How far can AI go in **substituting humans?**

Advances in AI-powered machine vision for example, have increased the potential of self-driving cars and of autonomous drones.

However, the current rapid success of AI may be misleading, since it has largely been accomplished through easy tasks that can be readily learned. In the near future, AI may be faced with increasingly difficult tasks of a more complex and context-dependent nature that cannot be automated with similar efficiency (Acemoglu, 2024a). In such cases, there may be no straightforward mapping between actions and defined outcomes of success and not enough data to teach machines about hidden relationships (Brynjolfsson and Mitchell, 2017). An example is in the diagnosis and treatment of psychiatric illnesses, which tend to have complex and historical causes that are difficult to capture in data. For such tasks, AI may be no more productive than existing technologies or human workers.[4]

At the same time, AI is also likely to create new "bad" tasks that can harm overall productivity and well-being (Korinek and Stiglitz, 2021). Examples are deepfakes, misinformation and AI-powered surveillance, which raises social, ethical and privacy-related concerns.

AI may bring job polarization and **widen income inequality**

It is too early to predict with any degree of confidence how AI systems will transform production in the long term, but it seems that AI technology, as in previous waves of technological innovation, may bring a welcome boost to economic growth, although it may be less impressive than some might have hoped. Moreover, maximizing the positive effects on societies depends on proper guidance and policy measures.[5]

Chapter IV focuses on national policies, to seize the opportunities brought by AI and chapter V considers AI policies and governance from an international perspective.

Uncertainty 2 – Long-term structural changes in the labour market

Productivity gains depend on the long-term structural adjustments in the labour market, as AI can augment or displace labour. If AI is designed and used primarily as a labour-substituting technology, in the long term, the declining employment share in sectors that are more AI intensive can diminish the overall economic effect of productivity gains (Aghion et al., 2017; OECD, 2024). While workers displaced from AI-impacted sectors may be partially absorbed by sectors with lower productivity, this could result in job polarization and widening income inequality (UNCTAD, 2021). Thus, although productivity can increase in AI-intensive sectors, the aggregate productivity impact could be limited by slower productivity growth in labour-intensive sectors.

This outcome resembles a scenario of Baumol's cost disease, in which aggregate productivity growth is defined less by the sectors at the forefront of technological change than by those that are slower to improve (Aghion et al., 2017; OECD, 2024). The actual outcome depends on future interactions between AI adoption and the labour market. If AI acts as a labour-complementing rather than labour-displacing technology in a sufficient number of sectors, it can raise aggregate productivity.[6]

4 Marcus (2018) identifies further limitations of current deep-learning techniques that prevent AI from becoming general-purpose problem solvers, including the need for significant amounts of training data, the inability to make sense of real-world, abstract ideas that underlie human thinking and the fact that the logic behind their outputs is hard to interpret. Many of these issues are extendable to new GenAI models.

5 This line of argument has been put forward, for example, by Gordon (2014).

6 AI implementors also need to watch out for "so-so" automation technologies, that is AI technologies that cut costs enough to replace workers but not enough to substantially raise productivity (Acemoglu and Restrepo, 2019). Such innovations do little for aggregate productivity and come with the cost of large displacement effects.

Another mitigating factor is the extent and nature of job creation. In the past, automation technologies initially caused job losses that were offset in the long term by the appearance of new jobs (Autor, 2015; Bessen, 2019). This reinstatement effect can be strong if AI spawns many complementary industries, particularly in areas in which humans retain a comparative advantage over machines. Yet this could take time. Due to skill mismatches and frictions in the labour market, the transition of workers into these new industries could be slow and costly, and fail to keep pace with rapid changes in AI (UNCTAD, 2021; Bessen et al., 2022; Edin et al., 2023).

Uncertainty 3 – AI adoption in developing countries

The adoption of AI in many developing countries may be hindered by constraints involving the three leverage points of infrastructure, data and skills, creating uncertainty about how these countries can fully exploit the potential of AI.

Developing countries have a higher proportion of occupations concentrated in primary and non-knowledge–intensive sectors and, in general, fewer opportunities for AI applications, but large countries can leverage their size and critical mass (see chapter III). More importantly, developing countries may be weaker with regard to critical digital infrastructure and complementary assets such as data and skills. The low level of penetration of reliable electricity and high-speed Internet limits the deployment of AI services, particularly in rural areas. A further impediment is the availability of relevant data. AI models need to be trained on large amounts of high-quality data, but the best data sets are often controlled by global corporations (UNCTAD, 2019).

This can significantly hinder the capacity of developing countries to tailor AI systems to local needs. In addition, with regard to skills, in developing countries in particular, only a small portion of the population has general digital literacy or specialized technical know-how, which hinders the adoption of AI.

The need for long-term and significant adjustments does not imply that AI is less relevant in developing countries. With careful and targeted implementation, the use of AI can generate immediate and positive changes. However, developing countries need to create the right conditions in order to seize the gains of AI and ensure that they are not left behind.

In addition to boosting productivity for workers and firms, the use of AI offers distinct benefits for sustainable development. It can, for example, help decision makers optimize the distribution of scarce resources. Using advanced analytics, they can draw insights from new sources of unstructured data. GenAI systems can also offer support for individuals who would otherwise not have access to specialized knowledge, for instance in education and agriculture (Björkegren, 2023; Björkegren and Blumenstock, 2023; Okolo, 2023).

To help fill the gap of systematic evidence about AI, section E showcases AI applications in developing countries that can deliver improvements in productivity and human welfare across three key sectors. The case studies also show how limitations in infrastructure, data and skills can be addressed through careful implementation and collaboration among stakeholders, to fit local contexts.

Developing countries should create favourable conditions to **harness the benefits of AI**

E. Case studies of AI adoption in developing countries

AI could serve as an accessible **source of expert information**

Agriculture

Agriculture is the primary source of sustenance for billions of people around the world and, in many developing countries, employs more than half the working population (World Bank, 2024). Agriculture is well suited for AI-powered productivity improvements because of its high volumes of unstructured data, reliance on labour and complex supply chain logistics, as well as the significant number of farmers who would value customized services that are not locally available.

Rural agricultural areas are typically short of the prerequisites for AI adoption (e.g. electricity, Internet access and digital literacy). Despite these challenges, the following case studies demonstrate how AI can be used in three main agricultural applications in developing countries, with significant impacts on the yield and quality of crops, as well as the livelihoods of farmers (table II.2).

Pest and disease control

Globally each year, pests and diseases decimate up to 40 per cent of the world's crops, causing substantial detriment to farmers (FAO, 2024a). Effectively addressing such problems requires specialist knowledge; it can take years of experience to diagnose infestations in a timely fashion and apply appropriate treatments. Such expertise is generally in short supply, particularly in areas in which smallholding farmers do not receive agricultural extension services.

With the use of AI, however, expert information can be made instantly available to any farmer who has a mobile telephone. In Colombia, the International Centre for Tropical Agriculture, for example, has developed a mobile application that helps farmers diagnose infestations of banana plants using photos of crops, called Tumaini, which means "hope" in Swahili (Salian, 2019).

Table II.2
Case studies of AI applications in agriculture

Application	Case study	Technology	Outcomes
Pest and disease control	Tumaini (International Centre for Tropical Agriculture, Colombia)	AI (deep learning)	Accessible diagnostic tool for banana farmers
	MkulimaGPT (university, United Republic of Tanzania, in collaboration with the Bill and Melinda Gates Foundation)	GenAI (large language model)	Accessible diagnostic tool and chatbot assistant for maize farmers
Yield prediction	Beijing Normal University	AI (deep learning)	Accurate yield prediction with open-source remote-sensing data
	South China Agriculture University	AI (deep learning)	Accurate yield prediction on smallholdings with imagery data from drones
Precision irrigation	Phyt'Eau (start-up, Tunisia, in collaboration with IBM)	AI and IoT	Optimized irrigation and reduction of water consumption on farms

Source: UNCTAD.

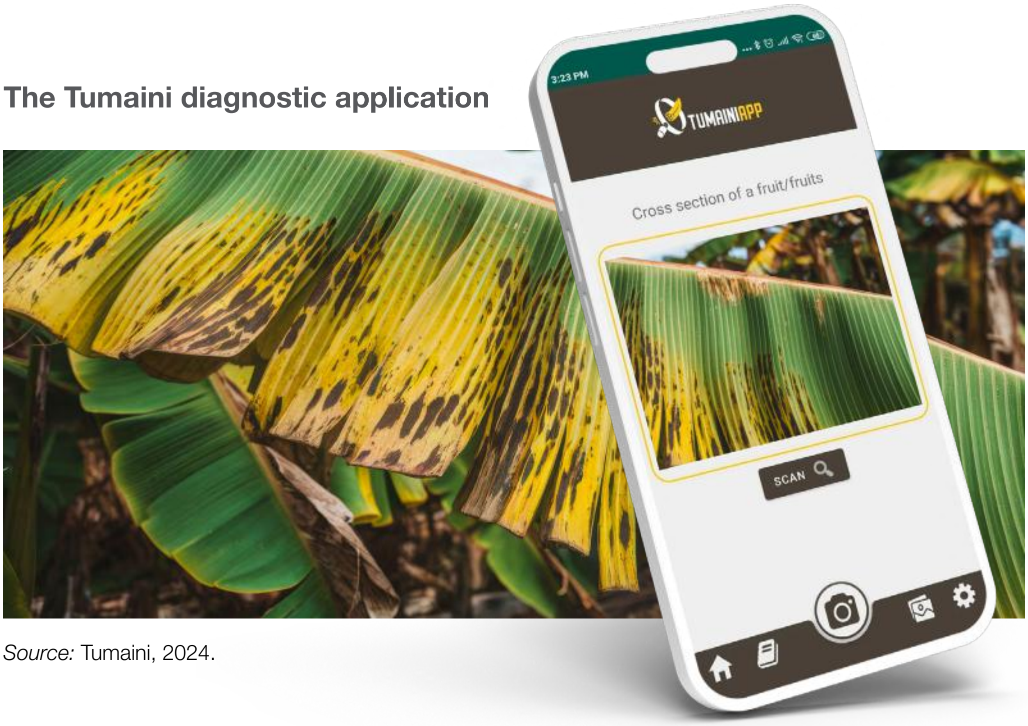
Tumaini uses a deep-learning–based computer vision system that has been trained on thousands of images of banana plants, both healthy and infected, and labelled by agricultural experts, providing the algorithm with comprehensive visual references in order to identify unique patterns indicative of crop diseases, which are often too subtle for untrained eyes to detect. A farmer uploads a photo of the plant and the application provides an instant diagnosis and suggests dedicated countermeasures. Tumaini can detect five diseases and one pest with an accuracy of above 90 per cent, giving farmers a diagnostic capacity comparable to that of highly trained experts (Selvaraj et al., 2019).

The application is also available in offline mode, although there may be some loss of accuracy, and can therefore be widely used even in rural areas that lack reliable Internet access. To date, Tumaini has been downloaded over 10,000 times in 15 countries across Africa, Latin America and South-East Asia (Tumaini, 2024).

Crop diseases in developing countries can also be addressed with the use of GenAI-powered chatbots. MkulimaGPT, for example, created for farmers in the United Republic of Tanzania, is a large language model that has an elaborate sensor-based disease-detection system for maize (Math Works News and Stories, 2024). The chatbot is delivered through a commonly used mobile messaging app, to facilitate diffusion among local farmers. A farmer uploads a photo of the crop, which is cross-referenced with an internal database and, if the application detects an abnormality, it initiates a chat session, offers a diagnosis and guides the user through the appropriate action, thereby significantly lowering the skill barrier for the average maize farmer (Mkulimagpt, 2024).

One limitation of deploying large language models in developing countries is a lack of training data in local languages. To address this with regard to MkulimaGPT, the developers have obtained funding from a private charitable foundation, to collect high-quality local data and build a chatbot that speaks Swahili, to ensure that the chatbot is tailored to local needs.

The Tumaini diagnostic application



Diagnosing a suspected infection on banana

Source: Tumaini, 2024.

Yield prediction

Another common application of AI in agriculture is in predicting local crop yields in order to allow farmers to make informed financial and management decisions about their crops. Such use also offers Governments accurate data needed in monitoring and ensuring food security.

AI can leverage new data sources to **provide reliable yield prediction**

Conventional data collection methods for crop yields, such as field surveys and aerial imagery, are costly and difficult to scale. In addition, traditional statistical methods struggle to capture the many complex factors that contribute to yields, such as climate and soil conditions and crop genotypes.

The ability of AI technology to jointly analyse different data from unconventional data sources can help unlock new opportunities. Drawing upon and analysing free open-source data, AI can generate reliable crop yield predictions. Researchers at Beijing Normal University, for example, have used AI techniques with three open-source data sets to estimate the yield of rice crops (Cao et al., 2021). Their model relies on climate and soil data from Google Earth Engine, historical crop yield data from official publications and open-access satellite imagery, all of which are readily accessible on the Internet; open-source data can thus help fill gaps when local data are sparse.

Once models have been calibrated and key information pre-processed, AI can offer an accessible and effective solution. Compared with traditional regression models, the deep neural network proved more efficient in extracting crop-yield–related features from the data, with up to 88 per cent accuracy compared with only 42 per cent when using traditional regression models. When used with data from China, the new model enabled accurate predictions of rice yields at the county level, covering 94 per cent of the rice cultivation area (Cao et al., 2021). This case study shows that the use of AI can open new ways to use data for accurate crop-yield prediction in low-resource conditions.

AI-managed agricultural systems help **optimize production processes**

In addition, in China, researchers from the South China Agriculture University have applied machine-learning techniques to images from unmanned aerial vehicles, to predict yields of cotton (Xu et al., 2021). Compared with satellite imagery, imagery from such vehicles offers higher resolutions and can thus facilitate yield predictions at a much more granular level, even individual fields. As in the previous study, the deep-learning model achieved significantly higher accuracy than one based on linear regression, namely, 80 per cent compared with 66 per cent. Such a model may be particularly helpful for smallholding farming communities that need to plan harvests and choose which crops or activities to invest in.

Precision irrigation

One of the most important resources for agriculture is water, which is often scarce. According to the Food and Agriculture Organization (FAO), 1.2 billion people live in agricultural areas with very high levels of water stress, mostly in developing countries (FAO, 2020). In recent years, the problem has been exacerbated by climate change, with the increasing intensity and frequency of droughts (World Bank, 2023).

These impacts can be alleviated by a combination of AI and other technologies. In Tunisia, for example, there have been regular severe droughts, the impacts of which are aggravated by intense agricultural production (Frost, 2024). Agriculture accounts for over 70 per cent of the country’s freshwater withdrawal; it is therefore both the main cause and a casualty of water shortages (FAO, 2024b).

The issue is being addressed, for example, by ifarming, a startup founded in Tunisia in 2017 to reduce water consumption through more accurate farming. The main service of the startup is Phyt’Eau, an AI-based programme that can analyse data on water use collected in real time through an array of IoT sensors on farms (Agritech, 2024). The sensors collect information that measures water stress on crops, including on temperature, soil humidity and wind. Based on the data, Phyt'Eau prescribes an optimal irrigation management plan for the plot that, when connected to an irrigation system, can be administered automatically. In initial trials, the prototype reduced water use by 20 per cent and increased crop production by 20 per cent (Galtier, 2017). IBM offered access to advanced AI and IoT platforms, and this collaboration boosted the water-saving capability of Phyt'Eau to 40 per cent and productivity by up to 30 per cent (IBM, 2024).

AI is also used in precision agriculture in Malaysia, for example, where drones equipped with AI vision systems are being deployed in palm-oil plantations to spray nutrients and pesticides with speed and precision (Chu, 2022). In Fiji and Samoa, an AI-based system developed in Australia is being used for automatic weeding and pesticide spraying (ITU, 2024). These and other projects are leveraging AI with other automation technologies to achieve more sustainable and productive farming.

Manufacturing

Manufacturing plays a key role in economic development, stimulating growth in different upstream and downstream sectors and generating significant employment opportunities (Haraguchi et al., 2017; Lautier, 2024). Examples from developing countries such as Brazil, China and India show how industrialization can reduce poverty and accelerate economic growth. Manufacturing has been subject to successive waves of technological innovation, the latest of which is Industry 4.0 technologies.[7] Developing countries that have applied these technologies have boosted productivity and growth rates in manufacturing value added and GDP (UNIDO, 2019).

The following case studies show how developing countries can use AI to cut costs, create better working environments and increase efficiency (table II.3).

AI-powered robots can **revolutionize production processes**

Table II.3
Case studies of AI applications in manufacturing

Application	Case study	Technology	Outcomes
Production automation	Smart welding robot (technology company, China)	AI (deep learning)	Accurate and adaptive robot for welding automation
Predictive maintenance	Predictive maintenance for plastic injection mould machine (industry–university partnership, Türkiye)	AI and IoT	Effective estimation of remaining useful life in manufacturing equipment
Smart factories	Tata Steel (manufacturer, India)	AI, robotics, IoT, systems integration	Factory-wide productivity increase and profit increase
	Unilever (United Kingdom manufacturer, Brazil)	AI, digital twins	Cost optimization, agility to the market and minimized environmental footprint

Source: UNCTAD.

[7] Industry 4.0, also known as the fourth industrial revolution, comprises the transformation of traditional manufacturing and industrial practices using the latest smart technology. It involves collecting systems, data and real-time analytics to achieve smarter and more efficient production.

Production automation

A major domain for AI applications in manufacturing is robotics. Over recent decades, industrial robots have automated many repetitive processes and replaced human workers in hazardous and physically demanding environments (Wang et al., 2023). One disadvantage is that they can be fairly rigid, generally built and programmed for particular tasks, and it is costly to adapt them to new tasks.

The use of AI enables robots to be more versatile and adaptive. In China, for instance, a technology company has developed a fully automated AI-driven robot for welding (Doubao, 2019). Its deep-learning algorithm uses three-dimensional laser sensors to recognize objects in real time and distinguish between various metal parts and weld joints and it can guide the robotic arm to perform accurate welding operations. An advantage of the technology is that it can weld on shiny metal surfaces, whereas previous robots could not make the necessary distinctions due to reflections.

More importantly, while traditional welding robots need to be reprogrammed for each new product, an AI-powered welding robot can quickly adapt to different functions and the new dimensions of incoming parts while requiring minimal human intervention. This can significantly reduce retraining costs and shorten downtimes.

Within the field of AI-guided industrial robots, an emerging trend is the use of collaborative robots, or cobots. These are unlike ordinary robots in that they are designed to work in close interaction with humans. Typically, they are smaller and less expensive and have built-in mechanisms that reduce the need for additional safety fencing. Due to these features, cobots can be more readily integrated into small-scale production lines or labour-intensive manufacturing settings.[8] AI enhances the collaborative qualities of cobots by improving safety and by enabling them to work in more dynamic environments (Mohammadi Amin et al., 2020).

AI-powered smart welding robot

Source: Adobe Stock.

[8] In Indonesia, for example, see https://www.universal-robots.com/case-stories/pt-jvc-electronics-indonesia/.

Predictive maintenance

Addressing equipment breakdowns can be costly. Breakdowns cause delays in production and require expensive replacements of parts. They are particularly burdensome for manufacturers in developing countries where skilled technicians and stocks of specialized spare parts may be in short supply.

Many of these problems can be prevented by using AI for predictive maintenance. In traditional machine maintenance, technicians carry out inspections and repairs manually, either when scheduled, or when a machine breaks down. In predictive maintenance, machinery is constantly monitored for signs of failure using IoT sensors, with data analysed by AI processors. By cross-referencing with past data, an AI processor detects patterns indicative of a future malfunction and alerts plant operators ahead of time.

In Türkiye, for example, Vestel Electronics, a home appliances manufacturer, has collaborated with a university to apply machine learning to predict the remaining useful life – the expected amount of time until a machine's next breakdown – of plastic injection moulding machines. The algorithm is trained on historical sensor data, including the clamping force of a machine, oil temperature and injection time, then analyses real-time sensor data in the factory. According to a study by the company, the algorithm correctly predicted the remaining useful life of the machines 98 per cent of the time (Aslantaş et al., 2022). Equipped with this information, managers can schedule maintenance and purchase spare parts in advance, thereby lowering costs and downtimes.

Predictive maintenance only requires AI data processors and a set of IoT sensors attached to machines. It is thus versatile and adaptable to different industrial environments.

In Chile, for example, large mining companies such as Codelco are using the technology to monitor the fleet of autonomous mining trucks (Jamasmie, 2019). Smaller manufacturers can also use the technology given the increasing availability of less-expensive, standardized packages.

AI enables efficient **preventive maintenance**

Smart factories

In large-scale manufacturing, multiple AI-enabled systems can be integrated within a single plant, to provide significant gains in production, savings in energy and greater profits. The synergistic effects of AI and other frontier technologies may also enable manufacturers in developing countries to catch up with counterparts in developed countries.

In India, Tata Steel, one of the country's largest steel manufacturers, has implemented more than 250 machine-learning systems across various production processes (Harichandan, 2023). One such application assesses the quality of welds on steel tubes. A machine-learning algorithm can automatically detect a faulty weld with more than 80 per cent accuracy and thereby significantly lower the number of defective products (Gujre and Anand, 2020). The use of AI can also help optimize the chemical mix in steel furnaces and speed up the transportation of materials within and between plants. Such improvements, combined with other digital technology upgrades, have increased the corporation's pre-tax profits (Das, 2021).

Another example is Unilever, who has built the world's largest laundry detergent powder factory in Indaiatuba, a municipality in the state of São Paulo, Brazil. The company has made the factory more agile and cost efficient while minimizing its environmental footprint by using technologies such as AI and digital twins, that is, virtual representations of physical objects.

Systematic integration of AI with other technologies can accelerate industrialization

A digital twin is used with machine learning to establish the optimal process parameters for new formulations of laundry powder. Reducing the need for physical trials has accelerated the launch of innovations while cutting energy consumption (Unilever, 2023). Between 2018 and 2023, the company also used AI-driven predictive maintenance to halve the cost of life cycle management for pneumatic devices. Other key use cases include a biomass-powered machine-learning spray-drying tower that has achieved a 96 per cent reduction in carbon dioxide emissions and a digitally enabled sealing solution that has eliminated chronic defects, reducing customer complaints about leakage by 94 per cent. As a result, the technologies have reduced innovation lead times by 33 per cent and production costs per ton by 23 per cent, while also reducing carbon dioxide emissions. In 2022, in recognition of its achievements in the field of advanced manufacturing, the Indaiatuba site was listed by the World Economic Forum as one of the 29 new "lighthouse" factories worldwide (World Economic Forum, 2023b).

Healthcare

The use of AI offers significant opportunities for improving access to and the quality of healthcare services in both developed and developing countries. Many developing regions lack medical services and infrastructure, which challenges citizen well-being and poverty reduction goals. With regard to healthcare services, the use of AI can improve both access and quality. The following case studies illustrate how AI has been implemented in developing countries to provide expert diagnoses of diseases, extend the coverage of healthcare services and manage pandemic outbreaks (table II.4).

Improving diagnoses

The timely and accurate treatment of diseases requires high-quality diagnostics, which are often unavailable to patients in developing countries, particularly in rural areas, due to a lack of skilled medical professionals, laboratory facilities and infrastructure. AI offers the prospect of new and cost-effective diagnostic methods and equipment in low-resource settings.

Table II.4
Case studies of AI applications in healthcare

Application	Case study	Technology	Outcomes
Improving diagnoses	Ubenwa (university startup, Nigeria)	AI (deep learning)	Accessible tool for quick and accurate perinatal asphyxia diagnosis
	AI-assisted portable X-ray machine (United Nations Development Programme and local health authorities, South Sudan and Tajikistan)	AI	Reliable tuberculosis diagnosis in remote and resource-constrained areas
Extending healthcare coverage	mMitra (non-profit organization, India)	AI	Targeted intervention for women with high dropout risk from programme
	mDaktari (healthcare company, Kenya, in collaboration with the Bill and Melinda Gates Foundation)	GenAI (large language model)	Preliminary clinical screening tool for low-resource areas
Assisting pandemic management and control	Refugee population modelling at the border of Brazil and the Bolivarian Republic of Venezuela (United Nations High Commissioner for Refugees and Government of Brazil)	AI	Accurate prediction of refugee inflows, for resource allocation in pandemic conditions

Source: UNCTAD.

AI offers new and **cost-effective diagnostic methods**

AI can, for example, be used to diagnose perinatal asphyxia, a birth complication that leaves infants unable to breathe properly and, in developing countries, is one of the top three causes of newborn deaths (WHO, 2024). Most cases can be treated if quickly diagnosed; in developed countries, this is commonly done by sending a sample of an infant's blood to a laboratory, for analysis of signs of low blood oxygen, a service that may be out of reach in rural areas.

In Nigeria, a team of AI researchers has offered a novel, simple and inexpensive alternative involving analysing an infant's cries. Crying and breathing rely on the same set of muscles, and irregular vocal sounds in an infant's cry are a reliable indicator of asphyxia. Such minute differences may not be heard by human ears, but can be readily detected by a machine-learning algorithm trained on a data set of infant cries. The researchers developed Ubenwa – meaning "cry of a baby" in Igbo – an AI-driven mobile application that analyses a short audio clip of a newborn's cry and can detect perinatal asphyxia with an accuracy of 86 per cent, securing valuable time for treatment (Onu et al., 2019).

Another example of an AI system that can enhance traditional diagnostics is a battery-powered X-ray machine with an embedded AI-driven tuberculosis screener. In countries with few expert radiologists, this can serve as a valuable tool for doctors. Unlike traditional X-ray machines, the battery-powered machines are portable and can be deployed in remote areas that may have limited electricity connections. For example, such machines are being used by health authorities in South Sudan and Tajikistan, with support from the United Nations Development Programme. In Tajikistan, 15 machines have already been used to screen 120,000 people in 2023, covering 15 per cent of the country's total diagnosed cases of tuberculosis (UNDP, 2024).

Extending healthcare coverage

A common problem among developing countries is the inadequate coverage of medical services. The World Health Organization recommends at least 45 skilled medical professionals for every 10,000 people. In many developing countries, this figure is not reached, making it difficult to extend life-saving resources. It takes time for countries to build up their healthcare systems, but the use of AI can help allocate existing resources to those in greatest need (WHO, 2016).

An AI-enhanced X-ray machine being deployed in Rudaki, Tajikistan

Source: UNDP.

AI can help **expand healthcare coverage** despite limited resources

Around 800 women died from preventable causes related to pregnancy and childbirth every day in 2020 (WHO, 2025). These could be avoided with better health information and access to medical care during pregnancy. Armman, a non-profit organization, helps provide maternal and child health services in urban slums using mMitra, a free mobile messaging service (Armaan, 2024). The service covers 3.6 million vulnerable women in India, sending curated voice messages about preventative care measures during different stages of pregnancy, to raise medical awareness and promote the health of both mothers and infants. Studies show that enrolment in the service enhances women's maternal knowledge, enhances their voice within their families regarding their pregnancies and increases their likelihood of seeking professional medical services (Murthy et al., 2019; Murthy et al., 2020).

However, about 40 per cent of enrolled women eventually stop listening to the messages and drop out. Due to limited resources, Armman staff cannot reach out to re-engage all of them, but are collaborating with Google India on an AI model that helps find and target the pregnant mothers at greatest risk of dropping out (Taneja and Tambe, 2022; Mate et al., 2021). The model analyses each woman's socioeconomic information, such as family size, income and age, as well as their call history, including call duration and missed calls, to predict those at highest risk of discontinuing and, of these, who would benefit most from the outreach service. Armman staff then allocate limited human resources more effectively and attempt to keep more women in the programme. After the introduction of the AI algorithm, engagement by subscribers rose by 30 per cent (Mate et al., 2021). This type of personalized messaging could be used in other sectors besides healthcare and help optimize the distribution of limited resources.

There is also limited healthcare outreach in Kenya; for every 10,000 people, there are only 23 available medical doctors (Our World in Data, 2024). Access Afya, a social enterprise, operates 12 small clinics using a telemedicine platform, mDaktari, that provides low-cost virtual doctor consultations (Philips Foundation Team, 2023). Using GenAI, the enterprise aims to reach more people. In a pilot programme, ChatGPT is integrated with mDaktari, to provide a chatbot that can be used as a preliminary screening tool (The Economist, 2024). The chatbot receives patients' inquiries, gathers information about symptoms and suggests that the patient should visit a clinic or collect medication at a pharmacy. This service saves clinics time on gathering patient information and, when appropriate, diverts individuals with mild conditions from the use of clinical services.

AI chatbots are not foolproof; they cannot tell what is real and what is fake and can be prone to fabrications (Alkaissi and McFarlane, 2023). Access Afya addresses the fallibility of chatbots by ensuring that human clinicians review and approve chatbot suggestions before they are sent to patients, in order to protect against mistakes. Use of the triage performed by AI allows human clinicians to focus on those patients in greatest need. The early success of the programme shows the potential of using GenAI as an effective triage tool, to improve efficiency and extend the reach of existing medical services. With financial support from a private charitable foundation, Access Afya plans to expand the service to accommodate multiple languages and have a greater role in supporting clinician diagnoses (Bill and Melinda Gates Foundation, 2024).

Pandemic management and control

As shown during the COVID-19 pandemic, managing outbreaks of infectious diseases requires providing public health administrators with accurate and up-to-date information, for example, about demographic movements, transmission patterns and healthcare capacity.

Equipped with such information, authorities may be better able to target interventions and bring an outbreak under control.

In developing countries, structured healthcare data are often not available, particularly with regard to minority and vulnerable populations. As an alternative, the use of AI can unlock the potential of significant amounts of unstructured data. In Brazil, for example, during the COVID-19 pandemic, in 2021, the Office of the United Nations High Commissioner for Refugees (UNHCR) worked with the Government on a machine-learning tool for predicting the inflow of refugees from the Bolivarian Republic of Venezuela and for coordinating resources to protect them from the coronavirus (Smith, 2021). The tool was used to predict future border crossings based on historical patterns.

Since the pandemic had disrupted data collection, researchers used unconventional open-source data. These included Internet search activity on migration and border-related topics, complemented by data on COVID-19 cases and news reports on local unrest in the Bolivarian Republic of Venezuela (de Rubalcava et al., 2023). Sources also included bus timetables in border regions and schedules for salary payments, as an indicator of when people might have additional funds for travel. By triangulating between these sources of data, the AI model predicted the inflow of refugees one month in advance with a high degree of confidence. This helped UNHCR and local partners plan for the number of migrants that arrived when borders reopened in June 2021 (UNHCR, 2022).

By combining and analysing significant and different data sets, AI can help inform key decisions during infectious outbreaks, using population movement models, such as in Brazil, or algorithms that forecast disease transmission (Jin et al., 2022) or enable rapid diagnosis and contact tracing (Huang et al., 2021).

AI data analytics can **enhance decision-making**

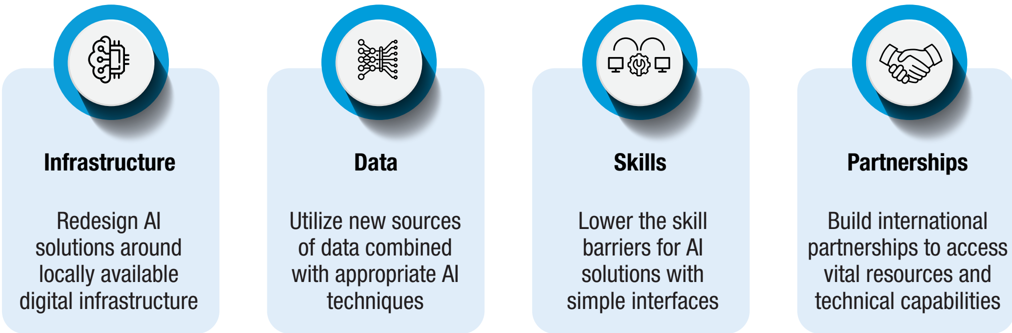
F. Good practices and lessons learned

The case studies considered are often limited in scale or in the pilot stage, but serve to illustrate the potential of AI in developing countries and how difficulties can be overcome through careful implementation and cooperation among stakeholders. There are no one-size-fits-all solutions, but a good starting point in each country is to assess local conditions and technological capacities and adopt AI strategically. This may mean, for example, supporting startups and industry–university collaborations, as well as non-profit organizations that help deploy AI solutions to serve local needs.

Governments should favour the emergence of AI ecosystems with investments supporting business development and networking. By showcasing successful experiences of AI adoption, they can raise awareness and diffusion and favour the accumulation of complementary assets and experience. It is also useful to engage with large companies or international organizations that can support promising local businesses with emerging technologies and connect them with international markets. This allows developing countries to accumulate relevant complementary assets and experience for the extensive and impactful diffusion of AI.

There are four main takeaways from the case studies along the key leverage points of infrastructure, data and skills, as well as partnerships (figure II.4).

Figure II.4
Four takeaways for promoting AI adoption in developing countries



Source: UNCTAD.

Takeaway 1: Adapting to local digital infrastructure

AI adoption should be designed according to the available digital infrastructure. In Colombia, for example, the banana disease detection application Tumaini has an offline mode that retains most of the diagnostic functions in the absence of an Internet connection, thereby remaining accessible and useful to farmers in rural areas where Internet connectivity is limited.

Similarly, AI adoption should take into account unstable supplies of electricity. The AI-assisted X-ray machines in South Sudan and Tajikistan, for example, operate on battery power and can therefore reach remote areas. Other case studies highlight different uses of AI applications based on mobile telephones, which offer a scalable platform for AI applications.

Takeaway 2: Utilizing new sources of data

AI depends on high-quality, relevant and interoperable data sets. In developing countries, such data sets may be limited, difficult to access or expensive to pay for, and innovative ways of collecting and using new forms of data are therefore key in ensuring AI capabilities and effective adoption.

In Brazil, for example, in modelling refugee flows at the border during the COVID-19 pandemic, UNHCR researchers relied on an unconventional nowcast data set, which included indicators scraped from local sources, then integrated, to produce accurate predictions of refugee movements.

Alternative data sources become viable and help overcome data limitations if the right AI techniques are applied. As shown by the case studies, in China, for example, deep neural network techniques enabled the use of open-access data in rice yield predictions and, in Nigeria, the Ubenwa application used deep-learning algorithms to employ anomalies in infant cries as a reliable indicator of a health complication after birth.

Takeaway 3: Making AI easy to use

One of the main impediments to technology adoption in developing countries is a low level of digital literacy. Governments need to build greater digital capacity. In addition, designers need to consider current standards of digital capacity and build applications that are attractive and simple to use, particularly on mobile telephones. Simple interfaces help facilitate interactions by novice users with new technology solutions and thereby help promote widespread and inclusive diffusion.

For example, in the United Republic of Tanzania, a chatbot for maize diseases allows users to access diagnostic information and make queries in a manner similar to messaging family or friends.

Application-based AI tools and visual aids such as icons and illustrations allow for an intuitive understanding of available functions. Such designs smooth the experience for those who may be unfamiliar with new technology and are critical in AI adoption in developing countries.

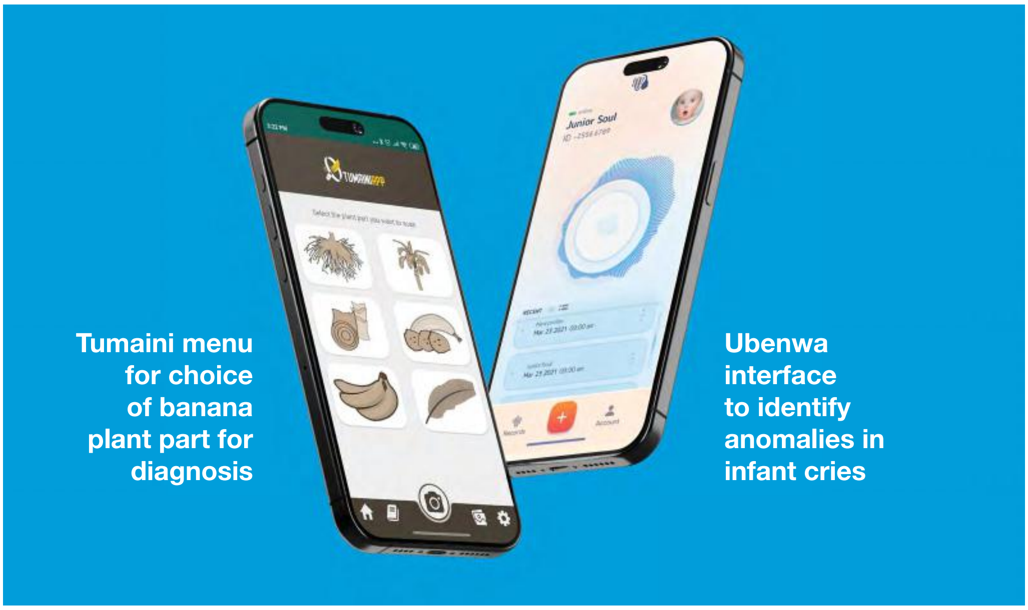
Takeaway 4: Building strategic partnerships

Developing countries aiming to accelerate the adoption of AI can benefit from strategic partnerships. A cross-country study by the World Bank showed that firms in developing countries that adopted more sophisticated technologies tended to be those with more external collaborations, through universities, foreign trade partners or large multinational corporations (Cirera et al., 2022).

Building strategic partnerships enables aspiring AI adopters to overcome barriers to adoption. In addition, Governments can overcome limitations of size through regional collaboration. For example, in many countries in East Africa, Swahili is a common language; a group of countries could collaborate to pool data in Swahili and jointly engage with technology companies to address common linguistic challenges.

Strategic partnerships can also provide essential resources for AI. Global Grand Challenges, under the Bill and Melinda Gates Foundation, for example, currently supports the development of AI models in local languages. The AI model for predicting the risk of dropping out among subscribers of a service provided by Armman was developed with technical assistance from Google India. In addition, in Tunisia, ifarming has a partnership with IBM to use high-performance AI platforms and receive funding to expand its operations. Chapter V further discusses the importance of international cooperation in global AI governance and suggests policies for ensuring that AI works for all.

Facilitating understanding with easy-to-read and intuitive icons



Source: Tumaini and Ubenwa.

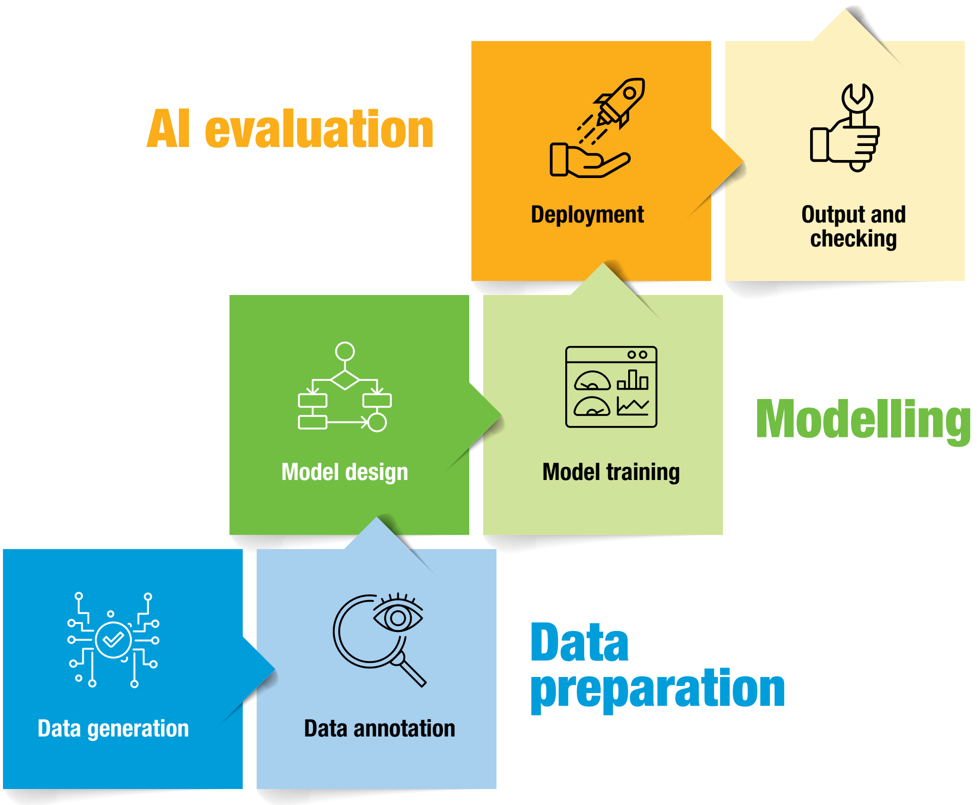
G. Workers throughout the AI life cycle

Human labour is essential throughout the AI life cycle

A growing body of research shows the crucial yet frequently forgotten role of human labour in AI. Each stage of an AI product life cycle, from development and production to maintenance, relies on human labour, often through digital platforms and business process outsourcing companies dispersed around the world (Rani and Dhir, 2024; Viana Braz et al., 2023; Tubaro and Casilli, 2019). An AI life cycle requires human labour at three stages, namely, data preparation, modelling and evaluation (figure II.5). Data preparation and AI evaluation may require different levels of content-specific expertise, while modelling generally requires higher competences in computer science.

The initial stage, data preparation, involves data collection and annotation. Despite the increase of unsupervised learning from unstructured data, AI systems rely on annotation by humans to label and mark data in order to add meaning (Tubaro et al., 2020). Computer vision models, for example, rely on semantic segmentation, a time-consuming process requiring each pixel in an image to be assigned a relevant label. Similarly, autonomous vehicles rely on databases of images annotated by humans through classification, object tagging and landmark detection (Wang et al., 2023; Schmidt et al., 2019).

Figure II.5
A simplified AI life cycle



Source: UNCTAD.

One source of such annotation is the use of a captcha [Completely Automated Public Turing test to tell Computers and Humans Apart] (Agarwal, 2023).

While some aspects of data preparation can be automated, many tasks still require human judgment. For ChatGPT, for example, the initial model training involved human trainers who engaged in conversations, posing as both users and AI assistants. To optimize its performance, the model's parameters and settings often need to be adjusted by machine-learning experts.

Creating training data for specialized fields such as translation or transcription requires workers with high levels of skill (Kenny, 2022). Medical systems require professionally trained workers to label and tag images and videos; common annotation tasks include the pixel-level segmentation of surgical images, bounding box annotations around organs and the plotting of characteristics within data. Such tasks can be time-consuming; an hour of video footage may require approximately 800 hours of human annotation.

The second stage, modelling, is more complex and technical and requires significant human expertise and decision-making. Developers and data scientists need to select the appropriate model architecture and algorithms and therefore require an understanding of the advantages and limitations of different models and algorithms, as well as expertise in a particular domain, such as medicine or transportation. During the model training, when an AI model learns patterns from data, human operators manage, optimize and guide the process. Engineers, for example, need to troubleshoot model errors or issues, check for signs of overfitting or underfitting[9] and adjust the model's hyperparameters.

In the final stage, evaluation, humans need to review the outputs in order to maintain quality control and feed information back into further model training. With regard to translation, for example, human experts assess the accuracy of machine translations and diagnose errors, providing feedback for improvement (Kenny, 2022).

This interplay between humans and machines extends to large language models such as ChatGPT. Humans are needed to evaluate performance both qualitatively and quantitatively and to ensure a model meets quality standards and avoids biases related to gender, race, religion or other attributes.[10] Human labellers rank model answers from best to worst, a process known as reinforcement learning from human feedback, which helps align systems with human values and preferences and to more closely match complex metrics of human quality (Teubner et al., 2023).

AI systems require continuous adaptation and, as they are employed to address new challenges, the demand for workers for their development will likely persist. AI systems can thus provide new forms of employment, but this is not necessarily "decent" work. In the data preparation stage, for example, employment can involve exploitative, often-precarious working conditions. Data annotators in developing countries often experience difficult conditions, including up to 10 hours of work per day at wages of less than $2 per hour, engaged in repetitive tasks, and with limited opportunities for career advancement, for example in Kenya and Uganda (ILO, 2024a; Muldoon et al., 2024).

With regard to content moderation (e.g. of social media posts), algorithms or machine-learning systems can help flag data for human attention. This process may be harmful for workers.

Human input is key in **evaluating and improving AI models**

[9] Overfitting and underfitting are common problems in statistics and machine learning. Overfitting occurs when a model is too complex, fitting the training data too closely and failing to generalize well to new data. Underfitting occurs when a model is too simple, leading to poor performance.

[10] One study showed that human judgment remains crucial, since "algorithms cannot always tell the difference between terrorist propaganda and human rights footage or hate speech and provocative comedy" (Google, 2023).

A mismatch between qualifications and tasks could result in the deskilling of highly educated workers

That is, in monitoring content online, workers may be exposed to disturbing or objectionable material that could negatively affect mental health (Ahmed et al., 2023).

There is also a risk of deskilling and dissatisfaction due to mismatches between qualifications and tasks. Workers annotating or deleting images, that is, carrying out repetitive low-skill tasks, may be highly educated. In India and Kenya, for example, a survey conducted in 2022 on microtask platforms and business process outsourcing companies showed that highly educated workers, with graduate degrees or specialized educations in science, technology, engineering or mathematics, were often relegated to relatively low-skill tasks such as text and image annotation and content moderation. Such significant wastes of human capital may be exacerbated in increasingly connected job markets, in which tasks are outsourced globally (ILO, 2024a; 2024b).

H. A worker-centric approach to AI

Achieving more inclusive and equitable technological development requires placing greater emphasis on workers and their professional growth. This involves broadening the focus of traditional goals of maximizing productivity and efficiency, to foster skill development and empower workers to adapt to and thrive in a rapidly evolving technological landscape. Increased automation in recent decades has contributed to higher productivity and lower prices, but the distribution of benefits has been largely in favour of capital. A worker-centric approach can contribute to an economic model that is socially and politically sustainable.

Translating technological progress into shared prosperity **requires labour-friendly policies**

Translating technological progress into shared prosperity requires labour-friendly policies in three stages: investments in education and skills, in pre-production; labour protection and worker empowerment, in production; and progressive taxation, in post-production. For example, such policies were implemented in the United States and Western Europe during the technological transitions in the early twentieth century and in the post-World War II era (Acemoglu and Johnson, 2023).

A basic step is to empower the workforce with digital literacy, reinforced through all stages of education and lifelong training systems that incorporate digital skills in curricula and are tailored to different occupations, to prepare for possible future transformations.

Technological advances continually perpetuate and amplify inequalities, and it is important to directly target inequality that arises during production (Rodrik and Stantcheva, 2021). With regard to jobs that are highly exposed to AI automation, Governments need to help workers transitioning to new occupations and tasks, through reskilling training and tailored social protection measures, for a smooth transition process. Workers whose jobs are subject to AI augmentation can also benefit from upskilling programmes to acquire new complementary competences, in order to make use of the latest technologies, and enhance their roles to include high-value tasks (United Nations and ILO, 2024).

To build trust and acceptance, workers should be actively involved in the design and implementation of AI tools. Job workflows and tasks should be rearranged to integrate AI effectively while addressing workers' needs and maintaining meaningful human roles.

Collaborative AI systems should empower rather than replace workers, foster job satisfaction and create opportunities for personal and professional growth.

Labour unions and worker representatives can play a key role in shaping such collaboration. During previous industrial revolutions, for example, unions helped set wages, working hours and safety standards. Similarly, they can provide a voice to workers worldwide, to direct AI towards a worker-centric transformation with a more equitable distribution of productivity gains between firms and workers (Oxfam International, 2024). Global union federations, such as UNI Global Union, are active in safeguarding workers' interests and human rights in the age of AI. For example, UNI Global Union has issued top 10 principles for ethical AI and negotiated over 50 global agreements with companies, to secure and enforce the rights of workers (UNI Global Union, 2017).

Setting a course for AI systems that enhance and complement human skills also depends on robust public policy. This should include increased R&D funding, strategic public procurement and targeted tax incentives for human-complementary AI technologies. Some countries have lower taxes for capital than for labour, thus encouraging technology for automation rather than for labour augmentation (Acemoglu et al., 2020). Consideration should be given to whether and how existing measures, such as tax rates, tax credits or deductions and accelerated depreciation, might incentivize technology and business development that is more labour-friendly and guide enterprises towards human-complementary AI technologies (Autor et al., 2022).

To prevent deskilling and mitigate the risk of brain drain to developed countries, it is essential for developing countries to improve labour market opportunities, provide continuous upskilling training and establish clear career development pathways. The private sector plays a leading role in AI, due to the concentration of resources, expertise and substantial financial investments within large multinational enterprises. Yet such companies can collaborate with Governments and academia on capacity-building initiatives that foster quality employment, such as placement programmes, apprenticeships and industry–academia research partnerships. Smaller developing countries may have less power to negotiate for socially beneficial public–private partnerships, but can still aim to maintain or improve standards and avoid a dangerous race to the bottom.

A worker-centric approach is part of a more general strategy to prepare for advances in AI, which is addressed in chapter III.

Inclusive AI requires putting **workers at the centre of technological development**

Annex II

Firm-level studies on AI productivity gains

Table 1
Summary of firm-level studies on AI productivity gains

Study	Economy (year)	Method	Measurement	Effect sizes and standard error	Remarks
Acemoglu et al. (2022)	United States (2019)	Controls for use of other technologies	Labour productivity	0.020 (0.016)	Adopters have higher labour productivity and lower labour shares
Alderucci et al. (2020)	United States (1997–2016)	Difference in difference	Labour productivity (revenue per worker)	0.068 (0.004)	Positive productivity effect in sales, negative in manufacturing
Babina et al. (2024)	United States (2010–2018)	Controls for firm and industry characteristics	Labour productivity	0.013 (0.022)	AI use linked to increased total sales, product innovation for large firms
			Total Factor Productivity (TFP)	0.003 (0.037)	
Bassetti et al. (2020)	Firms worldwide (2010–2016)	Generalized Methods of Moments (GMM)	TFP	0.032 (0.015)	Fintech and e-commerce firms
Benassi et al. (2022)	13 developed countries and China (2009–2014)	Fixed effects, controls for intangible assets and R&D among others	TFP	0.067 (0.040)	Panel of large manufacturing and services firms; AI development measured with patent stock.
Calvino and Fontanelli (2023a)	France (2019)	Controls for existing digitalization	Labour productivity (value added per worker)	All AI users: 0.074 (0.047)	Larger and younger firms tend to adopt AI more, but size gives no clear productivity advantage in using AI
				AI developers: 0.11 (0.053)	
Calvino and Fontanelli (2023b)	9 OECD countries (2017–2020)	Controls for existing digitalization and firm characteristics	Labour productivity	0.021 (0.052) (median effect in nine countries)	Productivity effect is greater for larger firms
Czarnitizki et al. (2023)	Germany (2018)	Controls for existing digitalization and instrumental variables	Labour productivity (sales per worker)	0.044 (0.02)	Sales and valued added of firms increase with greater use of AI

Study	Economy (year)	Method	Measurement	Effect sizes and standard error	Remarks
Damioli et al. (2021)	Firms worldwide (2000–2016)	GMM	Labour productivity	0.032 (0.011)	Productivity effect stronger in SMEs than large firms
Nucci et al. (2023)	Italy (2015–2018)	Propensity score matching with difference in difference	TFP	0.022 (0.006)	Productivity effect slightly stronger in small firms than large firms
Song and Cho (2023)	Republic of Korea (2017–2018)	Controls for existing digitalization and IV	Labour productivity (value added per worker)	All AI users: -0.026 (0.114) Multi-plant AI users: 0.151 (0.065)	Productivity effect comes from reducing performance gap between plants
Yang (2022)	Taiwan Province of China (2002–2018)	GMM and controls for firm characteristics	Labour productivity	0.079 (0.032)	Productivity effect greater for larger firms
			TFP	0.080 (0.024)	
Zhai and Liu (2023)	China (2006–2020)	Controls for firm and industry characteristics	TFP	0.089 (0.012)	Productivity effect greater for larger firms

Source: UNCTAD, based on cited sources.
Notes: Due to limitations in research design, most studies do not fully isolate AI productivity effects from firms' self-selection into AI use, that is, they cannot infer direct causality between AI use and firms' productivity increases and part of the reported productivity gains is likely driven by unobserved confounding firm characteristics, such as prior levels of productivity and willingness to adopt new technology. Many of the studies do not establish a statistically significant link between AI adoption in firms and productivity increases, for example Acemoglu et al. (2020) and Babina et al. (2024); some studies find no significant productivity effects for firms on average, but strong effects for particular types of firms, such as Song and Cho (2023), who identify zero productivity gains for the average firm in the Republic of Korea that uses AI, but find a productivity gain of 15 per cent for firms that use AI and own multiple plants. For the firms identified in this study and others, their uniquely large productivity gains may suggest within-firm mechanisms that are conducive to AI productivity effects; for example, Song and Cho (2023) show that the productivity increase in multi-plant firms originates from the creation of inter-plant channels that enable the narrowing of performance gaps between plants.

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