DIGITAL PROGRESS AND TRENDS REPORT 2025

Case Study 2

HARNESSING AI FOR EFFICIENCY

Transforming Agriculture and Energy Sectors

WORLD BANK GROUP

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Antonio Martins Neto

WORLD BANK GROUP

1818 H Street NW, Washington DC 20433
Telephone: 202-473-1000
Internet: www.worldbank.org

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Abbreviations

ABDI	Agência Brasileira de Desenvolvimento Industrial (Brazilian Agency for Industrial Development)
AI	artificial intelligence
CV	computer vision
GenAI	generative artificial intelligence
GHG	greenhouse gas
HICs	high-income countries
HVAC	heating, ventilation, and air conditioning
IoT	Internet of Things
IPM	integrated pest management
LAC	Latin America and the Caribbean
LICs	low-income countries
LLMs	large language models
ML	machine learning
PV	photovoltaic
R&D	research and development
ROI	return on investment
SKU	stock-keeping unit
SMS	short message service
SSA	Sub-Saharan Africa
XAI	explainable AI

Introduction

This case study, which complements the *Digital Progress and Trends Report 2025,* assesses the use of artificial intelligence (AI) in the agricultural and energy sectors, exemplifying AI applications and evaluating the main drivers of and barriers to AI adoption. AI has strong potential to improve efficiency across sectors by optimizing operations and enhancing decision-making. In energy production and distribution, AI is already streamlining processes and supporting the integration of renewable sources. In agriculture, it helps reduce inefficiencies by minimizing fertilizer use and water consumption. Beyond these efficiency gains, AI's adaptive learning and capacity for knowledge generation can fundamentally transform production systems and decision-making, unlocking even greater long-term value.

The agriculture and energy sectors stand at the nexus of sustainability and economic development, making them ideal candidates for exploring the transformative potential of AI. Agriculture accounts for about one-third of greenhouse gas emissions globally, primarily through methane emissions from livestock, deforestation for farmland, and the overuse of synthetic fertilizers. Increasing food demand because of global population growth places immense pressure on natural resources. Farmers need to produce more with less, requiring solutions that optimize irrigation, fertilization, and pest control while minimizing environmental degradation.

Meanwhile, the energy sector, especially renewable energy, stands at the heart of global efforts to combat climate change and transition to a sustainable, low-carbon economy. As renewable energy sources such as solar and wind become more prevalent, their intermittent nature presents a significant challenge for maintaining a reliable energy supply. AI can offer innovative solutions to these challenges, allowing the use of clean energy at scale.

This case study provides a series of insights to make AI adoption more inclusive, especially in developing countries, where the diffusion of AI is often hindered by systemic issues such as inadequate digital infrastructure, a dearth of data, limited digital skills, weak institutional frameworks, and insufficient regulatory mechanisms. Here I present an overview of AI applications in the agriculture and energy sectors, which are real-world examples of how AI is being leveraged to address sector-specific challenges.

By analyzing these examples, this case study identifies the early impact of AI, as well as common and sector-specific barriers to AI adoption, offering actionable insights for policy makers and practitioners aiming to harness AI for sustainable development. For instance, in agriculture,

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smallholder farmers often lack access to digital infrastructure and financial resources, impeding their access to more advanced digital technologies such as AI. In the energy sector, regulatory uncertainty and the high costs of upgrading legacy infrastructure hinder the deployment of AI solutions. I also offer a series of policies and insights to tackle these barriers and bottlenecks that may hinder the use of AI in each sector.

AI in the Agriculture Sector

Introduction

The agri-food system is vital for economic growth, poverty reduction, food security, nutrition, and employment. However, it is also a primary contributor to greenhouse gas (GHG) emissions and environmental degradation. Evidence suggests that a 1 percent increase in agricultural gross domestic product reduces poverty by more than 1 percent on average (Christiaensen and Martin 2018). In Sub-Saharan Africa (SSA), where agriculture employs nearly 70 percent of the population, it serves as a key tool for poverty alleviation. Nevertheless, from an environmental perspective, agri-food systems, spanning from crops and livestock production to food processing and disposal, account for roughly one-third of global GHG emissions.

In addition, agriculture consumes 70 percent of the world's freshwater resources, with an estimated 60 percent lost because of inefficient irrigation. Feeding a rapidly growing population without exacerbating environmental degradation is a critical challenge, and AI is emerging as a powerful tool to transform agriculture into a more productive and sustainable sector.[1]

Across the agricultural value chain—encompassing seed production, harvesting, processing, and retail—AI optimizes processes, reduces resource use, and minimizes environmental impacts. Figure CS2.1 depicts this complex agricultural value chain and provides some examples of the use of AI in each of the steps.

For instance, in the production processes, AI enhances critical activities such as planting, irrigation, and harvesting by leveraging data on soil and environmental conditions. This ensures better resource utilization, higher yields, and a more sustainable approach to agriculture. As agricultural products move through trading and warehousing stages, AI adds value by optimizing logistics and storage. AI algorithms analyze factors such as weather and traffic to streamline transportation routes, reducing delivery times and operational costs. In warehouses, AI systems monitor critical storage parameters such as temperature and humidity in real time, ensuring the optimal preservation of crops. By reducing post-harvest losses, these technologies address a critical inefficiency in the agricultural supply chain, enhancing overall productivity and minimizing waste. Further, AI significantly improves supply chain operations and inventory management at the processing and wholesale and

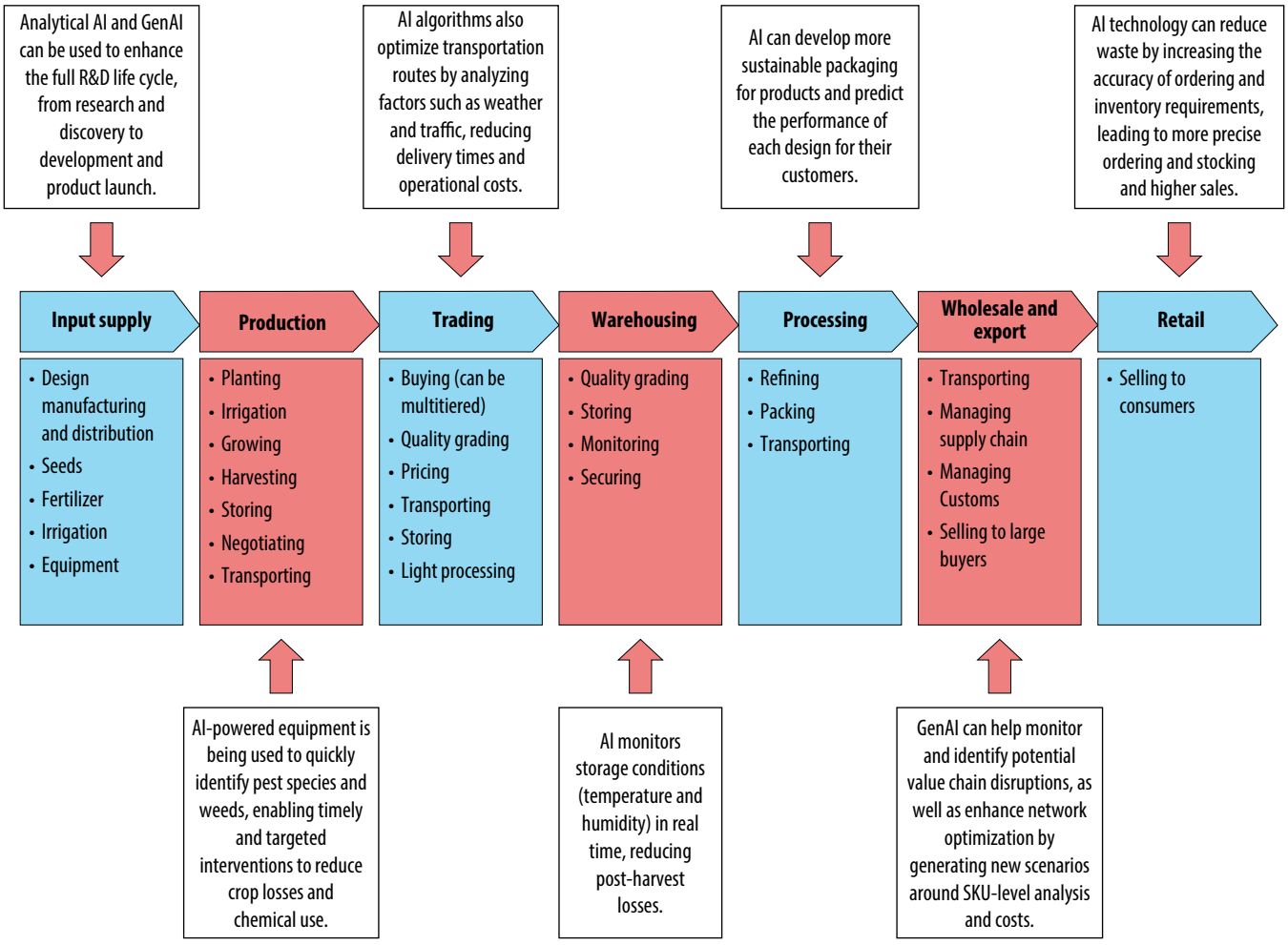
1 Other digital technologies—such as remote sensing, precision agriculture tools, and Internet of Things (IoT)–based monitoring systems—have also demonstrated strong potential to boost productivity and advance sustainability in agriculture (refer to, for instance, Kim et al. 2020). In many cases, these technologies are integrated with AI to enhance data analysis and decision-making, unlocking new opportunities for innovation across the sector. Although this case study focuses specifically on AI, it is important to acknowledge that a broader set of digital tools is already delivering significant benefits in agricultural contexts.

export stages. It identifies potential disruptions in the value chain, generating predictive scenarios for more effective decision-making. Finally, at the retail level, AI increases the accuracy of ordering and inventory management, aligning supply with consumer demand, reducing waste, enhancing stocking practices, and boosting overall sales (Javaid et al. 2023).

AI is revolutionizing animal husbandry in the livestock sector by improving efficiency, enhancing animal welfare, and mitigating environmental impacts. Livestock production is a significant driver of global GHG emissions, accounting for approximately 14.5 percent of human-induced emissions, according to the FAO (2013). A substantial share of these emissions originates from enteric fermentation, a digestive process in ruminants that releases methane—a GHG with a global warming potential 25 times greater than carbon dioxide. AI-driven solutions are emerging as powerful tools to address these challenges, offering innovative approaches to monitoring livestock health, optimizing feeding strategies, and reducing methane emissions.

The following sections explore specific AI applications that address key challenges in both crop and livestock production, showcasing how advanced technologies enhance efficiency, sustainability, and resilience in agriculture.

FIGURE CS2.1 Use of AI across the agriculture value chain



Source: Original figure for this publication.
Note: AI = artificial intelligence; GenAI = generative artificial intelligence; R&D = research and development; SKU = stock-keeping unit.

Addressing gaps in information asymmetry

Farmers in many developing countries often lack the necessary support, largely because of the limited availability of agricultural extension agents. Although the recommended ratio of extension agents to farmers is 1:750, the ratio in Ghana is a staggering 1:10,000 (Muhideen 2023). The ratio of agents to farmers is also low in Kenya (1:950) and Uganda (1:2,500) (Sones et al. 2015), leaving most farmers without access to expert guidance. Without adequate extension services, farmers may struggle to adopt improved (sustainable) farming techniques and are less equipped to adapt to changing weather patterns, soil degradation, or market fluctuations.

Digital technologies have already proven effective in bridging this divide by reducing the cost of information dissemination and improving farming outcomes. Programs such as Digital Green use short message service (SMS) reminders and video-based learning to enhance extension services, significantly affecting farming practices. For instance, research by Larochelle et al. (2017) found that text messages significantly improved farmers' knowledge and adoption of integrated pest management (IPM) techniques among potato growers in Ecuador—an overall increase in the overall knowledge of IPM by 18.4 percentage points and in the adoption of IPM practices by 6.7 percentage points. Similarly, Van Campenhout, Spielman, and Lecoutere (2021) demonstrated that SMS reminders boosted maize yields by 10.5 percent in Uganda, and Casaburi et al. (2014) noted an 11.5 percent increase in sugarcane yields in Kenya. Furthermore, Abate et al. (2023) showed that video-mediated extension services significantly enhance farmers' uptake of recommended technologies, improving knowledge and productivity.

Generative AI (GenAI) represents the next frontier in scaling these services, offering greater effectiveness and reach. For example, Silva et al. (2023) demonstrated that GPT-4 achieved 93 percent accuracy on agronomist certification exams, outperforming earlier models and even human participants in certain scenarios. Building on these capabilities, several new apps are using AI to help farmers' decision-making. AI systems such as Digital Green's Farmer.Chat exemplify how these technologies are transforming extension services, leveraging natural language processing and machine learning (ML) to support public extension agents with localized advisories, guiding farmers on planting schedules, pest control, and resource allocation, directly improving yields and incomes. AI chatbots go beyond traditional digital tools such as SMS and videos by enabling more intuitive and interactive communication with farmers. They can quickly interpret farmers' questions and provide tailored, actionable advice in real time.

By leveraging large language models (LLMs) fine-tuned on agricultural data, Farmer.Chat can accurately interpret farmers' queries and provide contextually relevant insights. This AI-driven approach has the potential to dramatically reduce the cost of extension services—from $35.00 per farmer to just $0.35—making expert agricultural advice far more accessible and scalable. Although the impact on farmers' yields and costs has not been empirically tested, anecdotal evidence suggests a positive impact on yields (Digital Green Team 2024).

Other apps include Opportunity International's UlangiziAI, which delivers extension services in English and Chichewa, the native language of about half of Malawi's more than 20 million people. Moreover, the International Labour Organization and the Department of Huila, Colombia, have launched a pilot AI tool, AgroasesorIA, to support coffee producers in improving productivity and working conditions. The platform, accessed via WhatsApp, provides personalized advice on labor formalization, business management, occupational health and safety, and sustainable agricultural

practices. Targeting at least 700 producers over 6 months, the tool aims to foster the transition from informal to formal economies while enhancing the competitiveness of Huila's coffee sector (ILO 2024).

The Saagu Baagu initiative in India, in partnership with Digital Green, demonstrates the potential of integrating AI to enhance agricultural productivity and farmer incomes. This initiative, implemented in the Khammam district, leverages Telugu-language chatbot advisory services, AI-powered quality assessment, soil testing technologies, and a digital marketplace to optimize chili farming. Over an 18-month pilot covering three crop cycles, farmers experienced a 21 percent increase in chili yield per acre, along with 9 percent and 5 percent reductions in pesticide and fertilizer use, respectively. Notably, these improvements translated into substantial economic gains, with net income per acre doubling to $800 per cycle, and improved quality standards resulted in an 8 percent increase in unit prices (Jurgens and Kaushik 2024).

However, the adoption of chatbots in agriculture remains in its early stages, with most pilot programs reaching only a small fraction of the farming population. For instance, Farmer.Chat, one of the largest initiatives, has been deployed in Ethiopia, India, Kenya, and Nigeria. Despite its broad geographic reach, the program has so far engaged only 15,000 farmers—a tiny share compared with the hundreds of millions of farmers across these countries.

The effectiveness of AI in agriculture hinges on the quality, quantity, and diversity of the data used to train these models. For example, a study in Nigeria revealed that ChatGPT-generated recommendations for cassava weed control were often too generic or impractical for resource-constrained smallholders, underscoring the risks of directly relying on such tools without localization. Other anecdotal evidence highlights that ChatGPT struggles to provide agronomic advice in multiple languages, further limiting its usability for farmers who rely on native languages (Tzachor et al. 2023). These challenges illustrate the importance of designing AI systems that account for the unique needs, language, and constraints of smallholder farmers, especially in developing economies where precise, actionable guidance is crucial.

One major concern is that most LLMs may be trained on data that underrepresent the knowledge and agricultural conditions of developing economies. Agriculture is inherently local, and for GenAI to be truly effective, it must rely on specific, localized data. Factors such as climate, soil composition, crop diseases, and farming practices vary widely across regions, making context-specific information essential for accurate and actionable agricultural insights. Farmer.Chat (Singh et al. 2024) is trained on proprietary Digital Green data, whereas Kissan GPT (Kissan 2025) leverages region-specific knowledge from institutions such as the Indian Kisan Call Centre and inputs from agriculture experts to improve the relevance and reliability of chatbot-generated advice. Integrating local data and agricultural specialists enabled these tools to better support smallholders. A deep integration into agriculture can only be successful if the underlying data are location specific, based on real observations, and kept up to date (Kuska, Wahabzada, and Paulus 2024).

The use of these AI chatbots also entails other challenges, including hallucination, language barriers, and basic digital literacy. *Hallucination,* or the generation of inaccurate or misleading information, can misguide farmers in making critical decisions about crops, irrigation, or pest control. In addition, literacy and basic digital literacy remain a significant hurdle among farmers in developing countries, making it difficult for them to effectively interact with and trust AI-based advisory systems. Language barriers further complicate accessibility, because many AI models are primarily trained in dominant global languages and may not fully support local dialects or technical agricultural terms. To overcome

some of these barriers, Farmer.Chat has focused on voice support in multiple languages and has deployed its application on popular messaging apps, such as WhatsApp and Telegram, reducing the barriers to entry by leveraging familiar communication tools (Singh et al. 2024).

Increasing efficiency in pest control

Pest and disease management is another critical area in which AI is transforming agricultural practices. Pests and diseases are responsible for the loss of up to 40 percent of global crop yields annually, posing a severe threat to food security. Traditional methods of pest control often rely on indiscriminate pesticide use, which is both costly and environmentally harmful. Regenerative agriculture prioritizes ecological approaches to pest control, including the use of beneficial insects and the strengthening of plant immunity. Sophisticated AI tools offer more efficient and sustainable solutions by analyzing historical data on weather patterns, pest infestation rates, and pest behavior to forecast when and where a pest outbreak is likely to occur. This information allows farmers to proactively take measures to prevent or control pest infestations, promoting a healthier soil environment. For instance, it can guide farmers in implementing regenerative practices such as cover cropping, no-till farming, and crop rotation, tailored to specific soil conditions.

Many start-ups have started to develop AI applications to optimize pesticide use. An interesting case is offered by the Israeli company Taranis, which uses advanced aerial imagery captured by drones and satellites to provide high-resolution visual data on fields. These data are processed using deep-learning algorithms and AI-powered analytics to detect and diagnose crop diseases, pests, nutrient deficiencies, and other potential issues at an early stage. Through ML and advanced analytics, the platform generates precise recommendations for fertilization, irrigation, and pest control tailored to the specific needs of individual crops and fields.

One key advantage of integrating AI into this process is its ability to rapidly analyze and interpret the vast amounts of data collected by drones and other IoT devices. This significantly reduces the need for manual editing, organization, and analysis, allowing farmers to obtain actionable insights in a fraction of the time as traditional methods. The company's latest application generates automated weed reports, builds performance zones for accurate herbicide spraying, and provides automatic prescriptions to be applied per detection. The company highlights the case of a soybean farm in Whitewater, Wisconsin, United States, where early detection of brown stem rot prevented the loss of $37,000 of crops (Taranis 2024a). Another example highlights that tar spot was identified in 41 percent of a cornfield in Bourbon, Indiana, United States, posing a significant threat to yields. To mitigate further damage, a fungicide application costing $40–$50 per acre was recommended, with a potential retailer profit of $12 per acre (Taranis 2024b). Across affected acres, this translates to an $86,280 profit opportunity for program-enrolled growers.

Many developing countries are also using and developing these technologies. In Brazil, the Brazilian Agency for Industrial Development (ABDI) has driven innovation in pest control through its Agro 4.0 program, which promotes the use of AI, IoT devices, and data analytics in agriculture. Through partnerships with private sector companies, research institutions, and farmers, ABDI has driven the adoption of transformative technologies to address critical challenges, including resource efficiency, pest management, and production forecasting. In a project involving AI-powered pest and disease management, advanced monitoring systems analyze real-time data from IoT devices—such as sensors and drones—to detect early signs of infestations. On a soybean farm in the state of Mato Grosso, the system reduced pesticide use by 30 percent, offering significant cost savings and minimizing

environmental impacts. In addition to reducing chemical inputs, the system enhanced yield predictions, enabling more efficient planning of harvests and market logistics (Dias et al. 2023).

Although these technologies pose significant benefits, the high cost associated with the use of advanced aerial imagery captured by drones poses enormous challenges for small farmers in developing countries. With these concerns in mind, other technologies aim to democratize the use of AI by reducing its cost. One notable example is Trapview, a device that uses pheromones to attract pests, photographs them, and identifies their species with the help of advanced AI algorithms. Trapview monitors more than 60 pest species, including the codling moth, which affects apples, and the cotton bollworm, which damages crops such as lettuce and tomatoes. Once pests are identified, the system leverages weather and location data to predict their likely spread and notifies farmers via an app. Trapview reports a 5 percent improvement in yields and quality, along with overall cost savings of €118 million for its users.

The Tumaini App, developed by Alliance Bioversity and CIAT, uses advanced image recognition technology to detect symptoms of major diseases such as Fusarium wilt and Sigatoka Negra and pests such as the banana weevil. Initially tailored for banana crops and recently adapted for common beans, the app now addresses five major bean diseases, including angular leaf spot and common bean mosaic virus, with a 90 percent success rate (Alliance Biodiversity and CIAT n.d.). A key feature of the app is that it can be used offline, facilitating its use by farmers in remote areas where internet connection is unavailable.

Using better irrigation practices

Irrigation faces increasing challenges as climate change intensifies pressure on water resources worldwide. Rising temperatures, shifting precipitation patterns, and prolonged droughts are exacerbating water scarcity, particularly in regions already prone to arid conditions. At the same time, population growth and changing dietary preferences are increasing the demand for water-intensive crops. In this context, inefficient irrigation practices can lead to significant water wastage, soil degradation, and declining agricultural productivity. Addressing these challenges requires innovative solutions that balance the competing demands of agricultural productivity, water conservation, and environmental protection.

Identifying areas that are being overwatered or underwatered is key. Yet, farm-level processes associated with irrigation rate and timing are influenced by several factors, including the type of crop, the volume of water available and required, water resource management, crop or pasture yield, water cost, and environmental impact, among others (Wei et al. 2024). Analyzing this enormous amount of data is challenging, such that AI-powered tools are emerging to enhance water use efficiency in agriculture. These technologies use advanced algorithms, sensor data, and ML models to optimize irrigation schedules, predict water needs, and minimize waste. By providing precise, real-time recommendations to farmers, AI can help reduce overirrigation and ensure that crops receive the exact amount of water required for optimal growth.

In Brazil, the Agro 4.0 program spearheaded by ABDI has supported innovations in precision irrigation. On a coffee plantation in Minas Gerais, AI-powered soil sensors monitored moisture levels and adjusted irrigation schedules accordingly. This resulted in a 35 percent reduction in water usage while maintaining robust crop health and high yields (Dias et al. 2023).

Another notable example is offered by the start-up CropX. By combining AI with soil sensor data, the company provides farmers with detailed insights into the precise amount of water and nutrients their crops need. In the Middle East, banana farmers using CropX's solutions saw a 27 percent increase in yields while reducing fertilizer use by approximately 15 percent (CropX 2022).

AI-driven irrigation solutions have significantly enhanced water efficiency across Latin America, enabling substantial water savings. Argentinian start-up Kilimo connects farmers willing to use technology to make water use more efficient with private companies who have made water-positive commitments and are willing to pay for those savings. Also, in Brazil, Amazon Web Services has announced a collaboration with Kilimo to tackle water scarcity around the Tietê River in São Paulo. The initiative leverages AI to calculate water consumption, monitor soil quality, and provide smart irrigation recommendations to participating farmers. This innovative approach is expected to save approximately 200 million liters of water annually, helping preserve one of São Paulo's most historically and economically significant rivers (DCD 2024). In addition to Brazil, Kilimo has also established projects in Argentina, Chile, Guatemala, Mexico, Peru, and Uruguay, which has saved 72 cubic meters (19 billion US gallons) of water in the past 2 years (Stones, Malleret, and Pinnow 2024).

Reducing food waste in restaurants and supermarkets

The agri-food system has many inefficiencies that result in substantial food waste. According to estimates, approximately 8 percent of global GHG emissions are from food waste (FAO 2020). Supermarkets are major contributors to this issue; inaccurate inventory decisions often lead to overstocking and spoilage. Afresh, an AI-driven inventory management platform, helps retailers optimize their inventory with remarkable results. The platform leverages ML, demand forecasting, and automation to ensure stores maintain the right amount of perishable goods while minimizing losses due to spoilage. Algorithms analyze historical sales data, local events, seasonality, and other external factors (for example, weather conditions, holidays, promotions) to predict demand more accurately than traditional rule-based systems. The company states that the methodology resulted in a more than 25 percent reduction in shrink, an 80 percent decrease in stockouts, and an additional 2 days of post-sale shelf life (Afresh 2024).

In retail, the Wasteless start-up uses dynamic pricing to reduce food waste. Using thousands of data points, including historical sales data, customer behavior, inventory levels, and expiration dates, Wasteless AI calculates the precise price to maximize supermarkets' revenue and minimize food waste. According to their estimates, their solution results in a 50 percent reduction in food waste and a 20 percent increase in revenues (Wasteless 2025).

The highest carbon footprint from food waste, however, occurs during the consumption phase, accounting for 37 percent of total emissions. One innovative approach to reducing waste in this phase involves AI-powered solutions in restaurants. Winnow Solutions, a UK-based company, has developed a digital food waste tracking system that uses AI and image classification algorithms to automatically identify wasted food items, supplementing weight-based measurements for greater accuracy (FAO 2015). In a quasi-experimental study involving the staggered implementation of the system across approximately 900 kitchens (Nu, Belavina, and Girotra 2024), researchers found that using Winnow Classic—a system requiring manual input of wasted items—enabled commercial kitchens to reduce food waste by 29 percent within 3 months. Upgrading to Winnow Vision, which uses computer vision (CV) to automate waste classification, led to an additional 30 percent reduction in food waste per year.

Tackling GHG emissions in the livestock sector

The livestock sector is a major contributor to global GHG emissions, responsible for approximately 14.5 percent of total emissions (FAO 2013). A significant portion of these emissions comes from enteric methane, a potent GHG that has 25 times more impact than carbon dioxide. Methane is predominantly released through cow burps, a natural digestive process in ruminants. AI can help reduce emissions from livestock, mainly through two processes.

First, AI technologies are transforming livestock management by streamlining cattle identification, enabling early disease detection, and optimizing feeding practices. Traditional identification methods—such as ear tags—are labor intensive and prone to human error. Similarly, health monitoring typically requires veterinarians to inspect animals individually, a process that becomes impractical on large farms. This limitation often leads to missed signs of disease and preventable livestock losses.

AI-powered systems, particularly those using CV, offer an effective alternative (Kumari 2023). CV systems equipped with cameras and advanced image-processing algorithms can identify, track, and monitor animals with minimal human intervention (Menezes et al. 2024). When enhanced by deep-learning techniques, these systems can recognize individual animals, analyze behavior, and detect early signs of illness by monitoring daily movements and interactions. For example, a sudden decrease in activity or deviation from typical feeding behavior may signal health issues, prompting timely intervention. Beyond health monitoring, AI also supports precision feeding. By analyzing data on animal health, diet, and behavior, AI systems can tailor feeding regimens to each animal's nutritional needs, reducing feed waste and optimizing nutrient intake. This targeted approach not only improves animal health and farm productivity but also contributes to environmental sustainability (Sajid 2024).

Second, AI is helping scientists search for methane inhibitors, potentially mitigating livestock emissions. Certain compound molecules are known to inhibit methane production, and advanced AI-driven molecular simulations are enabling researchers to identify novel inhibitors based on the properties of previously studied compounds. For example, researchers from the US Department of Agriculture's Agricultural Research Service and Iowa State University have successfully demonstrated the use of GenAI to discover compounds that reduce methane emissions in cows. Early studies estimate that incorporating such AI-identified inhibitors into livestock feed could reduce methane emissions by up to 30 percent while improving feed efficiency.

Understanding sector-specific barriers to AI adoption in the agricultural sector and policy insights

Despite the potential benefits, AI adoption in agriculture is currently very low, even in advanced countries, for several reasons. In the United States, the Business Trends and Outlook Survey conducted from December 2023 to early 2024 found that fewer than 2 percent of agricultural firms used any type of AI (Bonney et al. 2024). The cost-effectiveness of AI adoption in agriculture is reduced for several reasons, such as uncertain and variable return on investment (ROI) depending on farm size, conditions, crop type, high upfront costs in purchasing AI-powered equipment and solutions, data management complexity, high maintenance and support costs, and steep learning curves for farmers (US GAO 2024).

Developing countries face significantly steeper hurdles in adopting AI in agriculture than advanced countries. The challenges stem from various factors, notably infrastructural limitations and

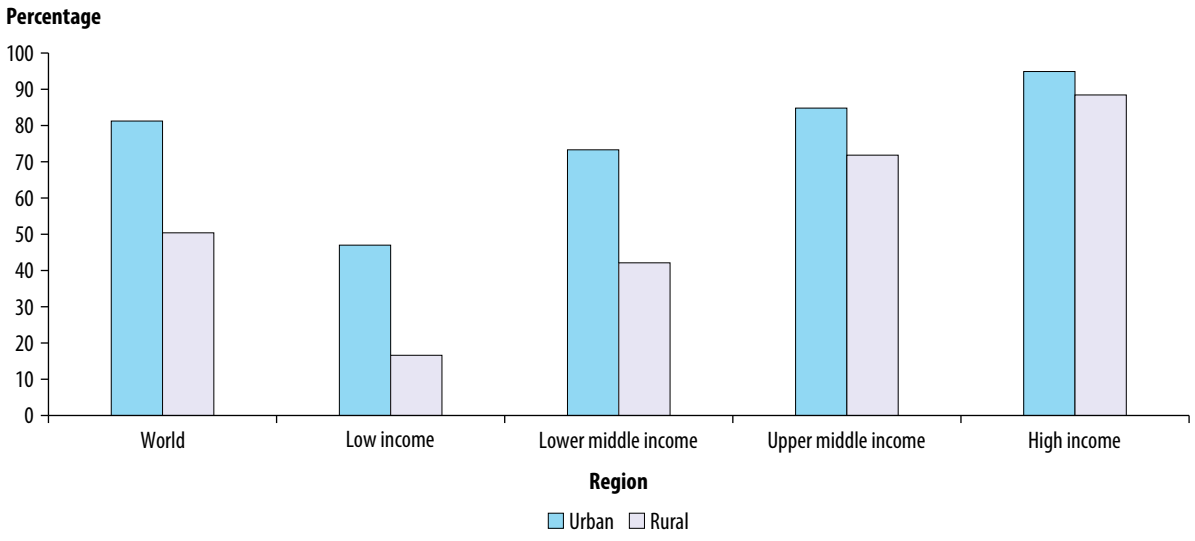
socioeconomic realities. The agricultural sector is highly mechanized in advanced economies and is dominated by large-scale farms. Conversely, developing countries frequently rely on traditional, labor-intensive practices, with small-scale subsistence farming dominating. Limited access to modern energy, irrigation, transportation, digital infrastructure, and equipment results in greater reliance on manual labor. Data constraints and skills gaps further hinder AI adoption.

Digital technologies differ in terms of their connectivity needs. Although mobile payment wallets can readily be used with limited internet access, the use of more sophisticated technologies such as farm robotics, production and forecasting optimization, and precision agriculture rely on reliable and high-speed internet. In that sense, a major barrier is the limited connectivity in rural areas, where much of the agricultural activity takes place. Poor internet and mobile network coverage make deploying IoT devices or accessing AI-based advisory platforms that rely on real-time data challenging.

Figure CS2.2 presents the percentage of individuals using the internet across different country income categories. Two clear patterns emerge. On the one hand, moving from low-income countries (LICs) to high-income countries (HICs), internet usage increases. More than 80 percent of individuals in HICs have access to the internet, compared with less than 40 percent in LICs. On the other hand, this gap in overall usage is accompanied by a gap between urban and rural areas. In particular, low-income economies face a much larger urban-rural gap than high-income economies.

One significant driver of the rural-urban digital divide is internet cost. A recent survey conducted in Latin America and the Caribbean (LAC) region revealed that 50 percent of individuals not connected to the internet via fixed or mobile broadband identified high cost as the primary barrier to access. This challenge is acute for households in rural areas, where farmers and other unconnected individuals often face compounded difficulties because of limited financial resources and low asset levels (Srinivasan et al. 2022).

FIGURE CS2.2 Percentage of individuals using the internet in urban and rural areas



Source: ITU World Telecommunication/ICT Indicators database (https://www.itu.int/en/ITU-D/Statistics/Pages/publications/wtid.aspx).

In addition, rural areas are also affected by poorer internet services. For instance, reliance on mobile devices rather than personal computers in rural regions reflects the limited access to high-speed internet. Even in advanced economies such as the United States, rural areas have significantly slower internet access, with 39 percent lacking access to broadband of 25/4 megabits per second, compared with only 4 percent in urban areas (Broom 2023). The compounded impact of these barriers leaves approximately 77 million rural inhabitants across LAC without access to significant connectivity standards (Ziegler et al. 2020).[2]

Expanding mobile-based solutions, providing subsidies for rural internet access and devices, and fostering community internet hubs can help address these challenges in the short term. Over the long term, fostering competition in the sector and investing in broadband infrastructure, including first-, middle- and last-mile networks, will be essential to closing the rural-urban digital divide.

Affordability remains a significant barrier to the widespread adoption of advanced AI technologies in agriculture. Although chatbots offer a more accessible entry point, many AI-driven solutions require substantial upfront investments, making them less realistic for small- and medium-size farms. For instance, implementing precision agriculture tools—such as sensors, drones, and specialized software—can cost between $30,000 and $300,000, depending on the scale and complexity of the system (Sharma 2024). In a survey of more than 5,000 farmers across different regions, the high cost of agricultural technology is the major barrier to adoption, with 47 percent of farmers citing it as a top concern (Fiocco et al. 2023).

High costs are further exacerbated by farmers' uncertainty about the ROI. In the same survey, 30 percent of farmers identified unclear ROI as a major barrier to adoption. Offering financial incentives, subsidies, and microfinancing options can provide short-term relief while fostering AI-as-a-service models and encouraging economies of scale through cooperative networks, which will help lower costs in the long run.

The cost of digital goods is particularly high in Africa, further impeding the investment in advanced technologies. A recent report from the International Finance Corporation (Cruz 2024) shows that digital goods in Africa are costly, both in absolute terms and relative to income levels. Machinery and equipment—whether digital or analog—are priced 35–39 percent higher in SSA and 13–15 percent higher in North Africa than in the United States. In addition, essential digital tools, including software and sector-specific technologies such as agricultural machinery, come at a premium, further constraining business adoption and growth. Implementing policies to increase market competition, reduce import tariffs on digital goods, and streamline cross-border trade regulations can help lower costs and improve access to these essential technologies.

Even the implementation of chatbots in agriculture faces multiple challenges, with localization and data access and quality being significant barriers. AI-powered chatbots' effectiveness depends on their ability to accommodate diverse linguistic and agricultural circumstances. In many countries, farmers speak local dialects that may not be well supported by existing chatbot models, limiting accessibility and usability. Moreover, the accuracy of chatbot recommendations depends on localized data, including soil conditions, weather patterns, and crop cycles, which may not always be readily available or well-integrated into AI systems.

2 In addition to affordability and quality-related issues, other infrastructure-related challenges such as power outages also affect those in rural areas. In LAC, nearly 40 percent of respondents with access to both fixed and mobile broadband reported experiencing frequent power disruptions, with more pronounced concerns in rural areas (Srinivasan et al. 2022).

Without proper data to train these models, chatbots risk providing generic or inaccurate advice, reducing farmer trust and adoption. Agricultural data, ranging from weather conditions to market prices, are often collected and stored in fragmented systems, owned by a mix of public agencies, private firms, and farmers themselves. Without common standards for data collection, sharing, and privacy, this fragmentation limits interoperability, reduces trust, and impedes the development of scalable digital solutions.

Developing localized AI models and partnering with local agricultural research centers can help mitigate these issues in the short term, and establishing national agricultural data repositories and open-access data sets can enhance long-term accessibility and reliability. A robust governance framework would help ensure data quality, promote responsible data sharing, and protect farmers' rights, particularly in developing countries, where regulatory oversight is often weak. By creating clear rules and standards, such frameworks can support AI adoption and ensure that the best information is readily available for farmers.

Cultural barriers may also play a significant role in shaping the adoption of advanced technologies in agriculture, often serving as hidden obstacles to progress. These barriers include deeply ingrained traditions, generational attitudes toward farming practices, and skepticism toward innovation. In many agricultural communities, especially in developing economies, farming practices are passed down through generations and are rooted in time-tested methods. Although these practices have ensured resilience, they can also foster resistance to change, because adopting new technologies might be perceived as abandoning traditional ways. This resistance is further compounded when the benefits of the technology are not immediately evident or easily measurable. Engaging local experts and partnering with local agricultural extension services can help bridge this gap in the short term, and integrating AI education into agricultural extension programs will foster long-term acceptance.

The agricultural workforce in many regions is aging (IFAD 2019), with younger generations increasingly seeking employment in urban centers. Older farmers often have less exposure to new technologies and may lack the digital literacy needed to effectively integrate innovations such as AI, precision farming tools, or data-driven decision-making platforms into their operations. This generational gap creates a dual challenge: Younger, tech-savvy individuals are exiting the agricultural sector, and the remaining older farmers are less inclined to adopt unfamiliar and complex technologies.

Cultural barriers also intersect with trust and social dynamics. Farmers may be hesitant to adopt technologies introduced by external factors, such as governments, corporations, or international organizations, particularly if they perceive these entities as lacking an understanding of local contexts. This skepticism can hinder the diffusion of innovations, even when the technologies have clear potential to improve productivity and profitability. Peer influence plays a crucial role in this context; farmers are more likely to adopt new tools if they see successful examples among their neighbors or within their community. However, cultural norms of risk aversion can delay this process, because individual farmers may be reluctant to act as early adopters.

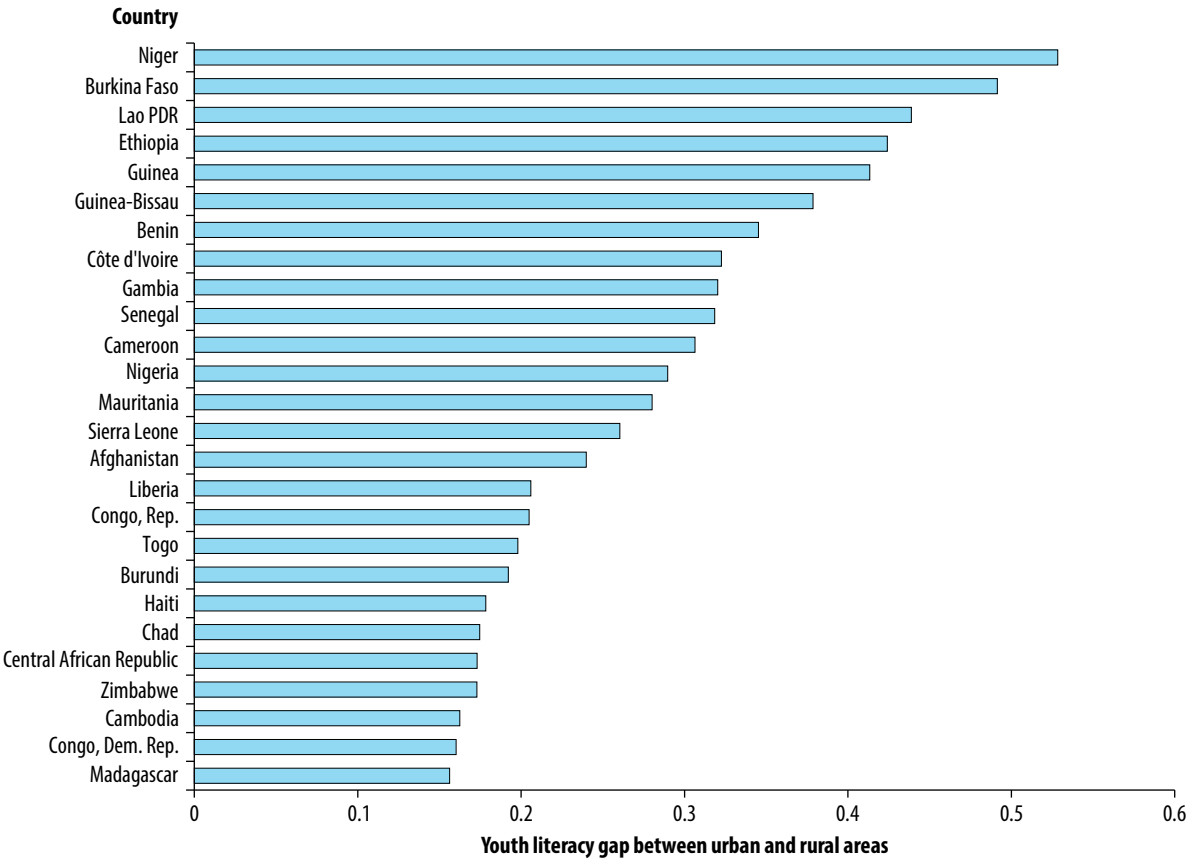
Challenges in the agricultural sector are exacerbated by low levels of educational attainment in rural areas, which hinder the development of skills needed to modernize farming practices and boost productivity. Research consistently shows a strong correlation between agricultural productivity and human capital. However, inadequate education limits farmers' ability to adopt modern technologies and implement more efficient agricultural methods. For example, in Thailand, only 32 percent of rural farm workers had completed at least grade 9 as of 2020, a significantly lower

percentage than that of their non-farm counterparts (World Bank 2022). Similarly, in Senegal, just 37 percent of rural farmers are literate, impeding their capacity to use new technologies and engage in higher-value activities (D'Alessandro et al. 2015).

This pattern is evident across many developing countries, where rural households often face severe deficits in human capital, perpetuating poverty and curbing agricultural progress. For instance, figure CS2.3 illustrates the youth literacy gap between urban and rural areas in various developing economies. In some countries, such as Burkina Faso, Ethiopia, the Lao People's Democratic Republic, and Niger, the gap exceeds 40 percent—an alarming disparity, especially considering the already low youth literacy rates in these economies.

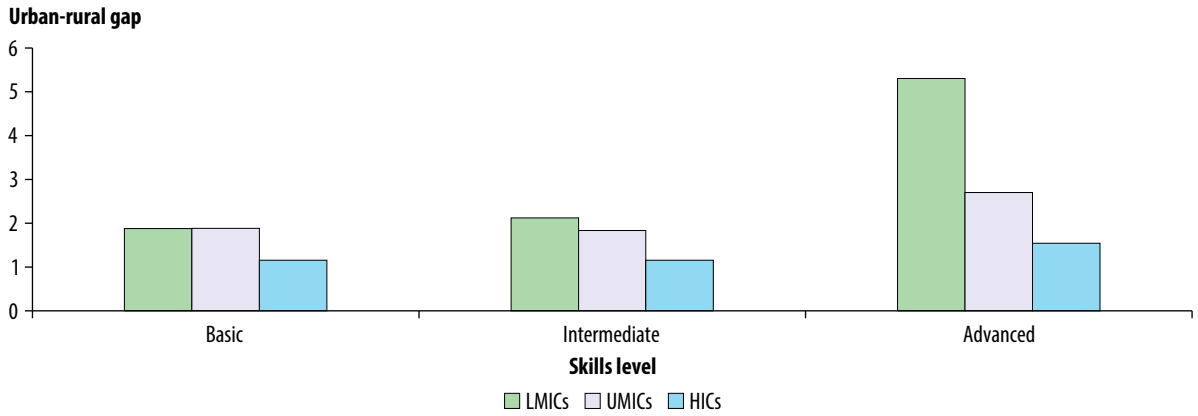
The educational gap becomes even more pronounced when considering digital skills. These skills span a broad spectrum, from basic competencies—such as the ability to use simple technologies such as chatbots designed to support agricultural extension programs—to advanced technical skills required to develop and maintain sophisticated AI systems. This digital skills gap is acute in less-developed economies, with urban populations significantly outpacing their rural counterparts in digital literacy and proficiency (refer to figure CS2.4). Not only does this gap hinder rural communities from fully benefiting from AI-driven solutions, it also exacerbates existing inequalities by preventing these communities from participating in the digital economy.

FIGURE CS2.3 Youth literacy gap between urban and rural areas for select countries



Source: Original figure for this publication using data from UNESCO Institute for Statistics (2025).

FIGURE CS2.4 Skills gap between urban and rural areas across income groups



Source: Original figure for this publication using author's calculations from the ITU World Telecommunication/ICT Indicators database (https://www.itu.int/en/ITU-D/Statistics/Pages/publications/wtid.aspx).
Note: HICs = high-income countries; LMICs = lower-middle-income countries; UMICs = upper-middle-income countries.

Implementing digital-literacy training programs for farmers, developing user-friendly AI interfaces, and providing government-supported AI training workshops can help farmers acquire the necessary skills to integrate digital tools into their operations. In the long term, reforming educational curricula to include digital literacy in rural schools and establishing AI training programs for extension workers will ensure sustained improvements in technological adoption and productivity growth in agriculture.

Table CS2.1 summarizes the main barriers to AI adoption in agriculture and outlines corresponding policy measures that countries can implement. These policies are categorized into short-, medium-, and long-term actions—primarily based on the time and cost required for implementation rather than their relative importance. It is important to note that policy priorities will vary significantly depending on a country's level of AI readiness.

For instance, LICs often continue to face foundational challenges, such as limited access to reliable electricity and basic digital infrastructure. In contrast, many middle-income countries have already made progress in building digital infrastructure and institutional capacity. As a result, whereas the former group must focus on foundational adoption efforts, the latter can pursue more targeted policies aimed at enhancing data access and quality and fostering the development of locally relevant AI tools. In other words, as countries advance in their AI capabilities, they can move from merely adopting existing technologies to adapting and innovating on their own.

In particular, low-readiness countries should focus on expanding internet access and addressing low levels of digital literacy. For countries with medium AI readiness, the priority shifts toward improving data availability and quality and fostering the development of AI applications tailored to local agricultural needs. High-readiness countries, however, are well positioned to drive AI innovation. With advanced digital infrastructure and a strong ecosystem of skilled researchers and firms, these countries can develop cutting-edge solutions and even export AI technologies adapted for agricultural use.

TABLE CS2.1 Barriers and policies for AI adoption in agriculture

Barrier and policy type	Policy
Rural-urban gap in internet access and quality	
Short term	• Expand mobile-based solutions. • Provide subsidies for internet access and devices. • Promote community internet hubs.
Medium term	• Foster competition. • Invest in broadband infrastructure, including first-, middle- and last-mile networks.
Long term	• Improve power grid in rural areas to guarantee connection stability.
High cost of AI-driven solutions	
Short term	• Offer financial incentives, subsidies, and microloans for AI adoption on small farms.
Medium term	• Support AI-as-a-service models. • Encourage economies of scale. • Integrate AI solutions into national agricultural policies.
Long term	• Reduce trade barriers for digital goods. • Strengthen competition in key sectors.
Localization and data scarcity and quality	
Short term	• Develop localized AI models. • Partner with local agricultural experts to ensure local conditions and practices are considered. • Establish data quality protocols in ongoing agricultural programs and ensure data consistency in current collection practices.
Medium term	• Invest in AI training with regional data sets. • Standardize data collection practices.
Long term	• Establish national agricultural data repositories.
Cultural barriers	
Short term	• Integrate local experts and partner with local institutions to facilitate acceptance.
Medium term	• Integrate AI education into agricultural extension programs. • Promote knowledge-sharing and community-based solutions.
Low education attainment and low digital skills	
Short term	• Implement digital-literacy training programs for farmers. • Develop user-friendly AI interfaces. • Provide government-supported AI training workshops.
Long term	• Establish long-term AI training for extension workers.

Source: Original table for this publication.
Note: AI = artificial intelligence.

AI in the Energy Sector

Introduction

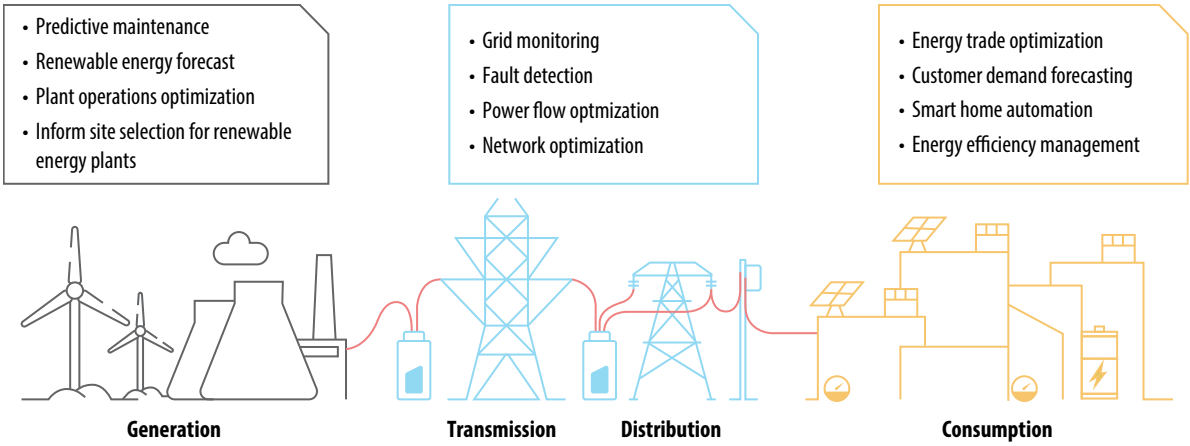
The energy sector plays a crucial role in fostering economic development, alleviating poverty, and addressing climate change. Access to modern and sustainable energy services is essential for improving living standards and providing opportunities for economic growth. Furthermore, the energy sector plays a crucial role in addressing climate change because of its significant contribution to global carbon emissions. The sector accounts for about three-quarters of total greenhouse gas emissions globally and reached a new record high of 37 billion tons (gross tonnage) in 2022, 1 percent above the pre-pandemic level ("Record-Breaking Carbon Emissions, and More—This Week's Best Science Graphics" 2022).

Reducing emissions in the energy sector requires urgent action to enhance efficiency, scale up renewable energy, and cut reliance on fossil fuels. By 2030, increasing renewables, improving energy efficiency, reducing methane emissions, and expanding electrification with existing technologies could achieve more than 80 percent of the necessary emissions reductions (IEA 2024). A comprehensive approach integrating these solutions is essential to improve the sector's efficiency, reversing emissions growth and ensuring a sustainable energy transition.[3]

From generation to consumption, a surge of new artificial intelligence (AI) applications can cut energy waste, lower energy costs, and increase the use of renewable energy sources. For instance, renewable energy systems face challenges in providing uninterrupted power to end users because of the variability of natural energy sources. To address this, AI-driven forecast systems are increasingly being developed to improve the reliability of power production forecasting. AI also has ample room in boosting predictive maintenance accuracy, minimizing equipment and plant downtime by identifying faults before they occur (Afridi, Ahmad, and Hassan 2022). Finally, at the consumption level, AI can support heating, ventilation, and air conditioning (HVAC) systems in buildings, reducing inefficiency and energy demand (refer to other examples in figure CS2.5).

3 AI can also increase energy demand and water consumption, with large negative effects on the environment. GenAI systems, in particular, stand out for their energy demand, consuming approximately 33 times more power to complete a task than traditional task-specific software. In addition, a significant amount of water is used to cool the servers that power AI applications. Each ChatGPT conversation of approximately 29–50 queries results in the evaporation of about half a liter of water. Despite the importance of the topic, this case study focuses solely on the use of AI in agriculture and energy sectors, highlighting its potential to improve efficiency. For further information on the effects of AI on the demand for energy, refer to the main report.

FIGURE CS2.5 Use of AI across the energy sector value chain



Source: Original figure for this publication based on IRENA 2019.
Note: AI = artificial intelligence.

Most firms in the sector have implemented or are exploring using AI, with increasing demand for AI skills. A 2024 IBM study revealed that 74 percent of surveyed energy and utility companies have implemented or are exploring using AI to address data-related challenges, indicating a significant level of engagement within the industry. Not surprisingly, we observe an increasing demand for AI skills in the energy sector. Using online job postings data collected between 2010 and 2019, Lyu and Liu (2021) showed that, among the emerging digital technologies (that is, AI, big data, Internet of Things, robotics, blockchain technology, and cloud computing), AI is the one most widely demanded in the energy sector, required for about 7 percent of posted jobs.

Supporting targeted and efficient maintenance

With the global energy demand steadily increasing, equipment faults, plant down times, and outages have become prohibitively costly, making the development of effective prognostic maintenance systems more critical than ever. Traditional maintenance models, which rely on reactive approaches to repair faulty equipment only after issues arise, are no longer sustainable. Modern systems leverage advanced data analysis to proactively identify potential equipment defects and operational inefficiencies, enabling timely interventions and minimizing disruptions.

AI has brought significant advancements to inspection and maintenance in the energy sector, for instance, in the case of dams and hydropower projects. Leveraging data from drones, sensors, and satellite imagery, AI tools can now analyze structural elements for signs of wear, such as cracks, deformation, or erosion, in a timely manner. A prominent example is the Oroville Dam in California in the United States. After a 2017 spillway failure that caused extensive damage and mass evacuations, the dam adopted advanced AI-powered monitoring systems. Drones equipped with high-resolution cameras capture detailed images of the dam's surface, which AI algorithms analyze to detect cracks, erosion, and other deterioration indicators. These systems effectively prioritize repairs and improve their predictive accuracy over time through machine learning (ML).

Similarly, the Itaipu Dam, located on the Brazil–Paraguay border and one of the largest hydropower plants in the world, has implemented AI to optimize turbine maintenance. AI systems analyze data from embedded sensors that track vibration, temperature, and wear patterns, predicting maintenance

needs with precision. This approach has significantly reduced downtime and maintenance costs while enhancing the efficiency and reliability of turbine operations (Stocks 2025).

Wind turbines are prone to many defects, with high associated maintenance costs and negative effects on performance. Blades and towers are heavily affected by wind, rain, airborne particles, and corrosion. Even small cracks, if not identified early, can result in major losses. According to an American Bureau of Safety and Environmental Enforcement report, 85 percent of blade failures are due to poor maintenance (ABSG Consulting 2015). AI can once again offer some valuable solutions to improve early detection of cracks and other maintenance needs. For instance, a recent study by Shin, Han, and Rhee (2021) highlighted the transformative impact of AI-assisted predictive maintenance for renewable energy systems. Analyzing 2,301 images collected from 138 wind turbines, the study found that AI significantly enhanced technical inspectors' specificity and time efficiency. Among generalist specialists, AI improved their ability to detect failures by 24.6 percent and increased time efficiency by 25.3 percent, demonstrating its effectiveness in optimizing inspection processes.

Several new solutions are being deployed, leveraging AI-powered drones to increase efficiency in wind turbine inspection. The Solomon start-up uses drones equipped with AI vision capabilities, employing META-aivi to swiftly detect the presence or absence of gaskets between the blade and motor with remarkable precision. This innovation streamlines the inspection process, reducing the risk of human error and minimizing the reliance on manual labor. These solutions not only enhance operational efficiency but also contribute to greater human safety by reducing the need for technicians to perform high-risk manual inspections (Solomon Technology 2025). This is also the case of Scottish company Ilosta, which has developed a physics-based AI algorithm to inspect wind blades and towers using various parameters, such as historical weather conditions, and to estimate the internal blade structure and tower damages (Ilosta 2025).

The energy losses in photovoltaic (PV) systems are mainly due to faults that seriously affect their efficiency. A PV module failure degrades its output power and reduces the overall system's performance and reliability. ML models continuously monitor factors such as temperature, irradiance, dirt accumulation, and power output to swiftly detect anomalies and prevent failures (Avelar and Borthwick 2024).

Swiss company SmartHelio leverages AI-driven diagnostics to remotely identify existing issues in solar panels, predict potential faults, and provide real-time prescriptive solutions. Its Autopilot software seamlessly integrates with supervisory control and data acquisition and content management system platforms, extracting critical data—including equipment specifications, maintenance records, single-line diagrams, and thermographic images—to create a digital twin within minutes. This enables immediate performance insights and actionable recommendations as the platform detects and localizes faults and component failures in real time. SmartHelio (n.d.) manages 6 gigawatts of solar assets and has reported an estimated 8 percent performance improvement across its client base, showcasing its potential to enhance solar energy reliability and optimize operational efficiency.

Solarify, developed by Turkish company Loggma, enables real-time tracking of key performance indicators such as downtime and performance ratio. With advanced energy loss detection and a flexible alarm management system, Solarify helps optimize energy production. Estimates indicate that a 1-megawatt-peak solar power plant using Solarify can generate up to 53 megawatt-hours of additional electricity per year compared with plants without such optimization.

Examples of AI use also exist in fault detection and preventive maintenance in transmission lines. E.ON, for example, has developed an ML algorithm to predict when medium-voltage cables need replacement. By analyzing diverse data sources, E.ON has reduced grid outages by up to 30 percent compared with conventional maintenance strategies. Similarly, Italy-based Enel uses sensors on power lines to monitor vibrations, with AI algorithms pinpointing potential issues and their causes, cutting power outages by 15 percent.

Transmission lines are often located in challenging environments, such as dense forests and high-altitude mountains, such that accessing them for manual inspections can be difficult, time-consuming, and hazardous. Estonian start-up Hepta Airborne uses drones combined with ML to detect defects in transmission lines, and China's State Grid Corporation uses AI extensively for tasks such as smart meter analysis to identify customer equipment issues (Rozite, Miller, and Oh 2023).

In the Latin America and the Caribbean (LAC) region, the Chilean start-up Innspatial has leveraged AI in Peru to implement an advanced inspection service for the electrical grid. This initiative includes creating an inventory of risk factors, such as detecting low-hanging cables, unauthorized construction near power lines, and other hazards that could lead to power outages and pose safety risks for residents in the Peruvian capital (Innspatial 2024).

In Viet Nam, the National Power Transmission Corporation uses AI to analyze drone-captured images, providing real-time alerts on faults, potential hazards, and other system issues that require immediate attention. The company also deploys AI cameras on top of power line towers in special locations to detect abnormal occurrences and quickly send warnings (World Bank 2023). Companies are increasingly leveraging AI and advanced sensors to enhance the detection and prevention of fire-starting faults in power systems. High-impedance faults—often triggered by fallen trees, broken conductors, or damaged insulators—remain difficult for utilities to detect. AI systems can process vast volumes of sensor data, flagging anomalies that deserve human intervention and enabling faster, more accurate responses to fire risks (Eaton Corp 2025).

Improving forecast accuracy

Energy forecasting was once a relatively straightforward task, primarily centered on stable gas- and fossil fuel–based resources. In this simpler system, the supply forecast was highly predictable, and higher demand could be met by simply burning more fossil fuels as needed. However, the rapid expansion of renewable energy sources—coupled with their intermittent nature—has introduced several new challenges to the sector. Notably, the volume of relevant data has surged because more variables now influence renewable energy supply. Factors such as cloud cover, precipitation, wind speed, and solar intensity all play a crucial role in determining a producer's ability to supply energy optimally.

Improved energy forecasting carries significant implications for the growth of renewable energy. By using advanced forecasting tools, producers can better anticipate fluctuations in energy generation and make more informed decisions about when to produce, store, or sell electricity. Accurate forecasts are essential for determining optimal locations for new investments, minimizing operation costs, and establishing the most efficient hourly delivery commitments to the power grid, ultimately maximizing the efficiency and value of wind and solar energy.

AI-driven platforms can integrate vast amounts of data from diverse sources, including real-time weather reports, forecasts, demand patterns, and distributed energy resources, to enhance forecasting accuracy. DeepMind, an AI lab under Google's parent company, Alphabet, has developed a neural

network capable of predicting wind power output 36 hours in advance with notable accuracy. This system, trained on weather forecasts and historical turbine data, addresses the inherent variability of wind energy by providing precise predictions. These forecasts enable optimal hourly delivery commitments to the power grid, enhancing the efficiency and value of wind energy.

Google reports that DeepMind's AI has increased the value of its US wind farms by 20 percent (Sheed 2019). The US Department of Energy has partnered with IBM to develop Watt-Sun, an innovative ML technology designed to enhance solar energy forecasting. By analyzing extensive weather data, Watt-Sun reduces uncertainties in solar power generation and minimizes energy storage and management costs. This advanced system, inspired by IBM's Watson supercomputer, has achieved a remarkable 30 percent improvement in forecasting accuracy, effectively managing sunlight fluctuations that can disrupt solar energy production (US DOE 2015).

Open Climate Fix, in collaboration with the Alan Turing Institute, is advancing solar energy forecasting through its Quartz Solar AI Nowcasting project, which aims to predict cloud movements up to 4 hours ahead. Leveraging AI to analyze vast data sets from historical satellite imagery and weather patterns, the project enhances the precision and speed of solar generation forecasts, reducing forecast errors by 15–20 percent (Travers, Kelly, and Deisenroth 2024).

Optimizing the grid

From the perspective of grid operators, precise energy supply and demand forecasting are crucial to balance supply and demand. Grid operators continuously monitor the flow of electricity across the grid to ensure that energy supply matches demand. Electricity and demand must be perfectly balanced in real time because electricity cannot be stored on a large scale (except in certain cases, such as battery storage). Not only is excess energy supply inefficient, it can also overwhelm the grid and damage infrastructure. Conversely, an energy deficit has clearer implications, resulting in power outages with severe economic and social consequences.

With the increasing share of renewable energy, grid operators must manage the variability and intermittency of sources such as wind and solar. These energy sources can fluctuate on the basis of weather conditions, so operators must forecast when energy production will be high or low. Accurate forecasting and adaptive strategies are critical for integrating renewables without destabilizing the grid. In addition, modern energy infrastructure has made demand and supply forecasting more challenging by generating vast amounts of data from smart meters and integrating multiple decentralized producers into an interconnected grid.

AI significantly enhances grid operators' performance by improving predictive supply and demand forecasting and enabling real-time grid monitoring and optimization. ML algorithms are valuable for demand forecasting, because they analyze historical consumption patterns, weather conditions, and time-of-day factors to generate more precise energy demand predictions. Neural networks' ability to model complex, nonlinear relationships is instrumental in optimizing energy flow and managing grid stability by making rapid, data-driven adjustments to maintain system balance. As energy networks become more complex, AI-driven solutions are increasingly critical in helping grid operators navigate supply and demand challenges. One such innovation is Sensewaves, a French start-up that leverages AI-powered analytics to enhance grid forecasting and management. Its platform provides high-resolution forecasts of energy loads and localized production, enabling grid operators to optimize performance in real time and helping grid operators anticipate and mitigate potential disruptions (Sensewaves 2024).

Curbing energy theft

Energy theft is a significant global issue, costing utility companies billions of dollars annually and affecting the reliability of power distribution systems. According to World Bank (2025b) estimates, global energy theft accounts for approximately 50 percent of electricity losses in some regions, particularly in developing economies. These losses undermine energy companies' ability to invest in infrastructure upgrades and limit consumer access to reliable electricity. OLADE (2017) estimates that, in 2019, the losses from electrical transmission and distribution systems in LAC could have supplied electricity to more than 50 million homes.

Integrating AI into energy theft detection systems offers a transformative solution to mitigate these challenges, combining accuracy, efficiency, and scalability. Companies such as Bidgely have demonstrated AI's potential to revolutionize energy theft detection. Using ML models to analyze patterns in energy consumption, the tool flags anomalous behavior and patterns in consumer energy usage, achieving anomaly detection rates of 70–95 percent, significantly outperforming traditional methods. The tool has recently been applied in India, with promising results (Bidgely 2024).

This is also the case with the Energizados project, supported by the Inter-American Development Bank in partnership with the distribution company CEEE. Energizados is an application that uses ML and statistical methods to help companies reduce fraud and theft in the electrical network. In a pilot in Brazil, Energizados increased the capture of fraudulent consumer units by 5 percent compared with the software currently used by the company (Giraldo et al. 2022).

Cutting energy consumption in buildings

Buildings are significant energy consumers, often operating inefficiently because of outdated technologies. According to the IEA (2025), building operations account for approximately 30 percent of global final energy consumption and 26 percent of energy-related emissions. Monitoring and optimizing HVAC systems can lead to substantial cost savings and reduced environmental impact.

AI offers promising solutions to enhance building energy efficiency by optimizing HVAC operations. AI systems can analyze real-time data—such as temperature, humidity, sun angle, wind speed, and occupancy patterns—to proactively adjust settings, reducing energy waste and improving occupant comfort. For example, a 32-story Broadway office building in New York City in the United States implemented an AI-driven HVAC optimization system, achieving a 15.8 percent reduction in HVAC-related energy consumption, resulting in $42,000 in savings and mitigating 37 metric tons of carbon dioxide in just 11 months (Chow 2024).

Scientific studies further validate these findings. Ding et al. (2024) highlighted the transformative potential of AI integration with HVAC systems. Their research estimates that AI can reduce energy consumption and carbon emissions by 8–19 percent—with even greater reductions possible if paired with aggressive policy measures. Their study also emphasizes AI's role throughout a building's entire life cycle, from design and construction to operation and maintenance, including predicting HVAC component failures to minimize downtime and repair costs.

Start-ups such as Verdigris have begun deploying intelligent automation systems that leverage real-time, high-frequency meter data along with local weather conditions, utility pricing, and building management system data to optimize energy consumption. Evidence from Verdigris customers

indicates that the implementation of adaptive automation has resulted in energy savings on HVAC costs exceeding 20 percent (Verdigris 2025). Similarly, BrainBox AI uses ML algorithms to optimize building energy use, reducing energy consumption by approximately 15–25 percent across more than 700 buildings to date (Brainbox AI n.d.).

Expanding access to vulnerable people

The need to expand access to electricity is still urgent in many areas, and new solutions using AI can have a real impact on the lives of many. Nearly 600 million people in SSA live without access to electricity, representing nearly 83 percent of the world's unelectrified population (World Bank 2025a). AI-powered predictive analytics, for instance, can enhance the efficiency of off-grid solar energy deployment by identifying high-priority areas for investment. A case study in Kenya by Atlas AI demonstrated how ML models can analyze satellite imagery, economic data, and demographic trends to predict demand for solar minigrids. In partnership with Engie, Atlas AI leverages data from several sources, including location data, spending power, area with grid or connectivity, electrical access, and population density data. By targeting regions where communities would benefit the most from electrification, these AI-driven insights help optimize resource allocation, reducing deployment costs and increasing solar home systems by 48 percent (Babayomi 2024).

In the Philippines, Omdena leveraged AI and geographic information systems to accelerate rural electrification by overcoming critical data limitations. One main challenge in planning electrification projects is the lack of reliable information on population density, energy consumption, and existing infrastructure. To address this issue, Omdena used high-resolution satellite imagery from Sentinel-2 and Landsat 8 to analyze land use and solar irradiance, and GRID3 data sets provided insights into off-grid communities by mapping population distribution and energy demand. AI-driven analytics played a crucial role in processing these data. Clustering algorithms identified regions with significant energy needs, and convolutional neural networks pinpointed optimal locations for solar installations by assessing terrain suitability. This AI-powered approach enabled the precise placement of solar containers, reducing deployment costs and ensuring that energy solutions efficiently reached the most underserved communities (Omdena 2024).

AI models are also used to facilitate planning for electrification and energy services by mapping future urbanization and associated infrastructure needs. Modeling Urban Growth is an open-source AI model designed to tackle this challenge resulting from a collaboration between IBM and the nonprofit Sustainable Energy for All. The model uses satellite images, geographic data, demographic data, and structural data to predict city expansions and facilitate the planning of future areas where the demand for electricity will increase. The model is currently trained on data from several African countries, including Benin, Cameroon, the Democratic Republic of Congo, Ghana, Kenya, Malawi, Nigeria, Rwanda, Tanzania, Togo, and Uganda.

One of Africa's biggest challenges in expanding renewable energy access is the difficulty of securing financing, particularly for projects in low-income and off-grid areas. AI-driven financial technologies are helping bridge this gap by improving risk assessment and streamlining investment decisions. Through ML and predictive analytics, AI can evaluate factors such as repayment history, economic activity, and energy demand to more accurately assess the viability of renewable energy projects. This approach not only enhances investor confidence but also ensures that funding is directed toward the most promising initiatives.

A key example of this innovation is Nithio, a financial technology company focused on expanding energy access in Africa. By integrating geospatial analysis, financial modeling, and consumer data, Nithio's AI platform standardizes credit risk assessment, making it easier to determine loan eligibility and predict repayment behavior. This allows financial institutions to offer tailored and affordable financing options, reducing the upfront costs of solar energy systems for households and businesses. By mitigating investment risks and facilitating access to capital, AI-powered solutions such as Nithio's are playing a crucial role in accelerating the deployment of off-grid renewable energy, ultimately making clean electricity more accessible to underserved communities across the continent (Babayomi 2024).

Understanding sector-specific barriers to AI adoption in the energy sector and policy insights

One primary challenge for AI adoption in the energy sector is the high cost associated with modernizing and repurposing legacy infrastructure. Integrating advanced digital tools into existing energy infrastructure presents significant challenges, primarily because of the reliance on legacy systems not designed for modern digital interfacing. Upgrading or replacing these outdated systems is often costly and time-consuming and can lead to operational disruptions. These substantial costs are further exacerbated by the costs of data preparation and purchase, as well as the investments in data centers and cloud storage to manage the vast amounts of data generated in the energy sector. These financial burdens can be prohibitive, particularly for smaller energy companies or those operating in low-income countries (LICs).

In many African countries, utility companies often struggle with large debts, because electricity tariffs are set below cost-reflective levels (Balabanyan et al. 2021). Revising tariffs and providing tax incentives and grants for AI adoption in energy management can help alleviate these costs in the short term. In addition, encouraging innovative public-private funding mechanisms to share the financial burden of infrastructure modernization can facilitate the transition to AI-integrated energy systems.

For cost-effective and specialized technologies, such as drones and AI-powered camera imaging, data availability and the high cost of data labeling present major challenges. Several cases demonstrate how drones and AI solutions are being leveraged to optimize predictive maintenance in transmission lines. Although these technologies require lower upfront investment, the primary hurdle is the substantial time and effort needed for data labeling to achieve the accuracy required for reliable recognition systems. Establishing frameworks that facilitate data sharing among organizations and ensuring compliance with privacy and security standards can enhance data availability and diversity, benefiting all stakeholders.

The adoption of AI in the energy sector requires not only substantial investments in upgrading legacy infrastructure but also significant spending on cybersecurity. Cyber threats pose significant challenges to adoption by increasing security risks, regulatory concerns, and financial burdens. Although cyber threats affect various industries, the energy sector is particularly vulnerable because of its critical role in economic stability and national security. Utility companies spend, on average, 8 percent of their information technology budget on cybersecurity, with significant obstacles in finding qualified professionals (Torkington 2023).

As energy companies modernize their grids and integrate AI-driven solutions, they become increasingly vulnerable to cyberattacks targeting critical infrastructure. The energy sector has

already faced a surge in cyber threats, with industry experts warning that European power grids are experiencing an unprecedented wave of cyberattacks (Jack 2023). One alarming example of cyber threats to the energy sector occurred in Ukraine, where hackers backed by the Russian Federation attempted to disrupt the country's power grid. Researchers have identified Russian intelligence agencies as being responsible for a cyberattack aimed at disabling Ukrainian substations, illustrating the severe geopolitical risks associated with unsecured energy infrastructure (Reuters 2023).

Enforcing regulations on AI data protection in energy systems and providing cybersecurity training can strengthen resilience against such threats. Over the long term, developing and enforcing comprehensive data protection regulations specific to the energy sector, implementing mandatory training and awareness programs for employees on data privacy and security best practices, and establishing clear guidelines for incident response and data breach notification will be critical to mitigating risks and ensuring data security.

In addition to the substantial investments, firms in the sector also face cumbersome regulatory and policy barriers. In many regions, existing regulations and policies may not be conducive to the deployment of advanced technologies. Clear guidelines and standards for the use of AI in energy systems may be lacking, leading to uncertainty and reluctance among energy companies to invest in these technologies. In addition, the regulatory approval process for new technologies can be lengthy and complex, further delaying their adoption. Investing in capacity-building and training programs for regulators and policy makers to enhance their understanding of AI technologies and their implications for the energy sector can help improve the regulatory landscape. Moreover, developing and implementing clear guidelines and standards for the use of AI in the energy sector and simplifying and expediting the regulatory approval process for new technologies will ensure a more enabling environment for AI adoption.

Adopting AI in the energy sector necessitates robust measures to ensure data privacy and security. As energy companies increasingly rely on digital tools and AI-driven solutions, they collect and process vast amounts of sensitive data, including customer information, operational data, and grid performance metrics. These data are critical for optimizing energy production, distribution, and consumption, but they also present significant privacy and security risks. Unauthorized access, data breaches, and cyberattacks can compromise the integrity and confidentiality of these data, leading to severe consequences for both the energy companies and their customers. Ensuring data privacy and security is paramount to maintaining trust, complying with regulatory requirements, and protecting critical infrastructure from malicious activities. Developing and enforcing comprehensive data protection regulations specific to the energy sector will play a key role in addressing these concerns.

Many utilities operate on siloed data systems that lack interoperability, preventing the seamless implementation of AI-driven analytics and automation. A major challenge for using data-driven technologies in the energy sector is the lack of standardization across energy systems and digital platforms. AI solutions rely on real-time data processing and advanced predictive capabilities, but integrating these technologies into legacy systems demands substantial upgrades to hardware, software, and data management practices. Without these upgrades, utilities struggle to leverage AI for grid optimization, predictive maintenance, and demand forecasting. In the short term, developing common AI data standards for energy systems and promoting open-source energy AI models can help improve interoperability. Over the longer run, implementing national AI data-sharing policies, creating a standardized AI energy database, and providing financial support for

upgrading data infrastructure—including hardware, software, and data management systems—will establish a more harmonized and efficient energy ecosystem.

Another major barrier is the lack of digital skills and expertise within the energy sector. The successful implementation and operation of AI requires a workforce with specialized knowledge of both energy systems and AI technologies. However, there is often a shortage of such skilled professionals, particularly in regions with less-developed educational and training systems. This skills gap can hinder the adoption and effective use of AI technologies in the energy sector. Also, AI-powered tools often require substantial upfront investment in hardware, software, and skilled personnel. This necessity can significantly deter many energy companies, especially smaller firms or those operating in developing economies. In addition, the integration of AI technologies into existing energy systems can be complex and costly, requiring significant modifications to infrastructure and processes.

Offering workforce training programs for AI adoption in energy sectors and incentivizing AI skill development can provide short-term solutions. In the long run, integrating AI and energy management education into university and technical school curricula and investing in training programs to develop a skilled cybersecurity workforce will help build a robust talent pipeline and ensure that the energy sector can fully capitalize on AI-driven innovations.

Even when other barriers to adoption are addressed, managers may still be reluctant to rely on the black box of AI because of its lack of transparency and accountability. When neither managers nor their teams understand the logic behind AI-generated outputs, a range of issues can emerge. This opacity can hinder the ability to assess the quality and reliability of AI algorithms and may undermine professionals' own judgment, ultimately affecting adoption. Although this is a cross-sector challenge, it becomes particularly problematic in a sector in which even small errors carry significant social consequences. To mitigate these risks, it is essential to establish mechanisms that promote transparency and clearly assign responsibility for AI-driven decisions.

One promising approach is the development of explainable AI (XAI), which aims to make algorithmic outputs more interpretable. Even when tools are not explicitly built on XAI principles, employees can still be trained to develop a basic understanding of how AI systems function and establish mechanisms to justify and assign responsibility for decisions made by AI. This work requires a shift in mindset—particularly among leaders and those overseeing learning and development initiatives (Gorny 2024).

Table CS2.2 outlines key obstacles to adopting AI in the energy sector and presents a range of policy responses, grouped into short-, medium-, and long-term measures. These categories reflect the relative time and investment needed to implement each intervention rather than their strategic priority. The relevance and sequencing of these policies will depend heavily on each country's level of technological maturity.

TABLE CS2.2 Barriers and policies for AI adoption in the energy sector

Barrier and policy type	Policy
High cost of AI-driven solutions	
Short term	• Provide tax incentives and grants for AI adoption in energy management. • Encourage public-private partnerships to share the financial burden of infrastructure modernization.
Medium term	• Foster AI-driven smart grid development. • Scale up AI-based predictive maintenance systems.
Long term	• Ensure that investments transition from isolated, purpose-specific solutions to a unified, interoperable digital infrastructure. This shift will enable seamless data integration, fostering agility and adaptability in response to the rapid pace of technological change.
Data interoperability	
Short term	• Develop common AI data standards for energy systems. • Promote open-source-energy AI models.
Medium term	• Implement national AI data-sharing policies. • Provide financial support for upgrading data infrastructure, including hardware, software, and data management systems.
Long term	• Create a standardized AI energy database that supports seamless integration and real-time analytics.
Data privacy and security	
Short term	• Enforce regulations on AI data protection in energy systems. • Provide cybersecurity training. • Implement mandatory training and awareness programs for employees on data privacy and security best practices.
Medium term	• Establish clear guidelines for incident response and data breach notification.
Long term	• Develop and enforce comprehensive data protection regulations specific to the energy sector.
Regulatory	
Short term	• Invest in capacity-building and training programs for regulators and policy makers to enhance their understanding of AI technologies and their implications for the energy sector.
Medium term	• Develop and implement clear guidelines and standards for using AI in the energy sector. • Simplify and expedite the regulatory approval process for new technologies.
Long term	• Establish a dedicated AI regulatory sandbox for the energy sector.

(Continued)

TABLE CS2.2 Barriers and policies for AI adoption in the energy sector *(Continued)*

Barrier and policy type	Policy
Lack of skills	
Short term	• Offer workforce training programs for AI adoption in energy sectors and incentivize AI skill development. • Invest in training programs to develop a skilled cybersecurity workforce.
Medium term	• Integrate AI modules into existing technical and vocational education and training programs for the energy sector. • Develop certification programs in AI for energy professionals.
Long term	• Integrate AI and energy management education into university and technical school curricula.
AI black box	
Short term	• Invest in training programs to develop teams' knowledge on how AI outputs are generated. • Incentivize and develop explainable AI tools, making algorithmic outputs more interpretable.
Medium term	• Develop clear guidelines to define accountability for AI's outputs. • Promote open algorithms and shared learning.

Source: Original table for this publication.
Note: AI = artificial intelligence.

In many LICs, the focus remains on overcoming basic infrastructure deficits, such as inconsistent electricity supply and limited internet connectivity, which are prerequisites for deploying AI. Meanwhile, middle-income countries that have already developed core digital infrastructure and regulatory frameworks can shift attention to enabling higher-value use cases, including promoting interoperability standards and supporting the creation of localized AI solutions. As countries progress, they can transition from basic adoption toward more advanced stages of adaptation and innovation in AI-driven energy systems.

Specifically, in low-readiness contexts, efforts should prioritize expanding basic infrastructure such as broadband access, enhancing digital literacy, and promoting the use of off-the-shelf AI tools. Medium-readiness countries can build on this foundation by investing in domestic data centers, promoting customized AI solutions, and strengthening digital skills pipelines to support adaptation of AI to local needs. High-readiness countries, by contrast, are positioned to lead in AI innovation, supported by advanced infrastructure such as domestic supercomputers and cutting-edge AI chips, alongside a robust ecosystem of top-tier researchers and firms capable of developing and exporting AI solutions.

Conclusion

Artificial intelligence (AI) holds significant promise for transforming the agriculture and renewable energy sectors by enhancing efficiency, sustainability, and resilience. This case study has explored various AI applications across these sectors, demonstrating how AI-powered tools can optimize production, improve resource management, and facilitate the transition to cleaner energy systems. In agriculture, GenAI-powered chatbots have demonstrated the ability to provide tailored recommendations at a fraction of the cost of traditional extension services. Similarly, AI-enabled pest control tools have significantly improved farmers' ability to monitor and mitigate pest infestations, reducing pesticide use while boosting yields. AI applications in energy forecasting, predictive maintenance, and grid optimization have also enhanced the reliability and efficiency of renewable energy sources. For instance, AI-driven predictive maintenance in wind turbines and hydropower plants has minimized downtime and reduced operational costs. Furthermore, advanced forecasting models have improved the accuracy of energy generation forecasts, enabling better integration of renewables into the grid.

However, although potential benefits of AI are substantial, widespread adoption remains constrained by critical barriers, particularly in developing economies. Addressing these challenges requires coordinated efforts. Governments should prioritize expanding broadband infrastructure in rural areas and subsidizing AI-powered solutions for smallholder farmers. In addition, efforts to develop localized AI models—such as incorporating regional languages and agricultural data—will enhance accessibility and effectiveness. Bridging the digital skills gap through farmer training programs and integrating AI literacy into agricultural extension services will also be crucial for fostering AI adoption. To foster AI integration in the energy sector, policy makers should provide financial incentives, such as tax breaks and grants, to support AI adoption and infrastructure modernization. Strengthening cybersecurity regulations and promoting AI-focused training programs will be essential to building resilience against cyber threats. In addition, governments should establish standardized AI data-sharing policies to improve interoperability across energy systems and facilitate collaboration between energy providers and AI developers.

Ultimately, AI should be leveraged as an inclusive tool that benefits all stakeholders, particularly smallholder farmers and energy providers in low-income regions. With the right policies and investments, AI can contribute significantly to sustainable development, resilience, and economic growth.

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