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AI and the future of industry: Challenges and opportunities for developing countries

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Abstract

The rapid evolution of artificial intelligence (AI) has the potential to reshape industrial production and policymaking worldwide. In manufacturing, AI can enhance productivity, efficiency and innovation through applications such as predictive maintenance, quality control and supply chain optimization. Although opportunities offered by AI are abundant, its adoption in industrial production remains slow and uneven. Developing countries face significant barriers to the adoption of AI, including limited infrastructure, skills shortages, financing constraints and restricted access to data. Similarly, the AI development market is becoming more concentrated and capital-intensive, making it difficult for newcomers to enter them. Industrial policy can play a pivotal role in addressing these challenges by supporting AI adoption, fostering capability development, enabling local data ecosystems, and encouraging collaborative innovation. Moreover, AI is starting to emerge as a tool for smarter industrial policymaking by potentially improving governments' ability to analyse, target and evaluate interventions. Strategic action is urgently required to ensure that AI is a driver of inclusive industrialization, rather than a force that deepens global divides.

Key Messages

1.
Industrial policy can drive AI adoption, boost local innovation, and support collaboration through coordinated action on infrastructure, skills, finance, and data sharing.

2.
Local data ecosystems are critical for developing context-specific AI applications and reducing dependence on foreign platforms.

3.
AI applications in policy formulation, implementation, and evaluation can help accelerate and optimize industrial policymaking.

A digital transition in the manufacturing sector

The manufacturing sector is changing with the introduction of digital production technologies. Digital, or "smart," manufacturing is characterized by adding multiple layers of hardware and software to traditional manufacturing processes. These include a sensing layer to obtain real-time data from production processes and the supply chain, a connectivity layer to enable machine-to-machine data transmission, an analytics layer to make sense of the collected data, and an actuator layer that can be autonomously manipulated to enact change in production processes.

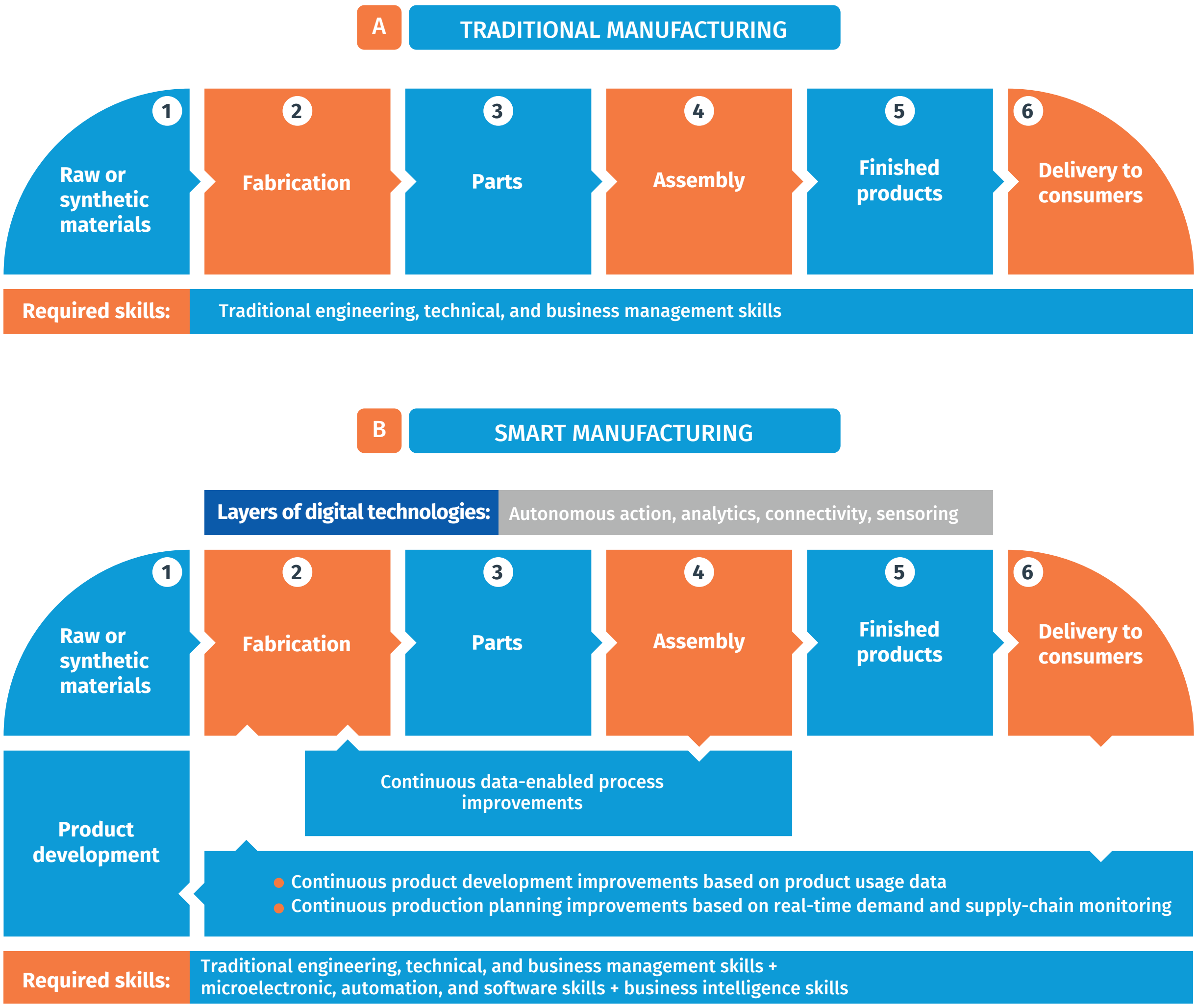
While traditional manufacturing processes follow a linear path from raw materials sourcing to delivering finished products to the consumer, smart manufacturing features many feedback loops enabled by data collection and analysis. For example, data from the sensors in the production line enables efficiency gains and continuous process improvements, such as reducing defect rates through quality control and cutting machinery downtime through predictive maintenance. Product usage data, in turn, provides key information for product development and adapts products to consumer preferences. Finally, real-time demand and supply chain data enable continuous production planning improvements (Figure 1).[1]

AI is key to smart manufacturing as it is the main technology behind the analytics layer. The manufacturing industry is estimated to be the most data-intensive sector in the world, producing an average of 1.9 petabytes[2] of data per year. Without AI, it would be impossible to make sense of the vast and often unstructured data generated by production processes. For example, General Electric Power uses Amazon Web Service data analytics to stream 500,000 data records per second and ingest 20 billion machine-data tags per day.[3] Recent advances in AI are making data models even more powerful, efficient, and accurate in transforming different types of data into actions that can lead to process improvements.

AI-driven opportunities for future industrialization

For developing countries, the main industrial opportunity offered by AI lies in using it to boost the productivity and efficiency of existing industries. In practice, AI in industry is still in the early stages of implementation, and its quick integration can generate benefits for early adopters. There are also opportunities to develop AI models and applications based on local knowledge and data. This is an effort that requires significant policy efforts and strong buy-in from industry.

Figure 1. From traditional to smart manufacturing



Source: Authors' elaboration based on Labrunie (2023).

AI adoption opportunities: the potential of AI applications

AI models and applications are undergoing fast development. What is meant by "AI" is actually a collection of many different types of models including supervised or unsupervised machine learning, deep learning, reinforcement learning, language models, amongst others. Many emerging applications can support businesses, especially micro-, small and medium-size enterprises (MSMEs), to carry out their activities more effectively and efficiently. Table 1 summarizes potential AI applications in manufacturing businesses across five business areas: business processes, manufacturing processes, product development processes, product, and supply chain. Some of these applications require basic technical and organizational capabilities, while others need more advanced capabilities.

Table 1. Potential applications of AI in manufacturing

Area	Capabilities required	Applications and benefits
Business processes	Basic	• **Market analysis** – automated surveys and trend prediction for faster insights. • **Chatbots** – instant customer support and recommendations. • **Finance automation** – payroll, invoicing, and forecasting with fewer errors. • **Cybersecurity** –fraud detection and blocking malicious bots.
	Advanced	• **IT/HR integration** – centralized platforms streamline operations. • **AI search assistants** – quick access to internal documents and knowledge.
Manufacturing	Basic	• **Sensors on machines** – downtime and performance monitoring.
	Advanced	• **Predictive maintenance** – detection of anomalies (heat, vibration) and prevents breakdowns. • **Quality control (computer vision)** – identification of defects beyond human capability. • **Autonomous robots** – selection and placement of items in complex scenarios. • **Energy optimisation** – smart heating and cooling to cut costs. • **Digital twins** – simulation of processes to test improvements.
Product development	Basic	• **Generative AI** – brainstorming product ideas and creating visuals. • **User feedback analysis** – sentiment analysis from text, video and audio.
	Advanced	• **Generative design** – optimization of parts for weight, performance, and sustainability. • **Natural language interfaces** – facilitating the use of design software.
Products	Advanced	• **Internet of things connectivity** – enabling smart devices and appliances. • **Embedded AI** – wearables that predict health issues, autonomous vehicles, smart homes and industrial robots.
Supply chain	Basic	• **Inventory optimization** – real-time stock management. • **AI drones** – scanning barcodes and tracking warehouse items. • **Damage detection** – identification of issues during fulfilment.
	Advanced	• **Analytics** – providing visibility across ports, carriers and weather. • **Predictive forecasting** – anticipating demand and disruptions. • **Sustainability tools** – measuring emissions (incl. Scope 3).

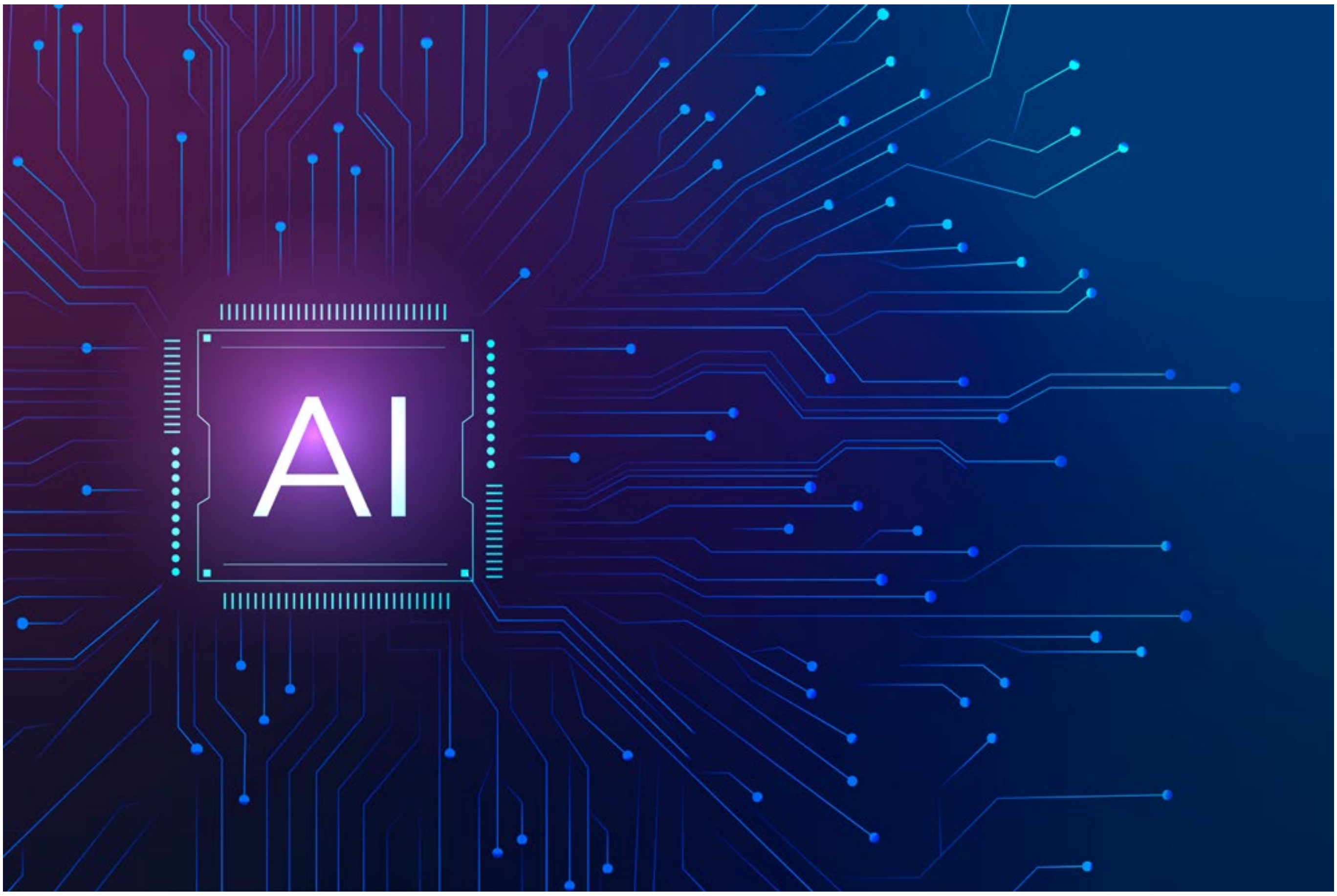
Source: Authors' elaboration based on secondary literature.[4]

Despite their potential impact, many of the applications mentioned above are still in the early stages of development and adoption across manufacturing industries. For example, according to a World Intellectual Property Organization (WIPO) report,[5] the manufacturing sector accounts for only a small fraction of the generative AI patents published to date, with the majority of the sector's patents focusing on software applications. This shows that AI in manufacturing is still in its early stages, but opportunities could increase significantly for developing countries in the coming years if concerted focus is placed on AI model development, training data and AI readiness. To seize these opportunities, policy action is urgently needed.

The potential of local AI solutions using local training data

One of the primary resources required for developing new AI solutions is high-quality data. Developing countries could leverage data from their own industries to develop localized AI solutions. However, manufacturing data is often proprietary and sensitive, making companies reluctant to share it. This creates a chance for governments to build secure platforms for industry collaboration to develop AI applications using local data.

While small and medium-sized enterprises (SMEs) might not individually produce enough data to train AI models, if companies pool their data, together they can develop AI models tailored to their needs. The Chinese government used this approach in the Industrial Brain programme (Box 1). For the Industrial Brain programme, the government created a unified company network for secure data sharing, enabling stakeholders to monitor industry data in real time and develop tailored AI applications to optimize production.

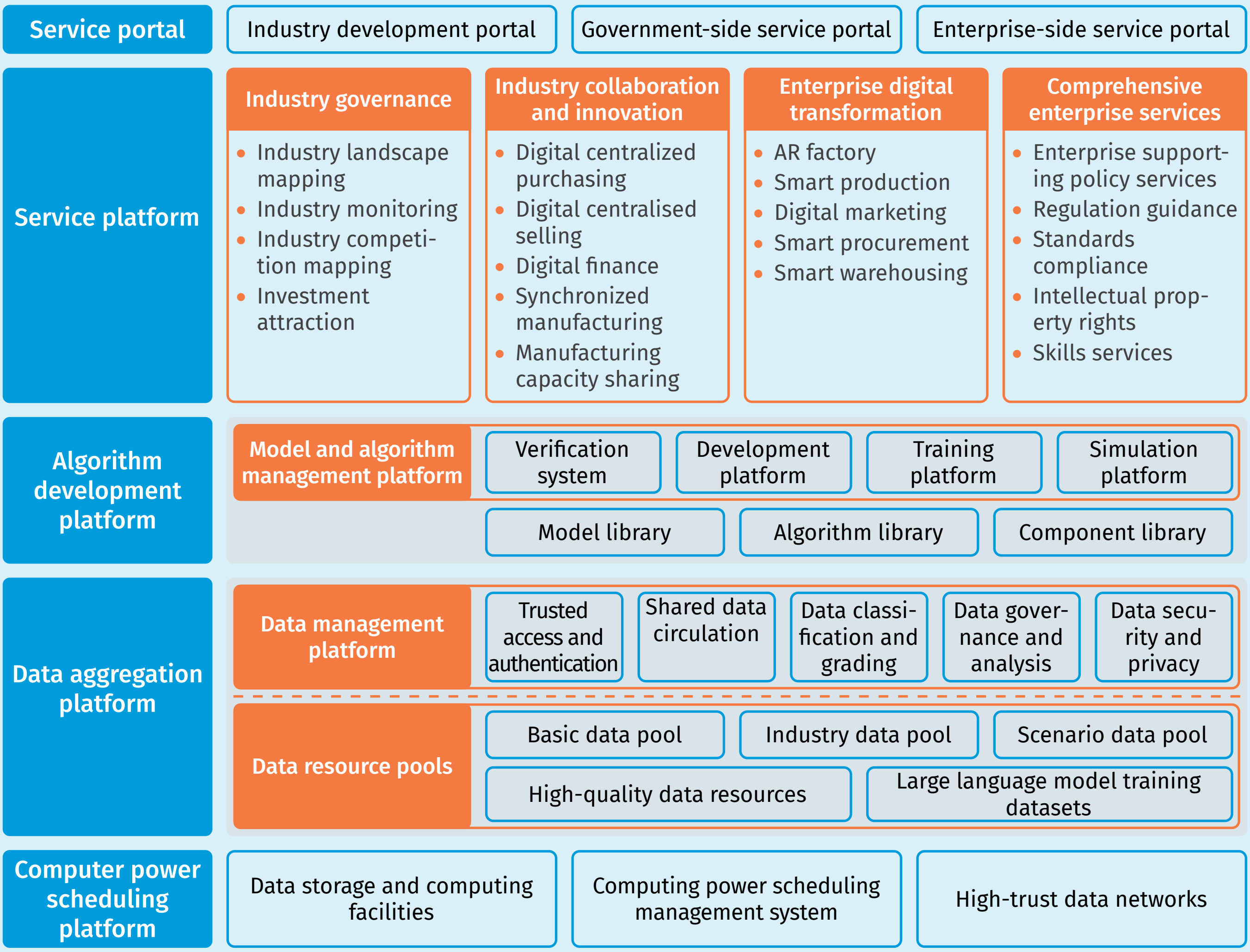


Box 1 **Pooling resources to develop tailored AI solutions: China's Industrial Brain programme**

The Industrial Brain programme in Shandong aims to unlock the potential of industrial data resources. To advance this initiative, the province built a single unified system to manage industrial data and support a comprehensive map to support innovative data applications (see Figure 2 for the programme's functional structure). By the end of 2024, Shandong launched 80 pilot projects for the Industrial Brain construction, 12 of which were recognized as provincial demonstration cases.

Similar programmes are being promoted in other provinces in Zhejiang and Shanghai, where authorities are working to digitalize the manufacturing sector using common databases, standards and equipment. This coordinated approach provides Chinese manufacturers with access to large datasets and broader influence across the supply chain, enhancing their ability to leverage AI technologies.

Figure 2. Functional structure of the Industrial Brain programme



Note: AR = Augmented Reality.

Source: Authors' elaboration based on Department of Industry and Information Technology of Shandong Province (2024).

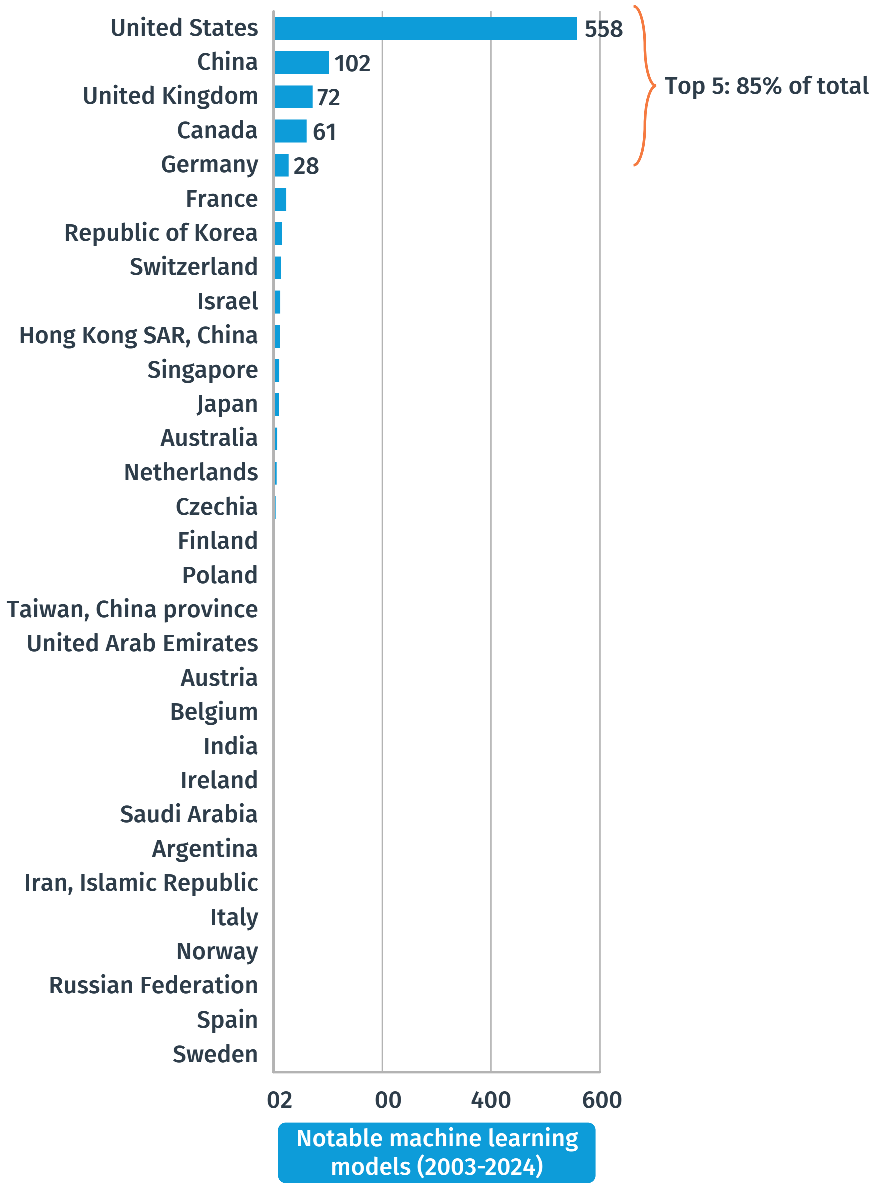
Challenges from the evolution of AI

AI and the transition to smart manufacturing present numerous industrial challenges for developing countries. Not only is the AI market becoming increasingly concentrated and capital-intensive, but developing countries face obstacles at the firm and system levels that hinder the development and adoption of AI.

AI development is concentrated in a few countries and market entry is challenging

First, it is worth noting that developing countries (except China) are primarily users of AI models, with only a few having notable models, but only a few have developed notable models (Figure 3).

Figure 3. Total number of notable AI models by geographic area, 2003–24



Note: Notable AI models are particularly influential within the AI/machine learning ecosystem.

Source: Authors' elaboration based on Stanford University (2025).

Second, the training of AI models is a capital-intensive effort. Figure 4 shows that the latest generative AI models have cost over USD 100 million, highlighting that entry into the AI market is becoming expensive.

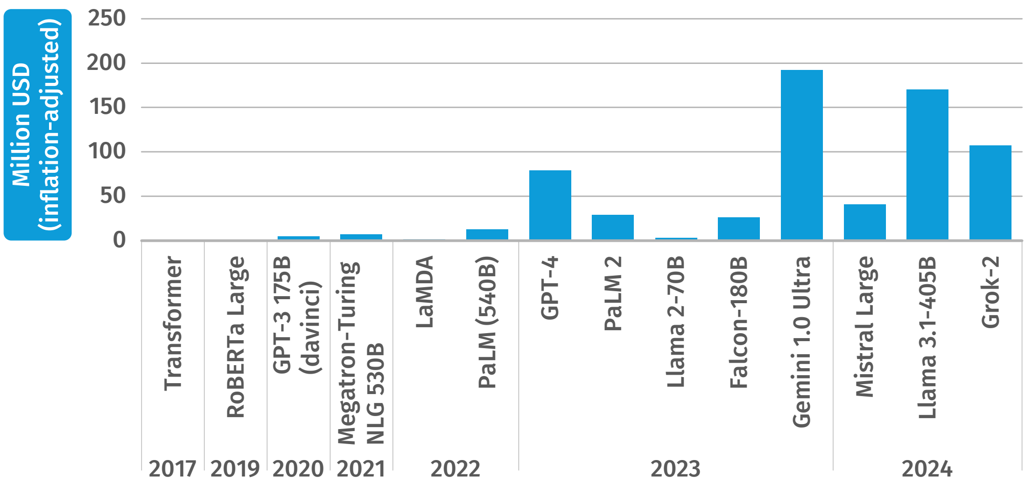
Third, there are difficulties in accessing appropriate infrastructure for AI development. Due to the substantial computational demands of modern AI, traditional IT systems are insufficient. AI development needs purpose-built systems that process large datasets, manage complex algorithms and deliver reliable model performance at scale. These systems consist of specialized hardware, software frameworks, data storage systems and networking components designed for high-performance AI workloads. Some of the infrastructural needs include:

- **AI hardware**: chips that can process large-scale training, such as graphics processing unit, tensor processing unit, field-programmable gate array, application-specific integrated circuit, etc.
- **Software frameworks**: for building models, managing workflows and monitoring performance. Common examples are TensorFlow, PyTorch, and scikit-learn.
- **Data storage and networking**: effective AI infrastructure requires robust storage and real-time data systems.[6]

Developing AI infrastructure is not only expensive but, in some cases, the supply of specialized hardware (i.e., AI chips) is controlled by companies in a few countries, and access to these products can be geopolitically challenging. For example, in January 2025, the United States government issued a *Framework for Artificial Intelligence Diffusion*,[7] introducing export restrictions on specialized AI chips for 120 countries. The framework was rescinded before it took effect and replaced by guidance on export controls specifically for China.[8] These policies highlight the strategic importance of geopolitics and its impact on AI-related hardware.

Finally, developing AI requires people with specialised skills and knowledge. Finding and attracting people with the right skills to develop AI models and applications can be difficult, especially in developing countries where these skills are relatively limited.

Figure 4. Estimated training cost of selected generative AI between 2019–24



Source: Authors' elaboration based on Stanford University (2025).

Barriers to adopting AI and digital technologies in industrial production

Difficulties in industry are not limited to AI development, but also extend to the adoption of AI and digital technologies. Figure 5 illustrates the wide range of barriers that firms in developing countries face in adopting AI and other digital technologies. These obstacles exist both within firms and in their broader operating environment. At the firm level, challenges include technical constraints, financial and organizational limitations and difficulties in attracting and managing skilled talent. At the contextual level, weak skills, underdeveloped entrepreneurial and innovation ecosystems, gaps in institutional frameworks and infrastructure deficits further inhibit technology adoption.

Figure 5. Barriers to adopting AI and digital technologies in industry in developing countries

Firm-level barriers

Technical
- Technical challenges to integrating new technologies into existing systems
- Dependence on foreign technology providers
- Limited understanding of the skills needed
- Limited capacity to attract talent
- Safety and cybersecurity risks
- A lack of access, use and protection of data

Economic
- A lack of awareness of technologies and their potential benefits (business case)
- Short-term profit-seeking
- Financial constraints
- Perception that technologies are too expensive

Organizational
- R&D activities performed abroad
- Technology adoption decisions made by the headquarters, usually located abroad
- Organizational and individual resistance to change
- Unclear implementation strategy
- Top-down implementation approaches with little involvement of workers
- Lack of cooperation among business functions and departments

Contextual barriers

Skills
- Mismatch between graduates' skills and the skills demanded by the industry
- Shortages in skills, such as: ICT; specialized manufacturing activities and processes; technology adaption and integration; data analysis; managerial; and fluency in foreign languages

Entrepreneurial and innovation systems
- Limited collaboration between industry and research organizations
- Absent or weak technology-transfer systems
- Limited access to specialized expertise and technology facilities
- Limited training services
- Limited access to finance for SMEs

Institutional framework
- Limited cyber-security, data protection and data privacy regulation
- Lack of reference architecture and standards
- Little focus on manufacturing in digital policy frameworks
- Lack of coordination across ministries
- Complex and lengthy processes for importing technologies

Infrastructure
- Limited physical infrastructure
- Costly and unstable electricity supply
- Limited and costly internet service and data-centres

Note: R&D = Research and development.
Source: Authors' elaboration based on Cambridge Industrial Innovation Policy (2022)[9] and The Commonwealth (2023).

Industrial policies can mitigate some barriers to AI adoption and development

Industrial policies can address some barriers to the adoption and development of AI and digital technology (Table 2). For AI and technology adoption, governments and institutions can raise awareness through demonstrations and advisory services, strengthen incentives with innovation vouchers, grants or subsidized loans, and build capacity through training, re-skilling and supplier development programmes. Measures to improve cybersecurity, develop infrastructure and set common technology standards are crucial. For AI and technology development, progress depends on consistent public investment in higher education and research, targeted financial support for technology development, the creation of secure data-sharing frameworks and the strengthening of international research and innovation networks.

Brazil's *Brasil Mais Produtivo (B+P)* programme is an interesting initiative that seeks to reduce barriers to the adoption of digital technology (see Box 2). The programme demonstrates how regional efforts can gain traction and become a more ambitious nationwide programme.

Table 2. Digitalization challenges and the policy tools to address them

Industrial digitalization challenges	Examples of policy tools
Adoption	
• Limited awareness of the existence and potential of AI and digital solutions	• Awareness raising tools: conferences, networking events, newsletters, bulletins, reports and technology advisory services • Public demonstration and the testing of new technologies
• Difficulties in making a business case for the adoption of new solutions	• Innovation vouchers • Awards for the successful digital adopters
• Capital constraints	• Adoption grants (usually with match funding from industry) • Subsidized loans
• Concerns about cybersecurity and data ownership	• Cybersecurity workshops • Establishment of data regulations • Incentives for data-sharing
• Low absorptive capacity	• Expert advice and technical assistance • Skills development programmes • Training and re-training systems • Attraction of foreign qualified workers
• Infrastructural gaps	• Public infrastructural development • Concessions to private infrastructure contractors
• Supplier gaps	• Supplier development programmes
• Interoperability of digital machines and products	• Setting and negotiating technology standards
Development	
• High skills requirements	• Public funding for higher education, science and basic research • Scholarships and grants for talented international students and researchers
• Capital constraints for technology development	• Subsidized loans • Credit guarantees
• Inadequate infrastructure for AI development	• Public infrastructure for large-scale data processing (data centres)
• Companies unwilling to share their data	• Creation of secure networks for data-sharing and pooling data from companies
• Internationalized research and innovation networks	• Funding, management of research and innovation networks • Workshops, seminars and conferences • Fellowships

Source: Authors' elaboration based on Cambridge Industrial Innovation Policy (2022) and The Commonwealth (2023).

Box 2 **Enhancing MSME productivity and digital transformation in Brazil: the Brasil Mais Produtivo (B+P) programme**

Launched in 2016, Brasil Mais Produtivo is Brazil's flagship initiative to boost the productivity, competitiveness and digital maturity of MSMEs across industry, commerce and services. Coordinated by the Ministry of Development, Industry, Trade and Services (MDIC), the programme is implemented through a broad network of partners, including the Brazilian Support Service for Micro and Small Enterprises (SEBRAE), the National Industrial Learning Service (SENAI), Brazilian Agency for Industrial Development (ABDI), the Brazilian Agency for Research and Industrial Innovation (EMBRAPII), the Brazilian Development Bank (BNDES) and the Funding Authority for Studies and Projects (FINEP).

The programme combines low-cost, high-impact consultancy and training services with a national digital platform for productivity enhancement. It provides participating firms with tailored diagnostics and technical assistance in areas such as lean manufacturing, energy efficiency, innovation management and digitalization. Support is segmented by sector: industrial MSMEs benefit from hands-on consultancy delivered by SENAI, while commerce and service firms are served through SEBRAE's network of Local Innovation Agents.

The initiative includes subsidies to support technology adoption and micro and small industrial firms receive fully subsidized consultancy, while medium-sized firms benefit from up to 70 per cent coverage. In the services sector, firms receive guidance on process improvements and may access reimbursements up to USD 400 for digital tools.

The programmes pilot (2016–2018) was successful and achieved average productivity gains of over 50 per cent among 3,000 industrial MSMEs. The revamped programme aims to reach 200,000 firms and deliver over 90,000 consultancy engagements by 2027. Just in São Paulo, a version of the programme (named Jornada de Transformação Digital) served around 18,000 firms which were supported by over 700 industrial consultants.

Brasil Mais Produtivo is a central component of Brazil's Nova Indústria Brasil industrial strategy (2024–2033) particularly Mission 4 focusing on the digital transformation of industry in the country. The programme aligns with broader efforts to modernize Brazil's productive base, improve energy and resource efficiency and foster innovation-led growth among smaller firms. Its scale, institutional coordination and cost-effectiveness position it as a promising model for other emerging economies seeking to upgrade the competitiveness of their MSME sectors.

Source: Authors' elaboration based on MDIC (2017), MDIC (2025), IPEA (2018) and SEBRAE (2025).

AI and future industrial policy formulation

Artificial intelligence is beginning to reshape how governments design and deliver industrial policies across the entire policy cycle (Figure 6).

In policy formulation, analysing public consultations can take months of work by dozens of analysts. To accelerate this, the United Kingdom's *Incubator for Artificial Intelligence (i.AI)* is developing *Consult* — an AI tool that identifies themes and presents them via dashboards and the open-source package ThemeFinder. Similarly, the Netherlands Enterprise Agency has applied an AI technique known as topic modelling to over 1,000 EU-funded projects to map R&D themes and identify synergies across programmes.

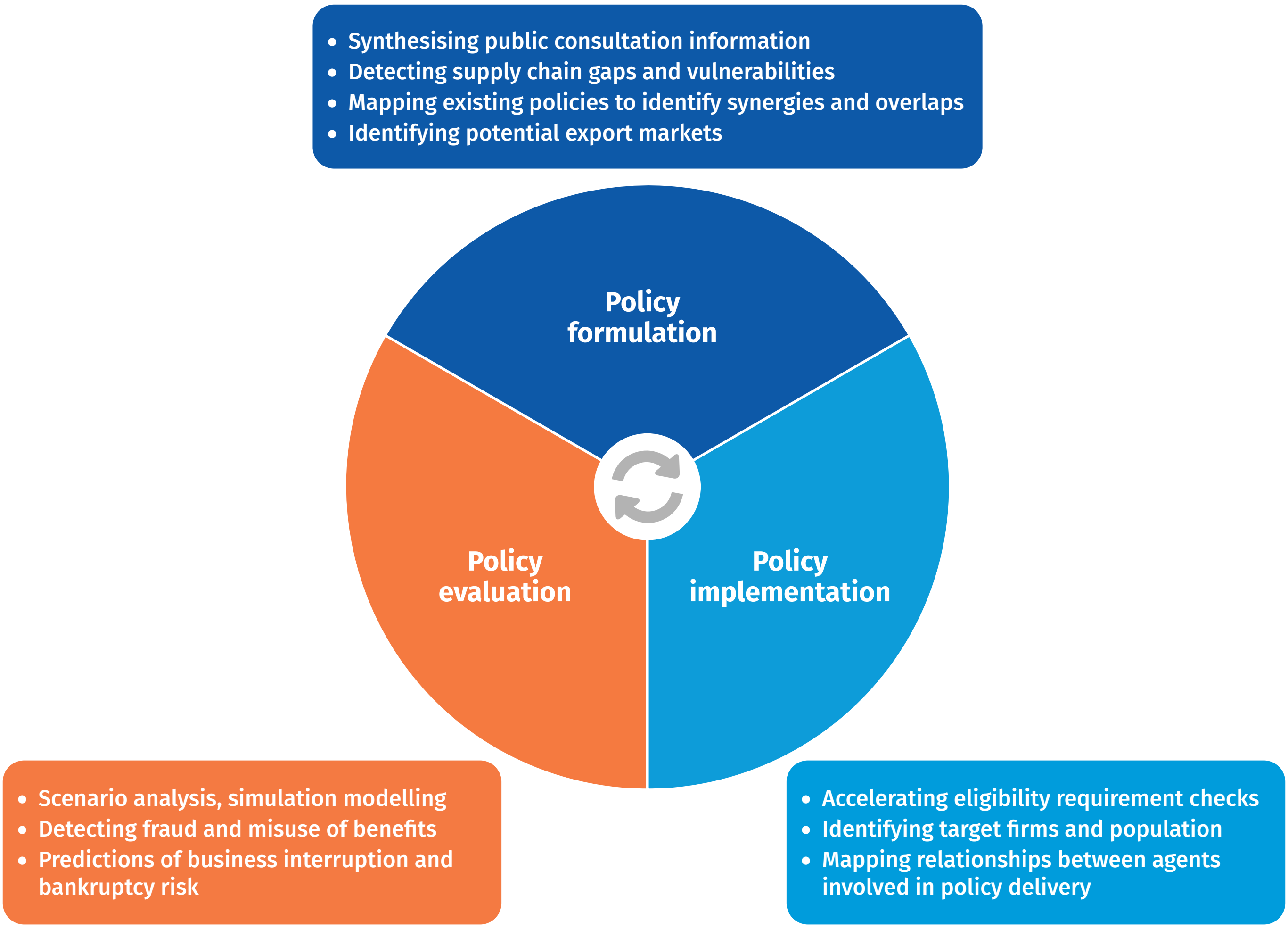
AI can also enhance supply chain analysis. The *Supply Chain AI Lab* at the Institute for

Manufacturing at the University of Cambridge applies complexity science and agent-based modelling to reveal vulnerabilities, risks and procurement strategies—insights crucial to policies aiming to strengthen competitiveness and resilience.

For policy implementation, AI can streamline eligibility checks, target firms more effectively and monitor programme delivery. China's *Industrial Brain* platform tracks industrial dynamics in real time to capture shifts in market fluctuations, technological change, or policy updates. At the same time, researchers at the Centre for European Economic Research have used the semantic analysis of patents and funding data to identify potential partnerships between universities and firms, thereby helping governments decide which collaborations to support.

AI is also proving valuable for policy monitoring and evaluation. In Russia, the Federal Service for Veterinary and Phytosanitary Supervision has deployed AI to trace counterfeit food products and strengthen supply chain integrity. Researchers elsewhere are using machine learning to simulate the effects of trade and tax policies, providing policymakers with more accurate impact analyses and forecasts. Finally, AI models are used to assess the financial health of firms applying for policy support and to predict bankruptcy risks, allowing governments to better prioritise assistance.

Figure 6. Potential AI applications across the industrial policymaking cycle



Source: Authors' elaboration based on secondary literature[10].

Policy implications and conclusions

This policy brief analysed the evolving technological landscape of industrial production and its implications for developing countries. The recommendations below are more relevant for middle-income countries, but developing countries can also benefit from the following:

1. **Monitor and share advances in industrial AI**: Establish mechanisms to continuously track emerging AI applications relevant to manufacturing, both globally and locally. Develop targeted knowledge-sharing platforms, such as case study repositories, workshops, and policy dialogues, to spread awareness about successful models and lessons learned across the industrial ecosystem, particularly to SMEs and resource-constrained stakeholders.

2. **Address barriers to adopting AI and digital technology:** Regularly conduct diagnostic assessments through surveys, focus groups, and stakeholder consultations, to identify key obstacles to the uptake of AI and digital technology in the manufacturing sector. Use various industrial policy instruments, including targeted funding, technical assistance, public procurement, standards development and innovation incentives to overcome barriers and build capacity.

3. **Create local data ecosystems to support local AI innovation**: Facilitate the formation of an industrial data-sharing consortia or community of practice that unites firms, research institutions and other stakeholders willing to securely share data. These initiatives can help develop contextually relevant AI solutions, foster trust and collaboration and reduce the dependency on external platforms and foreign technologies.

4. **Leverage AI for smarter industrial policymaking**: Encourage the experimentation and scaling of AI tools in public agencies to improve the design, targeting, implementation and evaluation of industrial policies. AI-enabled analytics can help policymakers detect emerging trends, simulate policy impacts and allocate resources effectively, particularly in data-scarce and capacity-constrained environments.

5. **Promote the adoption of responsible and inclusive AI**: Integrate safety, fairness, transparency and accountability principles into national AI strategies and industrial policy frameworks. Ensure that AI solutions deployed in the manufacturing sector comply with international standards and ethical guidelines. AI in the sector should support inclusive innovation by involving diverse stakeholders and prioritising applications that benefit a range of firms and workers.

Endnotes

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