AI and the future of manufacturing and industrial policy: challenges and opportunities for developing countries

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1. Introduction

The landscape of industrial production is undergoing a profound transformation. For over a decade, digital technologies have been steadily reshaping how goods are designed, manufactured, and delivered. This process of industrial digitalisation has brought with it new opportunities to enhance productivity, flexibility, and sustainability across manufacturing sectors. In recent years, however, the pace and scope of this transformation have accelerated markedly, driven in large part by rapid advances in artificial intelligence (AI). From predictive maintenance and quality control to supply chain optimisation and design automation, AI is now poised to become a defining feature of modern manufacturing systems.

Yet while the promise of AI in manufacturing is vast, its diffusion remains uneven. The global race to develop and deploy AI technologies is intensifying, and competitive advantage is increasingly being shaped by countries' and firms' capacity to harness these tools. However, many developing countries face considerable barriers to both the adoption and local development of AI in manufacturing. These challenges range from limited digital infrastructure and skills shortages to gaps in data availability, institutional capabilities, and access to finance. Without targeted policy action, there is a real risk that AI will deepen existing divides in industrial development, rather than bridge them.

Industrial policy has a central role to play in navigating this new terrain. By identifying priority sectors, supporting capability development, and fostering collaboration between firms, research institutions, and government agencies, industrial policy can help overcome the firm- and system-level barriers that hinder AI adoption. Crucially, AI is not only a target of policy but also a tool for policy itself. Emerging applications of AI are helping governments—especially those with limited resources—to better analyse data, design interventions, monitor implementation, and evaluate impact. These innovations have the potential to improve the effectiveness and agility of industrial policymaking in the face of rapid technological change.

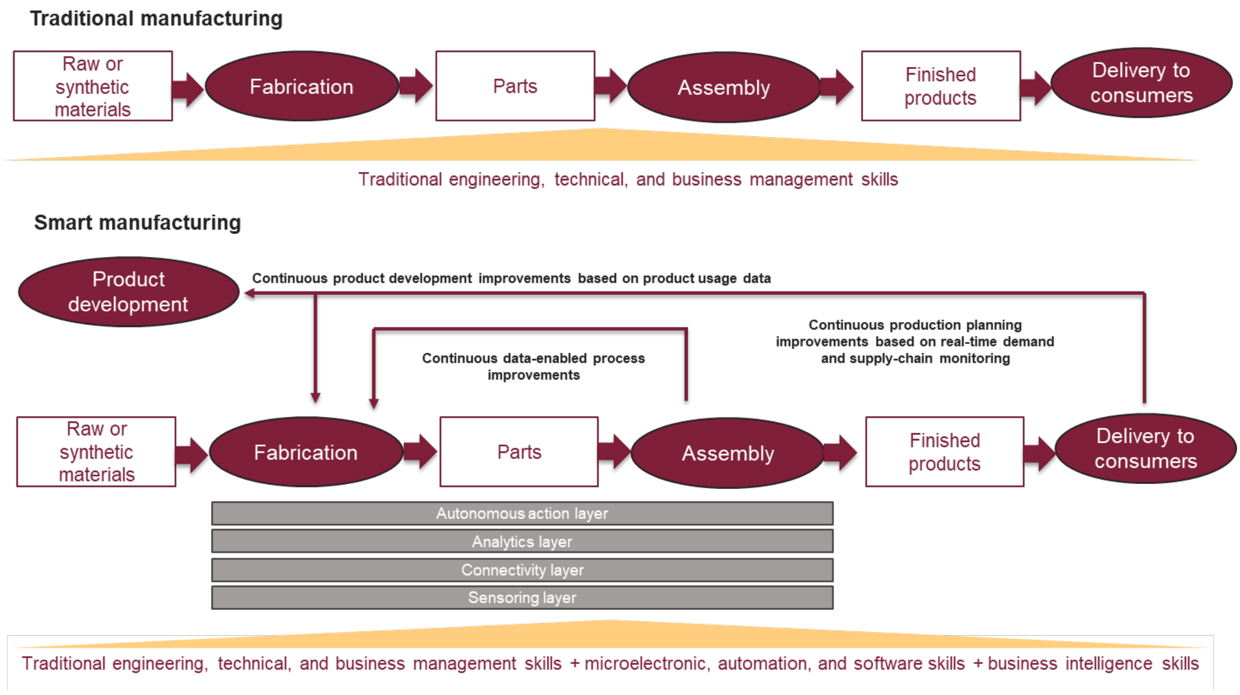
As countries grapple with how to position themselves in an increasingly digital industrial landscape, understanding the implications of AI for industrial development—and for industrial policy—is becoming increasingly urgent. This policy brief explores the opportunities and challenges associated with the use and development of AI solutions in manufacturing, highlights its relevance for policymakers in developing countries, and identifies areas where strategic interventions can make a critical difference.

2. Digital transition in the manufacturing sector

The manufacturing sector has been going through important transformations in recent years with the introduction of digital production technologies. Digital, or "smart", manufacturing is characterised by adding several layers of hardware and software to traditional manufacturing processes. These include a sensoring 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 a layer of actuators that can be autonomously manipulated to enact change to production processes.

While traditional manufacturing processes followed 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 obtained from sensors in the production line allows for efficiency gains and continuous process improvements, such as reducing defect rates through enhanced quality control and cutting machinery downtime through predictive maintenance. Product usage data, in turn, provides key information for product development – adapting products to how consumers actually use them. Finally, real-time demand and supply-chain data enables continuous production planning improvements (Figure 1).

FIGURE 1 – FROM DIGITAL TO SMART MANUFACTURING



Source: Own elaboration

Artificial intelligence is a key component of smart manufacturing as it is the main technology behind the "analytics layer". Without AI, it would be in many cases impossible to make sense of the vast quantities of (often unstructured) data being generated in production processes. Recent advances in AI are making models even more powerful, efficient, and accurate in transforming different types of data into actions that can lead to process improvements.

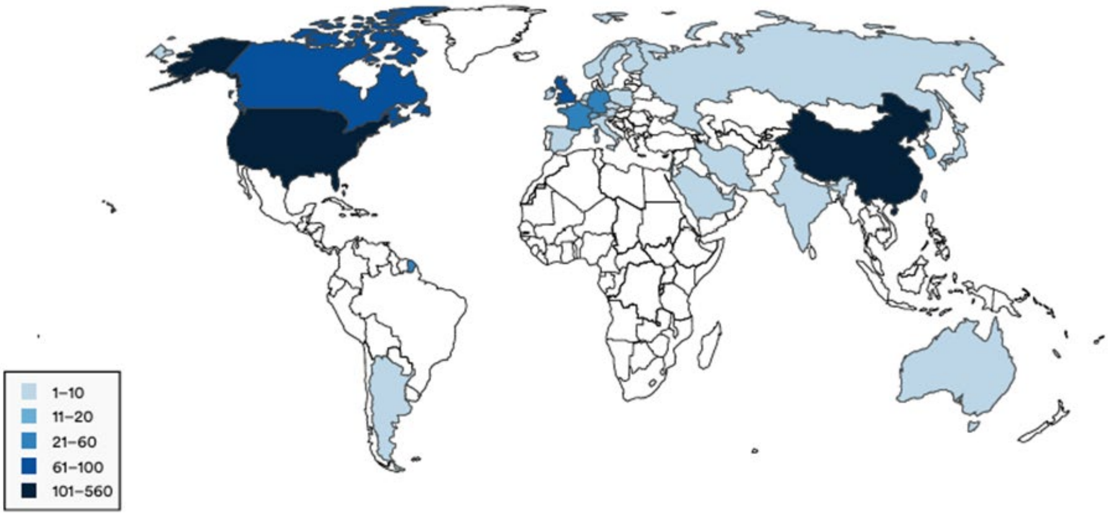
3. Challenges from the ongoing evolution of AI

The advent of AI and the transition to smart manufacturing present numerous industrial challenges for developing countries. Not only the AI market is becoming increasingly competitive and capital-intensive, but developing countries also face numerous firm-level and system-level barriers to AI development and adoption.

3.1 The AI development market is becoming increasingly capital-intensive

First, it is worth noting that developing countries (except China) are primarily *users* of AI models, with only a few of them having developed notable AI models (Figure 2).

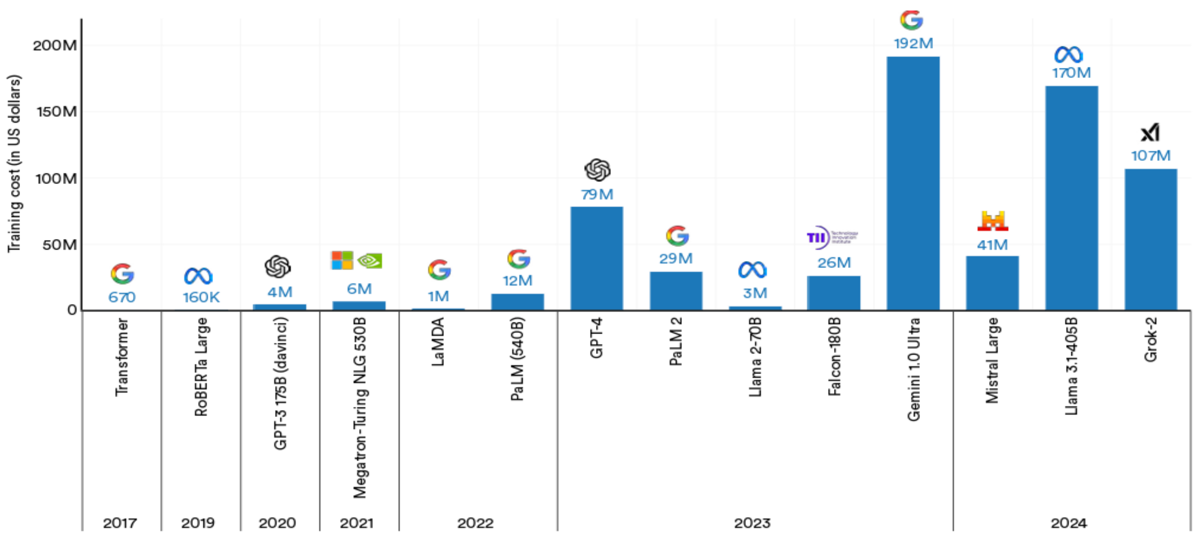
FIGURE 2 - NUMBER OF NOTABLE AI MODELS BY GEOGRAPHIC AREA, 2003–24 (IN TOTAL)



Note: notable AI models refer to particularly influential models within the AI/machine learning ecosystem
Source: Stanford University (2025). Artificial Intelligence Index Report 2025

Secondly, training AI models is becoming an increasingly capital-intensive effort. For example, Figure 3 below shows that the latest Large Language Models have cost over USD100 million, highlighting that the entry barriers in the AI market are becoming increasingly high.

FIGURE 3 - ESTIMATED TRAINING COST OF SELECTED GENERATIVE AI, 2019–24

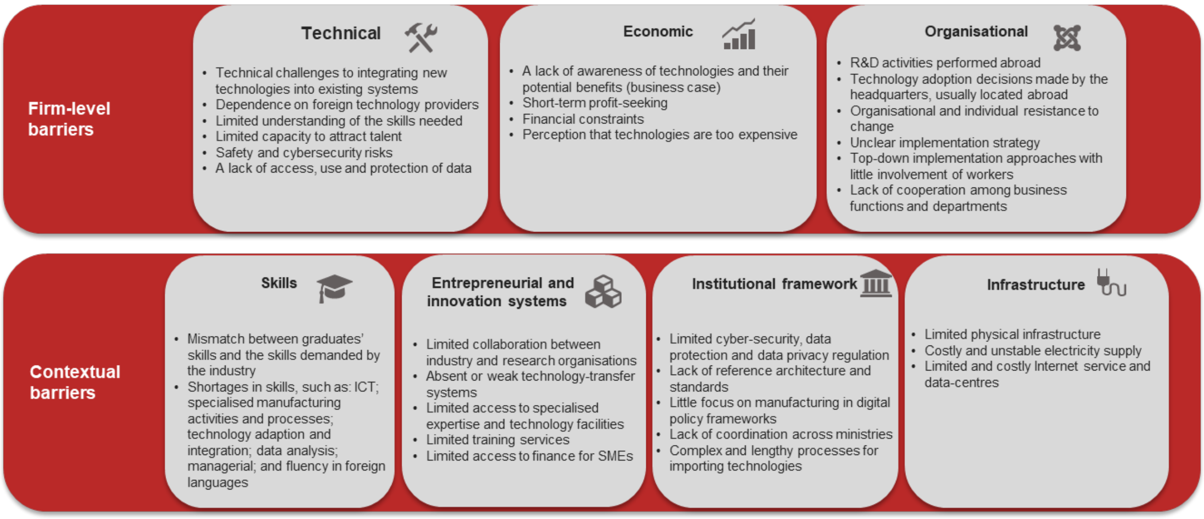


Source: Stanford University (2025). Artificial Intelligence Index Report 2025

3.2 There are many domestic barriers to adopting AI and digital technologies in industrial production

But the barriers to AI and digital technology adoption in industry are not only related to the market. There are barriers at the firm level – technical, economic, organisational –, and contextual barriers – skills availability, entrepreneurial and innovation systems, institutional frameworks, infrastructure –, as highlighted in Figure 4 below.

FIGURE 4 – BARRIERS TO THE ADOPTION OF AI AND DIGITAL TECHNOLOGIES IN INDUSTRY



Source: Cambridge Industrial Innovation Policy (2022). Policies and institutions for industrial digitalisation

3.3 Industrial policies can help mitigate some of these barriers

Industrial policies can help address some of the barriers to AI and digital technology adoption, production, and development. Table 1 below shows what are the policy tools and the institutions and organisations required to help mitigate those barriers.

TABLE 1 – POLICY TOOLS AND INSTITUTIONS REQUIRED TO ADDRESS THE BARRIERS TO AI AND DIGITAL TECHNOLOGIES

Industrial digitalisation challenges		Policy tools required	Institutions/organisations required
Adoption of AI and digital technologies in production	• Limited awareness of the existence and potential of industrial digital technologies	• Awareness-raising tools: Conferences, networking events, newsletters, bulletins, reports, and technology advisory services • Public demonstration and testing of new technologies	• Technology diffusion organisations • "One-stop-shop" for industrial support • Technology diffusion organisations • Demonstration facilities (e.g., model factories, testbeds, living labs, etc.)
	• Difficulties in making a business case for new tech adoption	• Innovation vouchers • Awards for successful adopters	• Technology diffusion organisations • Innovation agencies
	• Capital constraints	• Adoption grants (match funding) • Subsidised loans	• Technology diffusion organisations • Innovation agencies • Development banks

	• Concerns about cybersecurity and data ownership	• Cybersecurity workshops • Establishment of data regulations • Incentives to data-sharing	• Technology diffusion organisations • Parliamentary working groups
	• Low absorptive capacity	• Expert advice and technical assistance • Skills development programmes • Training and re-training • Attraction of foreign qualified workers	• Technology diffusion organisations • Education systems • Training systems
	• Infrastructural gaps	• Public infrastructural development • Concessions to private infrastructure contractors	• Public infrastructure companies • Private infrastructure companies
	• Supplier gaps	• Supplier development programmes	• Technology diffusion organisations
	• Interoperability of digital machines and products	• Setting and negotiating technology standards	• Metrology agencies
Production of AI and digital technologies in production	• Upgrading from low value-added production	• Technology transfer conditionalities to production contracts • Joint ventures • Local content requirements	• Ministries of industry, international trade, or science and technology
Development of AI and digital technologies in production	• Non-profitable basic science	• Public funding for basic research	• National research funding bodies
	• Innovation "valley of death"	• Support for translational research	• Bridging organisations
	• Internationalised research and innovation networks	• Funding and management of research and innovation networks • Workshops, seminars, conferences • Fellowships	• Innovation agencies, international research networks

Source: Cambridge Industrial Innovation Policy (2022). Policies and institutions for industrial digitalisation

An interesting programme that has been seeking to reduce barriers to digital technology adoption is Brazil's "Brasil Mais Produtivo (B+P)" programme, described in Box 1 below. The programme is a good example of a successful intervention at the regional level gaining traction and becoming a more ambitious nationwide programme.

BOX 1. ENHANCING MSME PRODUCTIVITY AND DIGITAL TRANSFORMATION IN BRAZIL: THE BRASIL MAIS PRODUTIVO (B+P) PROGRAMME

Launched in 2016 and significantly expanded in 2023, Brasil Mais Produtivo is Brazil's flagship initiative to boost the productivity, competitiveness, and digital maturity of micro, small, and medium-sized enterprises (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 SEBRAE, SENAI, ABDI, EMBRAPII, BNDES and 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 digitalisation. 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 (ALI).

The initiative also includes subsidies to support technology adoption: micro and small industrial firms receive fully subsidised consultancy, while medium-sized firms benefit from up to 70% coverage. In the services sector, firms receive guidance on process improvements and may access reimbursements for digital tools up to R$2,000 (~US$400).

Following a successful pilot (2016–2018), which achieved average productivity gains of over 50% 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, an early version of the programme (named Jornada de Transformação Digital) served around 18,000 firms delivered by over 700 industrial consultants.

Brasil Mais Produtivo is a central component of Brazil's Nova Indústria Brasil industrial strategy (2024–2033), serving as the main delivery vehicle for Mission 4: Digital Transformation of Industry. The programme aligns with broader efforts to modernise 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.

Sources: MDIC (n.d.) Brasil Mais Produtivo; SEBRAE (n.d.) Conheça o Brasil Mais Produtivo; MDIC (2017) Brasil Mais Produtivo; IPEA (2018) Avaliação de desempenho do Brasil Mais Produtivo

4. AI-driven opportunities for future industrialisation

Artificial intelligence and digital technologies bring not only industrial challenges, but also potential opportunities for developing countries. These opportunities are mainly related to: 1. The adoption of AI in manufacturing to increase the productivity and efficiency of existing industries; 2. Becoming a developer of AI models and applications based on local knowledge and data. Overall, while there are many potential applications of AI in manufacturing, in practice these are still at an early stage of implementation. Opportunities for development of algorithms based on local data can also be explored – an effort that requires strong buy-in and collaboration with industry.

4.1 AI adoption opportunities: there are many *potential* applications of AI in manufacturing

Artificial intelligence models and applications are undergoing fast development. Many of the emerging applications can help businesses, especially SMEs, carry out their activities more effectively and efficiently. Table 2 below summarises 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 organisational capabilities, while others are only accessible with a higher level of such capabilities.

TABLE 2. POTENTIAL APPLICATIONS OF AI IN MANUFACTURING

Production stage	Capabilities required	AI applications	Examples
Business processes	Basic	Market analysis	**Automated survey creation and analysis:** reducing setup time from weeks to days
			Competitive intelligence gathering: monitoring competitor activities across digital channels

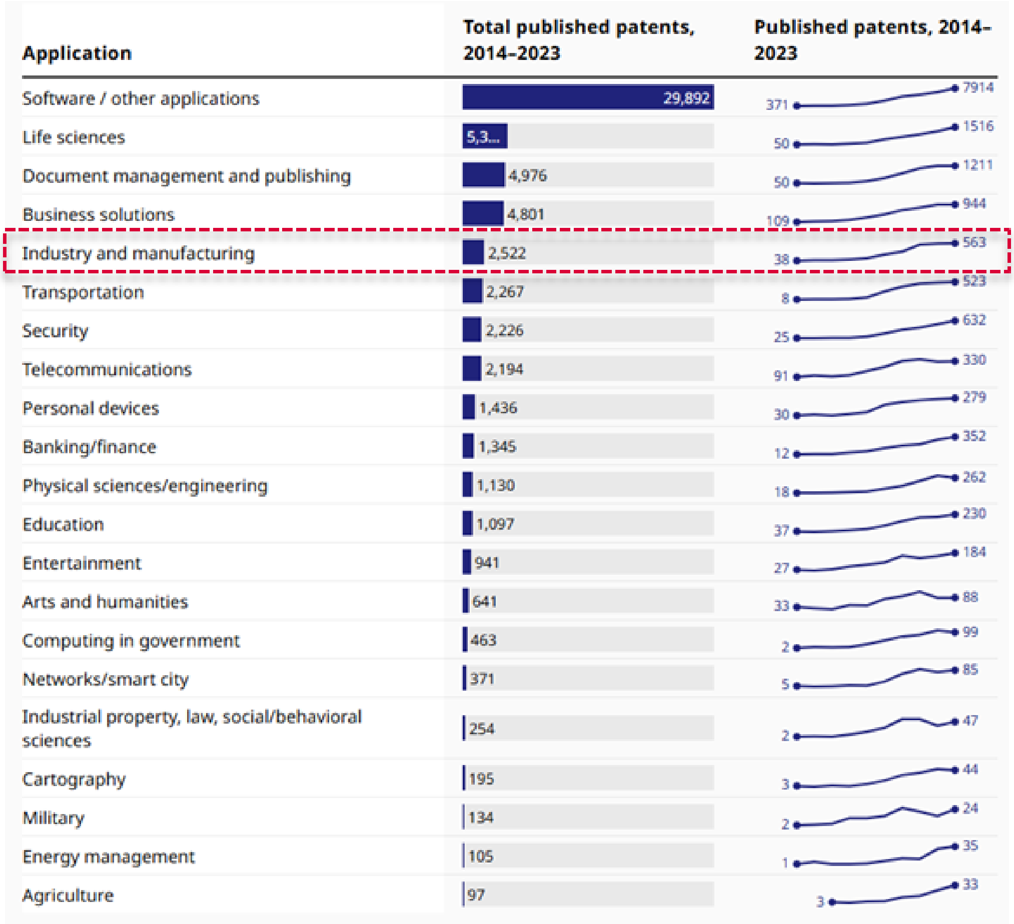
Production stage	Capabilities required	AI applications	Examples
			Social media listening and sentiment analysis: understanding consumer opinions at scale
			Predictive analytics: forecasting market trends and consumer behaviour changes
			Automated reporting: generating visual dashboards and insight summaries
			Lead generation and scoring: real-time updates to sales teams about prospects and leads
		Exports	**Automated analysis of import regulations:** identify markets where compliance is more easily achieved
			Language translation: perfectly translate large volumes of information instantly
		Customer service	**Smart chatbots:** quickly answer customer questions, offer personalised recommendations, and provide support
		Targeted advertising	**Customer segmentation:** segmenting customers into groups based on behaviour and other demographics to improve marketing and other messages
			Personalised customer journey: personalising a customer's journey based on their behaviour and making recommendations for future purchases
		Content generation	**Automated content generation:** emails, marketing copies, blog posts, recruitment materials, legal documents, etc.
		Human Resources	**Automating candidate screening:** applicant tracking systems and recruiting tools include AI technology to automatically screen candidates based on specific criteria and qualifications.
			Skill assessment and recommendations: provide tailored learning recommendations based on employee career goals and industry needs
		Cybersecurity	**Security monitoring:** AI-powered security monitoring solutions use data analytics to continually learn about and adapt to evolving threats and environments.
			Bot prevention: differentiate between authentic website traffic, good bots (such as search engine crawlers), and bad bots.
			Threat or fraud detection and response: AI can analyse large amounts of data to identify patterns in user behaviour and automatically flag anomalies that may indicate fraud or another cyber threat.
		Legal analysis	**Research and analysis:** automatically retrieve, organize, and analyse relevant legal documents
			Contract review and due diligence: review and analyse contract language to flag potential issues or unfavourable terms that may otherwise be overlooked.
			Compliance: AI tools to understand specific laws and regulations and identify discrepancies more efficiently than manual methods.
		Accounting & Finance	**Automating tasks:** automating data collection, data entry, categorisation, reconciliation, and invoicing
			Streamlined payroll management: automatically process payroll, saving time, eliminating human error, and ensuring payroll is accurate
			Tax audit support: help auditors and accountants effectively prepare financial statements and records to ensure they're accurate, up to date, relevant, and align with compliance regulations.
			Compliance: automate compliance checks and maintain real-time records of all financial transactions and activities, which can reduce the overall risk of regulatory breaches and penalties.
			Forecasting and budgeting: process large volumes of historical performance data, including market trends, economic indicators, and company-specific metrics, to generate predictions about future trends or outcomes, improving budgeting and resource allocation decisions
	Advanced	Integrating IT operations (AIOps)	**Centralised IT platforms:** enables IT operations teams to integrate multiple, separate IT operations tools using a centralised platform, which helps businesses more effectively manage an ever-expanding IT landscape.
		Integrating human resources management	**Talent management systems:** centralise employee data, making it easier for companies to manage and automate HR processes.
		AI-accelerated search for internal information	**Search chatbots:** enable workers to query document-based product knowledge managed in PLM environments, retrieving information quickly.
Manufacturing processes	Basic	Plug-and-play, digitalisation solutions for basic sensorisation of machines and production lines	**Improved visualisation and control of production:** sensors to identify machine downtimes, speed, and operation trends
			Improved calculation of performance indicators: more precise data on machine operation and downtime improves the calculation of key performance metrics such as Overall Equipment Effectiveness (OEE)
	Advanced	Predictive maintenance	**Anomaly detection:** complex equipment generates massive amounts of data, not only on vibration but also temperature, pressure, heat, and many other variables. AI systems not only gather and analyse this data to detect anomalies, but also learn from it as they go.
			Failure prediction: algorithms analyse data in real time and send reports to factory teams, flagging signs of potential failure—for example, overheated machines or improper voltage fluctuations. As the model ingests more data, it learns, adapts, and predicts with increasing accuracy.
		Smart quality control	**Automatic visual inspection:** by utilising computer vision and AI algorithms, companies can detect defects using infrared, thermal, magnifying, or other specialist cameras, that can pick up much more beyond the capability of humans.
		Smart or autonomous machines and production lines	**Autonomous robot picking and placing:** AI enables robots to autonomously reason about how to handle items in complex real-world scenarios without being specifically trained for it
		Energy efficiency	**Improved energy efficiency:** improve energy efficiency by analysing patterns and automating processes like heating, cooling and lighting based on usage trends
		GenAI applied to digital twins for process simulation	**Process simulation:** GenAI can simulate various conditions and predict outcomes for digital twins, offering insights into potential improvements. This allows organisations to test and refine their operations digitally, speeding up development and reducing costs.
Product development processes	Basic	Enhancing creativity and design workflows	**Using generative AI for new ideas:** generative AI models can be used to brainstorm new product features and help identify the most promising ideas
			Using pre-trained LLMs to simulate feedback on new products: accelerates the design, testing, and creation of minimum viable products
			Higher quality visuals for idea presentation: quickly develop multiple mediums for internal or stakeholder presentations
		User need identification and prototype feedback analysis	**Identifying user needs from market analysis:** enhanced market analysis (see above) can help identify user needs for new product development
			Sentiment analysis of feedback to new products: reads and predicts emotions and sentiment from text, video, and audio of different words and facial expressions. It can extract whether someone is happy or pleased when interacting with a new product.
	Advanced	Generative design	**Improved design of parts and products:** quickly generate a wide range of design alternatives based on defined parameters, such as materials, manufacturing methods and performance requirements. Common benefits are: lightweighting, improved performance, part consolidation, and sustainability.
		Natural language interfaces to complex design tools	**User interface for engineering and design software:** answering simple queries about selecting the best computer-aided engineering tool for a given task or executing a fully automated generative design capability that inputs product requirements and directly generates a compliant design.

Production stage	Capabilities required	AI applications	Examples
Product	Basic	Basic connectivity functionalities in products	**Internet of Things:** basic connectivity capabilities allow products (e.g., wearables, home appliances, vehicles, machines) to be connected to the internet, enabling potential access to AI-based services
	Advanced	Embedded AI: integrating AI into embedded systems, allowing devices to process data and make decisions autonomously.	**Healthcare wearables:** monitor patient vitals like heart rate and oxygen levels with predictive capabilities for patient health
			Industrial IoT: industrial machines with AI-powered embedded systems can monitor equipment, process real-time sensor data, and execute self-diagnoses, minimizing downtime and improving operational efficiency – all within a single process optimization platform.
			Autonomous vehicles: AI-powered vehicles rely heavily on embedded artificial intelligence to process real-time data from their surroundings. These vehicles can use edge AI and neural networks to make split-second decisions based on datasets gathered from cameras, radars, and other sensors, enhancing safety and navigation.
			Smart homes: In large-scale smart building management, embedded AI is vital in optimizing energy usage, security, and automation. AI-driven systems can adjust lighting, HVAC, and security systems automatically based on real-time data, ensuring optimized efficiency without delays caused by cloud processing.
			Robotics in manufacturing: embedded AI allows robots to process data locally, adapt to real-time changes, and execute tasks such as quality control and assembly with minimal human intervention.
Supply chain	Basic	Supply chain optimisation	**Inventory optimisation:** AI systems can help define the optimal mix of inventory across the manufacturer's supply chain to achieve service level targets.
			AI-equipped warehouse drones: some inventory management solutions use AI-equipped drones to read barcodes, text, and other information and automatically feed warehouse management systems (WMS), providing warehouse managers with real-time inventory data via a dashboard.
			Damage detection at fulfilment centres: trained on product photos, the AI identifies any damaged items in the fulfilment process and can divert them to workers for further checks.
	Advanced	Supply chain analytics	**Enhancing supply chain visibility:** AI can combine real-time Internet-of-Things (IoT) sensor with data streams from carriers, ports, airport operations, rail lines, traffic reports, and weather forecasts to provide visibility into supply chains.
			Sourcing materials for manufacturing: AI-powered supply management platforms can map lead times and spend data in several commodity areas, letting companies identify alternative suppliers to ensure supply continuity.
			Predictive analytics: helps forecast demand and future pricing of shipping and material costs, and predict production bottlenecks and disruptions based on weather and news data.
			Sustainability: AI-enabled solutions can help measure carbon and Scope 3 emissions from ports, terminal operators, maritime and rail carriers, shippers, and trade authorities.

4.2 AI adoption opportunities: sophisticated AI solutions are still not widely adopted in industry, but this can change

Many of the applications mentioned above are still in the early stages of development and adoption across manufacturing industries. For example, Figure 5 below shows that industry and manufacturing represent only a small fraction of generative AI patents, with the majority focusing on software applications. This shows that AI in manufacturing is still in its early stages, but with developments in AI models and training data, this could increase significantly in the coming years.

FIGURE 5. GLOBAL PATENT FAMILIES IN GENERATIVE AI APPLICATIONS, 2014-2023



Source: WIPO (2024). Patent Landscape Report – Generative Artificial Intelligence.

4.3 Local AI development opportunity: there is a potential for developing local AI solutions, using local training data

This lag in applications in industry relates to the myriad of barriers discussed above, but it is also linked to the fact that manufacturing data is proprietary and companies are often reluctant to share it. This opens a role for governments in creating platforms for industry collaboration in developing AI applications based on local data.

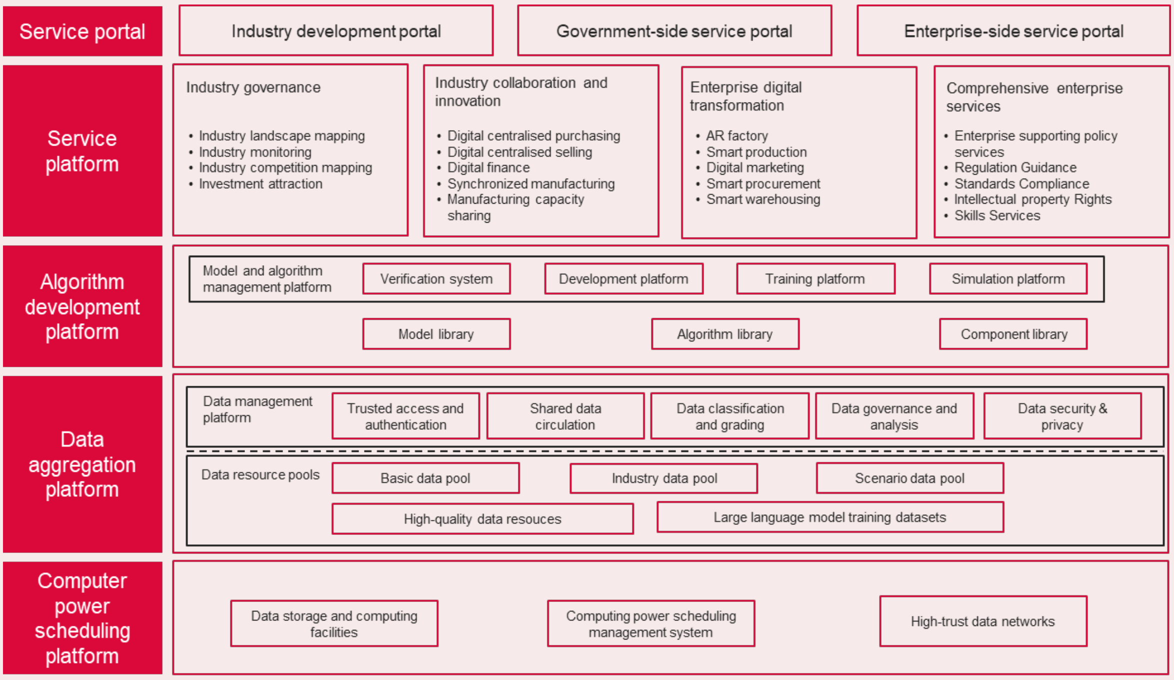
While SMEs might not individually generate enough data to train AI models, if companies come together and pool their data, they can develop AI models tailored to their needs. This has been the approach of the Chinese government with its “Industrial Brain” project (Box 2). In this programme, the government sought to create a unified network for secure data sharing and pool companies’ data resources. This allows them to monitor industry data in real-time and to develop tailored AI applications to optimise production.

BOX 2. 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 builds a “single account” system for managing industrial data, a “unified network” for secure data sharing, and a “comprehensive map” to support innovative data applications (see Figure 6 below for the programme’s functional structure). By the end of 2024, Shandong had launched 80 pilot projects for "Industrial Brain" construction, 12 of which were recognised as provincial demonstration cases.

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

FIGURE 6 – FUNCTIONAL STRUCTURE OF THE "INDUSTRIAL BRAIN" PROGRAMME

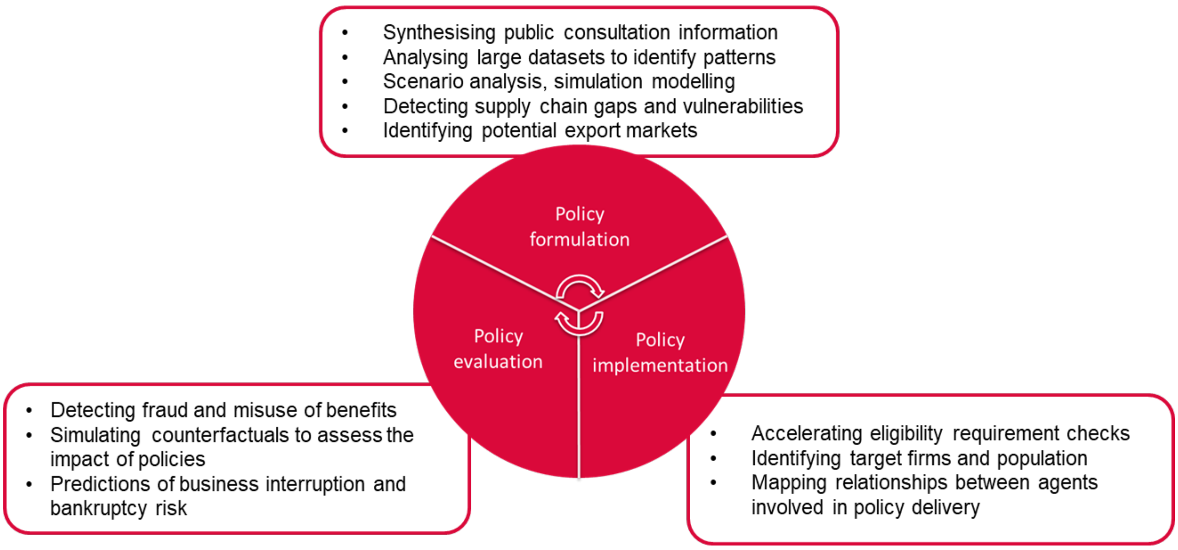


Source: Department of Industry and Information Technology of Shandong Province (2024). Shandong Province "Industrial Brain" Development Guidelines 1.0

5. The role of AI in shaping future industrial policy

Artificial intelligence is also changing how governments conduct industrial policies. As Figure 7 below highlights, there are AI applications that can help policymakers across all stages of the industrial policy cycle.

FIGURE 7 – POTENTIAL AI APPLICATIONS ACROSS THE INDUSTRIAL POLICYMAKING CYCLE



Source: Own elaboration

Some governments have begun integrating AI into the policy formulation process. One specific area where AI offers clear benefits is in the analysis of public consultations. These consultations play a vital role in policymaking, but reviewing and interpreting the feedback is both complex and highly resource-intensive. For instance, the UK government estimates that analysing a consultation with 30,000 responses typically demands a team of about 25 analysts working for three months. As a reference, the UK's recent Modern Industrial Strategy received 27,000 responses. To address this challenge, the UK government's Incubator for Artificial Intelligence (i.AI) is building a tool designed to make the analysis of consultation feedback both quicker and more equitable. The tool, called Consult, employs AI and data science methods to automatically identify key themes and patterns within the responses, presenting them through dashboards for policymakers. Notably, they have also released an open-source Python package named ThemeFinder, enabling others to use the same capabilities.[1]

AI can also be applied to supply chain analysis. For example, the Supply Chain AI Lab at the Institute for Manufacturing, University of Cambridge, studies complexity science, emerging artificial intelligence technology, and agent-based computing techniques to develop novel tools and methods for understanding and handling industrial systems. They create methods to discover hidden patterns in data that yield useful insights for improving supply chain operations. These insights can be used to identify hidden vulnerabilities, estimate risks, predict quality of goods and even estimate the best price for procurement negotiations.[2] This type of knowledge is crucial when developing industrial policies to boost industrial competitiveness and economic resilience.

AI-based semantic analysis can also help map the content and beneficiaries of existing policies, to leverage synergies and avoid overlaps. For example, the Netherlands Enterprise Agency used a semantic technique known as topic modelling to analyse information from 1,122 projects funded through various EU innovation initiatives (including the European Fund for Regional Development, the SME Innovation Programme, and the Public-Private Partnership Programme). The aim was to gain insights into the R&D themes being funded and to assess how these programmes align or complement one another.[3]

In terms of policy implementation, AI tools are good at analysing large quantities of data and detecting potential anomalies. This can potentially be applied to the eligibility checks for a large number of companies applying for policy programmes, identifying target firms, or monitoring policy implementation to ensure the support is being used for the intended purposes. For example, China's Shandong Province's "Industrial Brain" platform (see Box 2) utilises AI to enable local officials to monitor industrial dynamics in real-time, capturing shifts influenced by factors such as policy changes, market fluctuations, technological developments, investment trends, and workforce skills.

Artificial intelligence techniques can also be used to map the relationship between agents of an innovation system. For example, a research group at the Centre for European Economic Research (ZEW) has applied semantic analysis to patent, firm-level, and public R&D funding data to explore the technological proximity between university patents and those of several firms. This allows the

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[1] Incubator for Artificial Intelligence (n.d.) Consult
[2] Institute for Manufacturing (n.d.) Supply Chain AI Lab
[3] OECD-CSTP (2018) Semantic analysis for innovation policy

identification of potential partnerships capable of taking new technologies to the market. This can give insights to governments on what types of partnerships are worth supporting the most.[4]

Finally, there are AI applications in industrial policy monitoring and evaluation. First, AI tools can be used to detect fraud or misuse of benefits. For example, the Federal Service for Veterinary and Phytosanitary Supervision of Russia has utilised AI technology to reveal counterfeit and falsified food products. To reduce the proportion of counterfeits and strengthen the traceability system, the agency developed and implemented an AI-based technology to detect violations across the various stages of the production and movement of food products, by analysing veterinary certificates and processing a large volume of datasets to reveal suspicious patterns of falsifications.[5]

Secondly, AI can be leveraged to simulate policy outcomes or counterfactual scenarios. For example, researchers have used machine learning to analyse the impact of trade agreements, tax policies, and trade policies.[6] This can provide a more accurate estimate of policy impacts, as well as help with policy formulation by providing insights on expected impacts.

Finally, researchers have used an AI model to assess the financial health of companies that apply for economic help or funding and predict well in advance the risk of bankruptcy in the future. This can help governments assess which firms to prioritise or to more accurately assess the level of risk when supporting different firms.

Overall, there are many potential AI applications to industrial policymaking. Governments of developing countries should keep abreast of these developments and explore the emerging opportunities to leverage these techniques as they can significantly cut costs and enable civil servants to do more under budget constraints.

6. Policy implications and conclusions

This policy brief has analysed the changing technological landscape of industrial production and its implications for developing countries. AI is rapidly emerging as both a transformative force in industrial production and a strategic tool for more effective policymaking. While its full potential is still unfolding, early evidence suggests that AI can significantly enhance productivity, competitiveness, and policy delivery—particularly when embedded within broader digitalisation efforts. For developing countries, the challenge lies not only in catching up with technological frontrunners but in shaping AI adoption in ways that align with national development goals. This will require deliberate and inclusive industrial policy strategies that address adoption barriers, foster local innovation ecosystems, and ensure the responsible use of AI across both the public and private sectors.

Some specific policy implications can be derived from the analysis conducted in this policy brief:

- **Monitor and disseminate industrial AI advancements:** 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 of successful implementation models

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[4] Ibid.
[5] OECD-OPSI (2021) Artificial Intelligence Reveals Counterfeit and Falsified Products
[6] UNCTAD (2021) Economic Nowcasting with Long Short-term Memory Artificial Neural Networks (LSTM)

and lessons learned across the industrial ecosystem, particularly among SMEs and resource-constrained stakeholders.

- **Address barriers to AI and digital technology adoption:** Conduct regular diagnostic assessments—through surveys, focus groups, and stakeholder consultations—to identify key obstacles to AI and digital technology uptake in the manufacturing sector. Leverage the full range of industrial policy instruments, including targeted funding, technical assistance, public procurement, standards development, and innovation incentives, to systematically address these barriers and support capability building.

- **Enable local data ecosystems for local AI innovation:** Facilitate the formation of industrial data-sharing consortia or communities of practice that bring together firms, research institutions, and other stakeholders willing to securely pool data. Such initiatives can support the development of contextually relevant AI solutions, foster trust and collaboration, and reduce the dependency on external platforms and foreign technologies.

- **Leverage AI for smarter industrial policymaking:** Encourage the experimentation and scaling of AI tools within 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 more effectively—particularly in data-scarce and capacity-constrained environments.

- **Promote responsible and inclusive AI adoption:** 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, and support inclusive innovation by involving diverse stakeholders and prioritising applications that benefit a broad base of firms and workers.

About us

Cambridge Industrial Innovation Policy (CIIP) is a global, not-for-profit policy group based at the Institute for Manufacturing (IfM), University of Cambridge. CIIP works with governments and global organisations to promote industrial competitiveness and technological innovation. We offer new evidence, insights and tools based on the latest academic thinking and international best practices.

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