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AI Investments Allow Emerging Markets to Develop and Expand Sophisticated Manufacturing Capabilities

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As advances in machine learning, computer vision, and robotics help manufacturers around the world improve their processes and produce new and more complex products, artificial intelligence (AI) is becoming an integral tool of modern manufacturing, and one that is increasingly important to the industry's future. By combining large volumes of data with the computing power to simulate human thinking, AI is increasing the efficiency, capacity, and complexity of factory floors, and is introducing robotics, the Internet of Things, and other cutting-edge innovations to manufacturing value chains across the globe. Artificial intelligence is a critical enabler of manufacturing complexity that is essential for companies to produce an expansive range of sophisticated products and dynamically engage with regional and global value chains. Firms and economies can increase both their manufacturing complexity and their market competitiveness by developing the foundational capabilities and know-how needed to adopt AI and other advanced technologies.

Companies in both advanced and developing economies increase their levels of manufacturing complexity and contribute to economic growth and societal advances by identifying and capitalizing on disruptive technologies. Investments in artificial intelligence in particular will be critical to development, as they will allow emerging markets to create and expand sophisticated manufacturing sectors, participate in increasingly interconnected value chains, and compete in markets where speed and data are essential.

Historically, there has been a strong relationship between economic complexity, technical know-how, and economic growth. All countries that have been able to harness new technologies have consequently been able to expand their economies. It was true during the First Industrial Revolution, when machines and mechanized factories began to replace hand production, and it remains true today as automation, cognitive computing, and high-speed data exchanges recast the methods of production and accelerate the development of new and more sophisticated products.

AI accelerates economic complexity and economic growth in three specific aspects of manufacturing: products, processes, and value chains. For the purposes of this note, we follow the definition and description of basic, advanced, and autonomous artificial intelligence that were put forward in EM Compass Note 69.[1] That is, that artificial intelligence is the science and engineering of making machines intelligent. In this note, the term AI refers to all computer systems that can continuously scan their environment, learn from it, and

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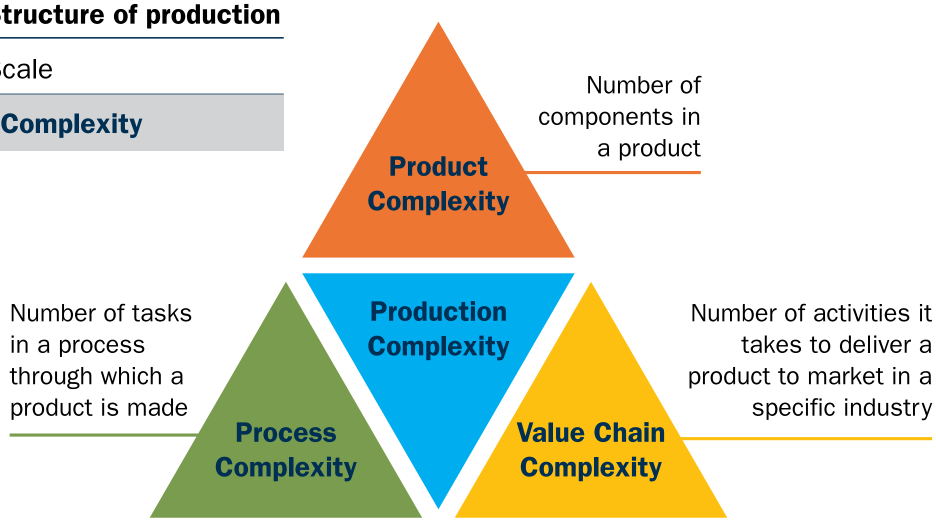
Drivers of production	Structure of production
Technology and innovation	Scale
Human capital	**Complexity**
Global trade and investment	
Institutional framework	
Sustainable resources	
Demand enforcement	



- Technological changes impact the structure of production in all dimensions (complexity and scale)
- Positive changes in product, process, and value chain complexity are important for industrialization

FIGURE 1 Manufacturing Contributes to Economic Complexity

Source: IFC Analysis.

take action in response to what they sense, as well as to human-defined objectives.

What Is a Complex Manufacturing Economy?

Countries with a high degree of economic complexity are able to manufacture an expansive range of sophisticated products using advanced processes. They also have dynamic relationships with multiple regional and global value chains. These economies possess specialized know-how, and are generally where market leading firms and conglomerates have cultivated sophisticated relationships with a network of companies in the supply chain. Examples of high-complexity countries include Germany, Japan, the United States, and the Republic of Korea.

On the distribution side, advanced economies possess recognizable global brands; strong research and development, design and innovation capabilities; client-oriented quality controls; and a flexible network of outsourcing partners. On the buying and selling side, competition is based on brand and quality, with many companies operating at the forefront of the technology frontier.

The Three Dimensions of Manufacturing Complexity

AI accelerates manufacturing complexity in three ways:

1. **Product complexity:** AI enables companies to more efficiently manufacture sophisticated products such as automobiles, which contain a large number of complex parts and components, all of which are separately produced and ultimately assembled into a single unit.
2. **Process complexity:** Today, by combining large volumes of data with computing power, manufacturers are using AI to simulate human cognitive abilities such as reasoning, language, perception, vision, and spatial processing. AI is being used for predictive maintenance, assembly line inspections, and other tasks that range from the mundane to the cutting edge.
3. **Value chain complexity:** The real-world benefits of AI were emphasized recently in a World Economic Forum survey of corporate executives that was conducted during the Covid-19 crisis.[2] The executives said that “their past investments in new technologies are paying off now.” They emphasized, for example, how big data platforms and the Internet of Things (IoT) enabled them to quickly gather large quantities of information that helped to predict supply chain disruptions that would impact production. AI helped provide instant visibility into the value chain and enabled quicker mitigation, which may have allowed some manufacturers to survive.

Mounting Momentum for Smart Machines

According to market intelligence firm TrendForce, the demand for global technology-based manufacturing applications will increase to more than $320 billion in 2020, from about $200 billion in 2019, and will grow at a compound annual rate of 12.5 percent.[3] In a 2017 report published by Infosys,[4] 75 percent of a sample of medium and large U.S. companies said they had yet to reach their automation potential because of complexity and legacy issues. Seventy-six percent viewed AI as a key factor in transformation where artificial intelligence agents could replace human cognitive tasks. The Covid-19 pandemic has disrupted adoption of AI in all regions as companies work to rebuild and countries rethink their industrial strategies in the wake of the crisis. But it is reasonable to assume that the global appetite for smart technologies that can accelerate growth and complexity will continue, and companies will weigh their future AI investment decisions, in part, on how well AI performed during the crisis. Major manufacturers plan to monitor, record, and analyze data across all stages of manufacturing.[5]

In September 2019, the International Federation of Robotics predicted that industrial robot shipments would increase 12 percent annually from 2020 to 2022, on average.[6] Today, robots are used almost exclusively for automation. But robotics is advancing rapidly, integrating cutting-edge technologies that enhance automation and functionality. While most demand for commercial robots has been in advanced economies and higher-income emerging markets, manufacturers in low-income countries are beginning to invest as costs decline.

As Industry 4.0 matures, technology companies will continue backward integration into existing manufacturing functions, retrofitting machines and processes to make them smarter, analytical, and increasingly data-oriented. At the same time, established industrial companies will continue to innovate and incorporate more complex technologies into their production processes. Enterprises will continue to adopt technologies that are relevant to the stage of development of the economies in which they operate, and AI—as it becomes less expensive and more commonplace throughout the value chain—will inevitably spread to countries at every stage of complexity and will play an increasingly important role in the industrialization process. As Figure 2 illustrates, over the past two centuries, every industrial revolution has been distinguished by a new technology that has driven manufacturers to a more complex economic stage.

An AI Solution for Every Level of Complexity

Manufacturing economies can be categorized into three broad pillars of complexity depending on the level of maturity and sophistication in their manufacturing subsectors. As would be expected, AI can be more economically justified in wealthier, complex manufacturing economies where it is applied in large-scale industrial applications. But equally important, there are many instances around the globe where AI could have a profound impact on the manufacturing processes and growth of less complex economies. Already, AI is being used in some of those countries for capital-intensive and labor-intensive processes such as monitoring and scheduling pipeline maintenance and performing heat inspections in cement kilns—critical and often dangerous tasks normally relegated to specially trained employees.

Pillar 1 Economies: Low-income countries and those in fragile and conflict-affected situations.

Goal: Lay a foundation for industrial production in countries with a low-complexity manufacturing sector.

Country classification: These countries generally have a small industrial base, lack economic diversity, have limited skills and technology intensity, and have low or no manufacturing exports. They are narrowly engaged with global value chains, usually in agriculture, textiles, ready-made garments, light engineering, electronics assembly, footwear, and leather goods. They are also typically characterized by low labor costs (this includes most countries in Sub-Saharan Africa). Low-income economies are generally less technologically advanced in manufacturing and remain dependent on manual labor and processes. They often lack the requisite capacity to develop diversified manufacturing bases to broaden the complexity of their economies, or to provide people with opportunities to gain the skills that can drive human development. Advanced technologies, however, can improve these countries' manufacturing processes, help them produce more sophisticated products, and enable them to engage with increasingly complex regional and global markets and value chains. Advanced data analytics and artificial intelligence have enormous potential to propel manufacturing forward in these economies.

AI adoption and use: AI in Pillar 1 countries is mostly limited to digitalization of production data with IoT, including in account payments and inventory management systems. At the consumer level, mobile technology and financial services companies such as Ant Financial in East Asia, M-Shwari in East Africa, M-Kajy in Madagascar, and MoMo Kash in Cote d'Ivoire are harnessing AI applications to better predict customer default probabilities, increasing their confidence in credit scores and enabling them to expand financial services to unserved, underserved, and unbanked populations, while facilitating industrywide

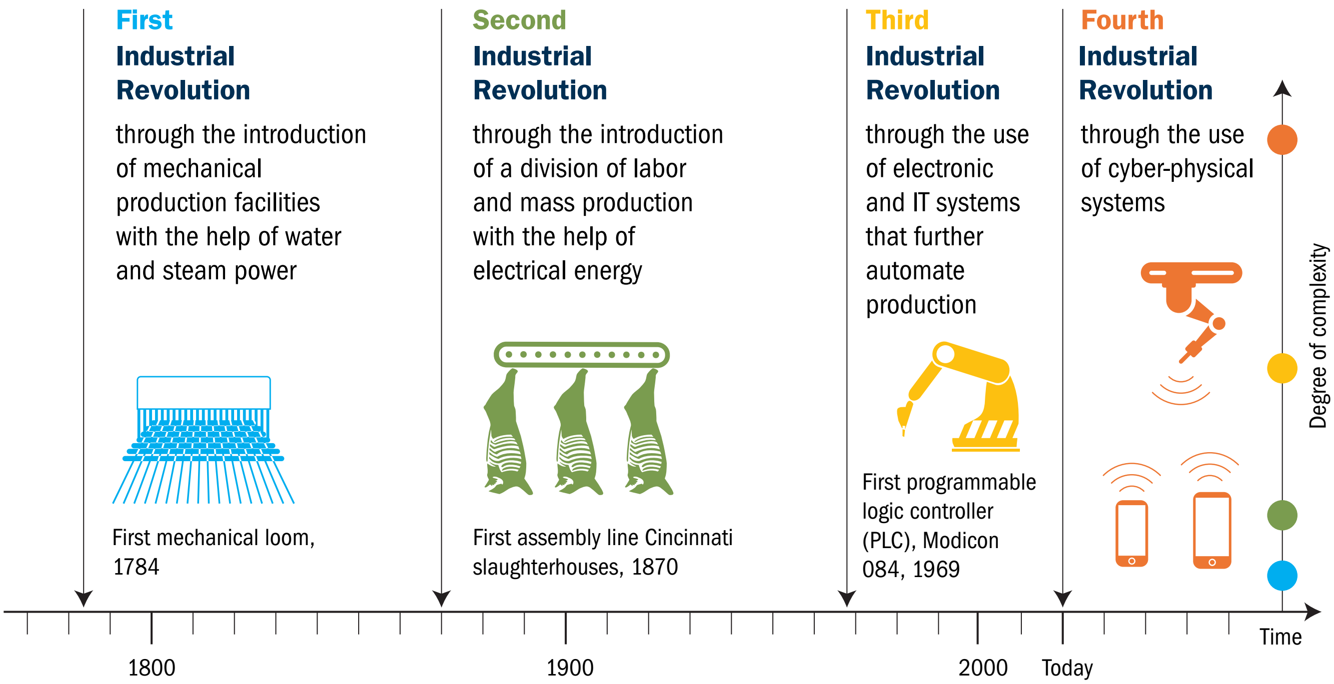


FIGURE 2 **Four Stages of Industrial Revolutions Leading to Industry 4.0**

Source: Pouliquen, Emmanuel, Hassan Kaleem, and Sabine Schlorke. 2018. "IFC Manufacturing Sector Deep Dive: Unlocking the Value of Manufacturing for Development." International Finance Corporation, World Bank Group, slide 11 (internal document).

financial efficiencies such as digital wage payments.

Pillar 2 Economies: Emerging markets.

Goal: Expand and diversify the manufacturing base in countries with a mid-complexity manufacturing sector.

Country classification: These countries have an evolving industrial base that is becoming more diversified and competitive, the technology skills of their workforces are improving, and they have developed some global value chain relationships (e.g., Brazil, Turkey, India, Serbia, Thailand, and Greece).

AI adoption and use: Pillar 2 countries adopt and use artificial intelligence algorithms more broadly, including for asset performance management, smart image recognition, process and quality control, and product engineering, as well as optimization of resources and supply chain management. These countries are involved in all industrial sectors and interact with companies that span the range of complexity. In some cases, Pillar 2 overlaps with Pillar 3 and, consequently, these economies often adopt advanced AI applications.

Pillar 3 Economies: More advanced markets.

Goal: Support more complex manufacturing in countries with a higher-complexity manufacturing sector.

Country classification: These countries have broad and sophisticated industrial bases where technology, education, and skills traverse sectors to drive growth via collective know-how and resilient industry networks. Pillar 3 economies are characterized by their global competitiveness in multiple value chains and their high levels of technological sophistication (e.g., Germany, Japan, United States, and China).

AI adoption and use: AI is adopted faster and has more impact opportunities in Pillar 3 countries where applications are used for planning, designing, mocking up, prototyping, testing, fine-tuning, producing, and post-design product and process improvements. What distinguishes Pillar 3 countries is the volume and capability of companies that can invent, access, and utilize cutting-edge technologies to manufacture a range of sophisticated products such as autonomous cars, smart robotic applications, and passenger jets. Many Pillar 3 manufacturers are capable of optimizing their supply chains, production processes, inventory-management systems, and transportation logistics.

How AI Can Accelerate Complexity

Investment in artificial intelligence tooling can be costly and therefore constitutes an impediment to adoption. But AI is being readily adopted for a slew of industrial applications ranging from robotic assembly to high-speed communications to air filtration systems for sterile manufacturing. And AI can accelerate complexity by empowering companies to manufacture more sophisticated products that are sought in more affluent markets. Another benefit is that the development of AI may be encouraging greater skills building and education achievement by labor forces eager for more sophisticated and higher-paying jobs.

Industrial robots in emerging markets. Some industrial robots can be seen as potential opportunities for AI applications. This is the case with some robots equipped for image recognition-oriented tasks. The vast majority of industrial robots were shipped to more advanced manufacturing subsectors in emerging economies in Asia between 2015 and 2017. Robots are mostly used in the automotive, electrical, and electronics industries, although applications are deployed in other sectors, mainly in handling.[7] There has been very limited adoption of industrial robots in lower-income and fragile and conflict-affected countries, where resource-intensive manufacturing is the main focus.

Asset performance management. Data-driven maintenance decisions are a cost-effective way to predict and prevent breakdowns in machinery and production. Effective maintenance practices are critical to an efficient manufacturing value chain. Oniqua Enterprise Analytics estimates that 40 percent of scheduled machinery and plant maintenance costs are spent on assets with negligible failure impact.[8] Up to 30 percent of maintenance activities are carried out too frequently, and up to 45 percent of all maintenance efforts are ineffective, according to T. A. Cook.[9] Data-driven AI solutions leverage historical data and correlate manufacturing breakdowns with critical process parameters to create rules that allow manufacturers to operate more reliably and with less downtime.

Smart image recognition in advanced countries. Smart image recognition, or the use of AI in machine vision, has many potential manufacturing applications, such as detecting product defects by conducting pixel-to-pixel comparisons. The global machine vision market is not highly concentrated, and the key players are American, Japanese, and Chinese companies. But with the advent of AI, other companies are emerging in this space, including Facebook and Alibaba, which have made acquisitions in machine vision firms.[10] The California-based company Similarity specializes in Automated Image Anomaly Detection, which uses vast amounts of satellite imagery data to generate rapid awareness of critical anomalies on the ground.[11] Machine makers have also developed such algorithms for manufacturing applications, where, for example, image recognition is part of a quality-control process. In the food processing industry, Domino's Pizza has integrated an image-recognition video control system driven by artificial intelligence that checks whether pizzas meet the company's quality standards before they are delivered to customers.[12]

Process and quality improvement in more advanced countries. The Advanced Manufacturing Research Centre's Factory 2025 demonstrated that computing devices fitted in computer numerical-control machines could collect power consumption data, run it through an AI algorithm, and analyze production variations against the production cycle to achieve efficiency gains and cost savings. The ramifications for production processes are myriad, ranging from improved product quality, increased savings on repairs and warranties, and a reduction in production downtime, all of which are efficiencies that can bolster a company's market share and profits. Taking these factors into account and weighing the costs and benefits is an important exercise for companies contemplating an investment in AI applications.

Resource and supply chain optimization in more advanced countries. The increasing importance of global value chains has driven demand for data-hungry applications that can sense, control, monitor, analyze, and independently maintain not only machinery but also the processes—from raw material extraction to successful product delivery—that companies rely on. The focus on value chain optimization with AI is largely due to: (1) the increasingly important revenue-generating role that services play for manufacturers; and (2) the increasing dependence on efficient global value chains.[13] Historically, the gap between revenues from services and revenues from direct sales of products has been blurry. An example of a company that has successfully bridged that gap is IBM, which has evolved from a "box" manufacturer into a high value-added and complex services company. Communication and data exchange have been an essential part of this transformation. In most industrial environments, communication within and between industrial sites has been based almost exclusively on wired networks due to a need for reliability.

Remote maintenance, network, and enterprise communication in emerging markets. Time-critical process optimization inside factories of different tiers of suppliers can reduce inefficiencies, support zero-defect manufacturing, increase worker satisfaction, and improve safety. In the most sophisticated cases, this could include: remote maintenance and control that may use connected cameras and possibly 3D

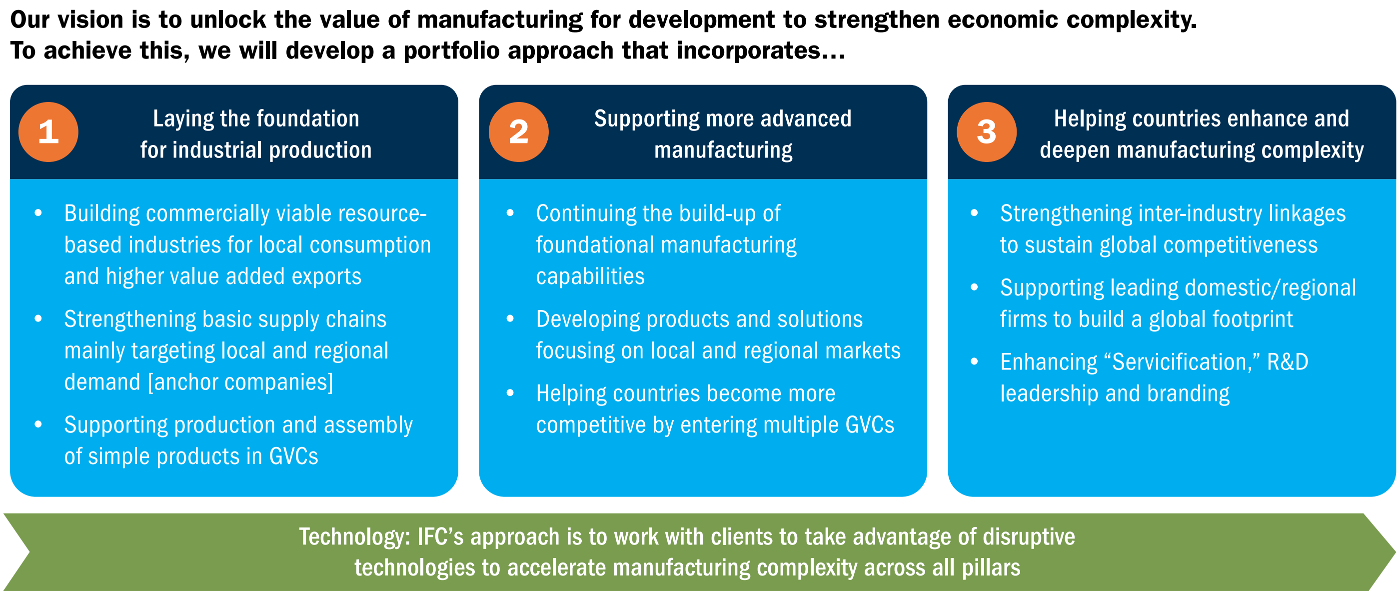


FIGURE 3 **A Framework for the Manufacturing Sector, from Low-Income Countries to Advanced Economies: The Three Pillars of Manufacturing Complexity**

Source: IFC.

virtual reality applications; connected goods that can create new value-added services, including real-time monitoring of fluid levels in engines; seamless intra/inter-enterprise communication, for example, the widespread use of tracking devices such as RFID stickers or connected sensors that can monitor assets distributed over large areas; and the efficient coordination of cross-value chain activities and optimization of logistical flow.

New cellular network technologies. With the advent of 5G, seamless real-time data communication between a manufacturer and its value chain partners allows for more comprehensive and precise tracking of deliveries and usage of products, not to mention quicker identification and response to problems and failures. 5G will impact manufactured products that need to exchange massive amounts of data in real-time with the rest of the world.

Over the years, the progressive introduction of 2.5G and 3G mobile communication systems on plant floors has helped open more options in mobile Internet for digitalized communications. But it is the more recent preponderance of remote video surveillance, which requires a massive amount of data transmission broadband,[14] that augers for more robust networks. Machine communication aims for lower complexity, less power usage, deeper coverage, and higher device density. As the volume of data grows with data-heavy applications, so will the need for higher data transmission rates for such applications. In oil, gas, and water plants, 4G LTE, which is low-cost, reliable, and flexible, has aided physical security and cybersecurity protection.[15]

AI-based virtual reality is being applied in creative ways to improve productivity and complexity in manufacturing. At Ericsson's factory in Tallinn, Estonia, the company uses AI-based augmented reality to help predict and troubleshoot breakdowns that could interrupt production, idle workers, and increase costs. Using AI, the company, which has an established data and quality culture, can reduce the cost of a breakdown by as much as half. Generally speaking, AI technology provides incrementally increasing benefits for companies that grow their data-based learning methods. Therefore, it is critical for manufacturing companies in Pillars 1 and 2 to establish data and quality cultures based on conventional approaches before embarking on AI-based techniques.

An Approach for Each Pillar

Pillar 1 Economies: In fragile and conflict-affected situations and low-income countries, it is necessary to build commercially viable, resource-based industries that manufacture products for local consumption and for higher value-added exports. Strengthening local supply chains and building capacity to produce and assemble low-complexity products as part of global value chains is key. AI adoption is limited, but it is important for new investments in resource-based industries to involve the best available process technologies, including AI. It is also important for these countries to build technical foundations in data usage, capture, and statistical analysis.

The Dangote Group, for example, uses cement-loading robots. Sophisticated cement companies have kiln control systems with rules-based programs that optimize yield, reduce thermal and electricity consumption, and improve process quality and reliability.[16] This conserves fossil fuels, minimizes CO2 emissions, and encourages a sustainable industrialization approach. Chemical companies typically incorporate similar technologies in their offerings. Thus, a few process-heavy Pillar 1 industries already use some AI applications. But because of the low cost of labor in most Pillar 1 countries, the economic calculus for making an expensive investment in AI is very different than in an expensive labor market. On the other hand, engineers and technicians may cost much less in low-income countries, significantly reducing the cost of developing and implementing advanced applications.

Pillar 2 & 3 Economies: In recent years, more advanced developing countries have embraced sophisticated manufacturing applications, including some powered by AI and machine learning. Mexico, for example, added 6,334 industrial robots in 2017, largely to service its automobile industry. AI adoption by Pillar 2 countries, particularly in established applications such as asset performance management, smart image recognition, process and quality control, and product engineering, as well as supply chain management, is encouraging.

For example, IFC is exploring a partnership with a textile manufacturer that uses computer vision and AI to detect defects on its production line. The technology will allow the company to reduce waste and shrink its environmental footprint.

In areas such as resource efficiency, DataProphet,[17] a business consulting firm in Cape Town, specializes in AI for manufacturing by improving process efficiencies through optimization of process variables.[18] It has helped a major engine-block manufacturer attain zero-percent external scrap, and helped an international car manufacturer reduce stud-welding defects by 75 percent.[19] These examples are indicative of various AI efforts in emerging markets. However, the reality is that most manufacturers in emerging markets are still using traditional data analysis methods.

Developed countries: The most advanced industrial countries, which are also part of the Pillar 3 group of economies described above, are the primary users of AI across many manufacturing sectors. For example, the automotive industry has triggered tremendous interest with self-driving vehicles, a very sophisticated example of AI-based robotization and driving automation. A large automotive parts manufacturer that is an IFC client is developing an AI-based virtual-simulation program in collaboration with a German start-up to accelerate development of the company's advanced driver assistance systems and automated driving functions. The simulation program creates a realistic traffic environment that enables new driver assistance products to be tested virtually. Up to 8,000 kilometers per hour of testing can be performed with virtual simulation, while only about 10,000 test kilometers per month can be driven by a real vehicle.

Another IFC client in the automotive sector is adapting AI-integrated sensors in air filtration systems in its paint shops to predict and analyze dust particles in the air and create cleaner and more sterile manufacturing environments for production of sensitive products. That technology promises to have multiple applications for manufacturers in a range of industries that require such production environments. At a major original equipment manufacturer, an innovative "dust particle analysis technology" has been deployed as a pilot project in the automaker's paint shop. The application can forecast and identify instances when there will be an increase in dust particles in the air that can mar a car's painted finish. It can then fine-tune filter replacement based on a series of factors such as historical levels of airborne dust by season, or by monitoring trends in prolonged dry periods. The algorithm monitors 160 factors related to the application of paint and can make highly accurate predictions about the quality of the paint process.

This AI solution can also be applied in production facilities of Pillar 2 and 3 countries to series production as the database expands, capturing more and more sensitive information and enabling manufacturers to produce more complex products. Robots and smart factory floor automation are other indicators of industrial complexity. According to the International Federation of Robotics, in 2017, robot sales increased by 30 percent to a new peak for the fifth year in a row. Five major markets—all of them among the world's most diverse and complex economies—represented 73 percent of the total sales volume in 2017: China, Japan, Korea, the United States, and Germany.[20]

Conclusion

Similar to previous industrial revolutions, when innovative machines and technologies replaced conventional methods of production and spurred the invention of sophisticated new products, artificial intelligence has the potential to transform today's manufacturing. The most complex economies are predictably the earliest and biggest adopters of AI technologies, as they already had the foundations and well-established tech centers in place, where some of the earliest AI applications were created. These economies possess a wealth of capital and an abundance of data for machines to analyze and adapt into the algorithmic patterns that are economically scalable for AI.

Yet AI is not confined to the world's biggest and most complex economies. As cloud computing capacity expands, global data volumes balloon, and processing power becomes more affordable, cutting-edge applications have been winding their way through global value chains and planting seeds in every pillar of complexity.

In less complex economies, companies can gradually acquire and adapt AI to address unique market needs. This will require additional investment to cultivate and strengthen sustainable and socially sound manufacturing cultures. In Pillar 1 economies, manufacturers need to build more sustainable and efficient industrial sectors and minimize the negative impacts of pollution, CO2 emissions, and weak labor standards by adopting advanced technologies that bolster complexity.

For years—and particularly in emerging economies—the biggest obstacle to adopting AI was the extravagant cost. Measured against inexpensive workers in low-wage economies, the investment made little sense. Now, however, as the price of implementing AI falls and data analytics increasingly become the language of global value chains, companies and governments are reevaluating their options and rethinking their policies.

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[1] Strusani, Davide and Georges Vivien Houngbonon. 2019. "The Role of Artificial Intelligence in Supporting Development in Emerging Markets." *EM Compass Note 69*, IFC, July 2019, pp. 1-2. That note defines AI as "the science and engineering of making machines intelligent, especially intelligent computer programs." This definition is also guided by the AI100 Panel at Stanford University, which defined intelligence as "that quality that enables an entity to function appropriately and with foresight in its environment." See "One Hundred Year Study on Artificial Intelligence (AI100)." 2016. Stanford University. https://ai100.stanford.edu/. See also Meltzer, Joshua, 2018. "The Impact of Artificial Intelligence on International Trade." 2018. Brookings. https://www.brookings.edu/research/the-impact-of-artificial-intelligence-on-international-trade/; Nilsson, Nils. 2010. "The Quest for Artificial Intelligence: A History of Ideas and Achievements." Cambridge University Press; OECD. 2019. "Recommendation of the Council on Artificial Intelligence." OECD Legal 0449 as adopted on May 21, 2019. https://legalinstruments.oecd.org/en/instruments/OECD-LEGAL-0449; and PwC. 2018. "The Macroeconomic Impact of Artificial Intelligence." February 2018. https://www.pwc.co.uk/economic-services/assets/macroeconomic-impact-of-ai-technical-report-feb-18.pdf.

[2] Doherty, Sean, and Kimberley Botwright. 2020. "What Past Disruptions Can Teach As About Reviving Supply Chains After COVID-19." World Economic Forum. https://www.weforum.org/agenda/2020/03/covid-19-coronavirus-lessons-past-supply-chain-disruptions/.

[3] ResearchandMarkets.com. 2019. "Smart Manufacturing Market, 2025 - Global Market Is Expected to Grow by $320 Billion, Driven by a Compounded Growth of 13.5%." www.prnewswire.com/news-releases/smart-manufacturing-market-2025---global-market-is-expected-to-grow-by-320-billion-driven-by-a-compounded-growth-of-13-5-300907605.html.

[4] Infosys. 2019. "Amplifying Human Potential – Towards Purposeful Artificial Intelligence." https://www.infosys.com/aimaturity/Documents/amplifying-human-potential-CEO-report.pdf.

[5] Walker, Jon. 2019. "Machine Learning in Manufacturing – Present and Future Use-Cases." August 13, 2019. https://emerj.com/ai-sector-overviews/machine-learning-in-manufacturing/.

[6] IFR.org. 2018. "Executive Summary World Robotics 2018 Industrial Robots." https://ifr.org/downloads/press2018/Executive_Summary_WR_2018_Industrial_Roots.pdf.

[7] Rosen, Rebecca J. 2011. "Unimate: The Story of George Devol and the First Robotic Arm." August 16, 2011. https://www.theatlantic.com/technology/archive/2011/08/unimate-the-story-of-george-devol-and-the-first-robotic-arm/243716/y-320-billion-driven-by-a-compounded-growth-of-13-5-300907605.html.

[8] Walker, Jon. 2019. "Machine Learning in Manufacturing – Present and Future."

[9] T.A. Cook. 2013. "Maintenance Efficiency Report 2013", August 2013. https://www.tacook.com/en/expertise/.com/ai-sector-overviews/machine-learning-in-manufacturing/

[10] Walker, Jon. 2019. "Machine Learning in Manufacturing – Present and Future Use-Cases." August 13, 2019. https://emerj.com/ai-sector-overviews/machine-learning-in-manufacturing/.

[11] See https://simularity.com/solutions/.

[12] Fantozzi, J. 2019. "Domino's Using AI Cameras to Ensure Pizzas Are Cooked Correctly." *Nation's Restaurant News*. https://www.nrn.com/quick-service/domino-s-using-ai-cameras-ensure-pizzas-are-cooked-correctly.

[13] 5G Infrastructure Public Private Partnership. 2015. "5G and Factories of the Future – White Paper." https://5g-ppp.eu/wp-content/uploads/2014/02/5G-PPP-White-Paper-on-Factories-of-the-Future-Vertical-Sector.pdf.

[14] Lou, David Zhe, Jan Holler, Cliff Whitehead, Sari Germanos, Michael Hilgner, and Wei Qiu. 2018. "Industrial Networking Enabling IIOT Communication." https://www.iiconsortium.org/pdf/Industrial_Networking_Enabling_IIoT_Communication_2018_08_29.pdf.

[15] Al-Saeed, Mohammed A., Soliman Al-Walaie, Kahlid Y. Alusail, and Turki K. Al-Anezi. No year. "How to Use 4G LTE Wireless Technology to Secure Industrial Automation and Control Systems." https://automation.isa.org/4g-lte-wireless-technology-secure-industrial-automation-process-control-systems/.

[16] Galbraith, Christina. 2015. "Artificial Intelligence Catches Fire in Ethiopia." August 25, 2015. https://techonomy.com/2015/08/artificial-intelligence-catches-fire-in-ethiopia/.

[17] See https://dataprophet.com/.

[18] Ibid.

[19] Ibid.

[20] Ifr.org. 2018. "Executive Summary World Robotics 2018 Industrial Robots." https://ifr.org/downloads/press2018/Executive_Summary_WR_2018_Industrial_Robots.pdf.