THE NEXT GREAT DIVERGENCE
WHY AI MAY WIDEN INEQUALITY BETWEEN COUNTRIES

The Macroeconomic Consequences of AI

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While new technologies have transformed many economies and societies, they have not necessarily boosted labor productivity – a phenomenon often called the 'Solow paradox.' Now, another opportunity for progress is emerging: artificial intelligence (AI) has the hallmarks of a general-purpose technology, much like electricity and computing, with the potential to spur widespread innovation and drive productivity gains across entire economies. Countries with more advanced digital infrastructure and investment capacity are better positioned to reap these rewards. Yet even in the most advanced nations, the benefits may take decades to fully materialize – and their distribution is likely to be uneven, exacerbating disparities both within and between countries.

In 1990, US Economist Paul Krugman observed that "productivity isn't everything but in the long run it is almost everything".[1] The statement is even more pertinent today.[2] The slowing of growth worldwide since the turn of the century is in large part because productivity is contributing less than it used to (Table 1). This is true even in the superstar middle-income Asia-Pacific countries of yesteryear, which are now sourcing much of their growth from increasing factor inputs, principally capital (Figure 1).

For the balance of the 2020s and into the first half of the 2030s[3], the growth of Asian economies is projected to slow. The GDP of high-income Asian countries is inching upwards at only between 1 and 2 percent per annum and current projections over the medium term suggest more of the same. If leading economies remain embroiled in trade disputes, global value chains unravel, and foreign direct investment falters, that trend might steepen.

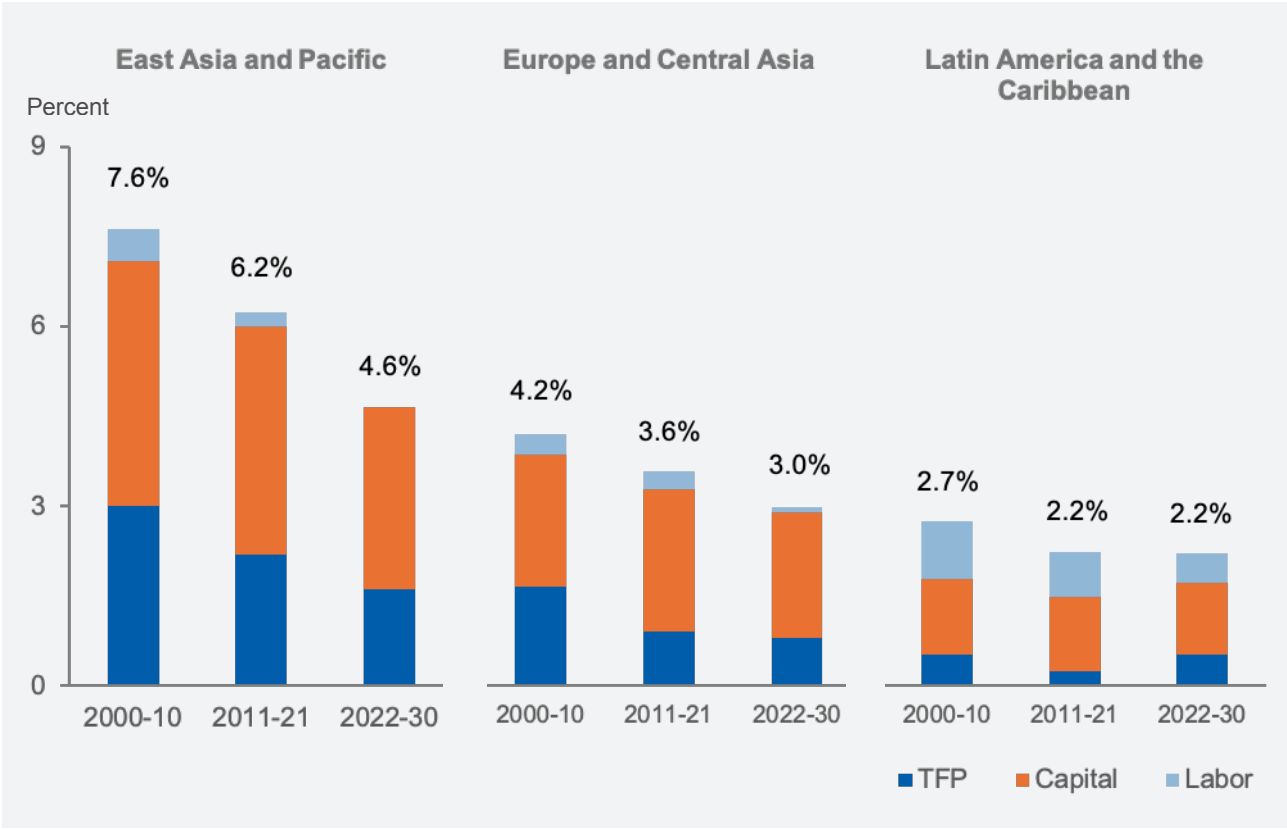
Table 1 – Total factor productivity growth by major region: 2000–2024

	2000-2007	2011-2019	2020	2021	2022	2023	2024 (Forecast)
Global	0.8	0.1	-1.6	1.7	-0.6	0.0	0.7
Europe	0.2	0.1	-3.6	1.7	0.5	-1.1	0.0
Euro area	-0.1	-0.1	-3.2	1.4	0.4	-1.0	0.0
Germany	0.3	0.4	-1.7	1.2	0.0	-1.3	0.0
France	0.1	-0.2	-4.3	0.3	-1.2	-1.1	0.0
Italy	-0.8	-0.4	-3.1	2.1	0.9	-1.4	0.2
United Kingdom	0.2	-0.1	-6.1	3.8	0.7	-0.9	0.5
Japan	-0.3	0.1	-3.2	1.8	0.1	1.1	0.6

	2000-2007	2011-2019	2020	2021	2022	2023	2024 (Forecast)
Other mature economies	0.6	0.2	0.2	1.8	-0.1	-1.4	0.6
Mature economies	**0.3**	**0.1**	**-1.3**	**1.7**	**-0.3**	**-0.4**	**0.2**
China	2.1	0.8	-0.7	3.5	-1.2	0.8	0.4
India	1.2	1.8	-6.0	4.8	1.4	2.1	2.8
Other Developing Asian economies	1.3	0.4	-2.7	-1.1	-0.7	-0.2	1.4
Latin America	0.3	-1.2	-1.8	-0.9	-0.6	-0.5	1.5

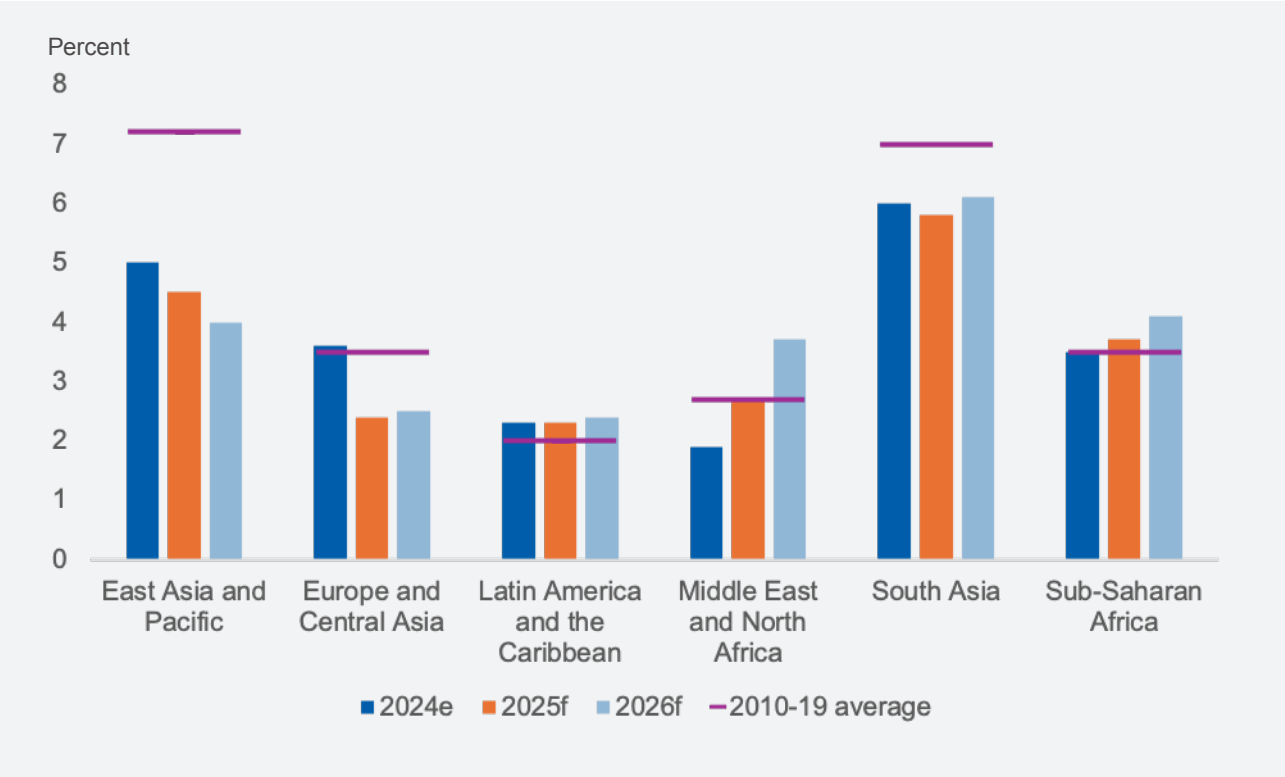
Source: (Conference Board, 2024)

Figure 1 – Sources of actual and potential GDP growth: 2000–2030



Source: (Kose and Ohnsorge, 2024)

Figure 2 – GDP growth: past and projected



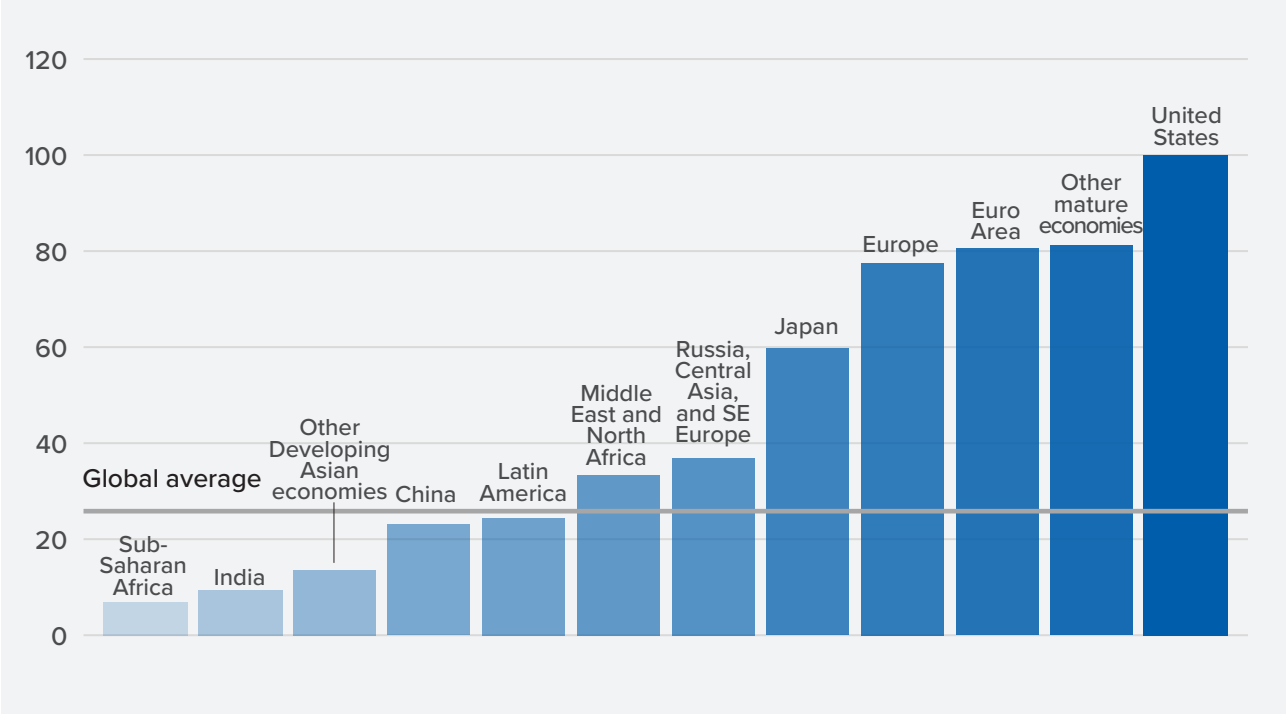
Source: (World Bank, 2025a)

For most Asia-Pacific countries, average labor productivity is far below that of the United States and major European economies – and is also less than the global average. To address the productivity drought and partially or fully reverse the decline in economic performance, Asia-Pacific economies are searching for ways to boost investment. The low- and middle-income countries, which are targeting relatively high growth rates, will need to bring their investment shares of GDP into the mid-30 percent range. As noted by the contributors to Adarov (2025), private investment will need to take the lead. Several countries in the region are already close to this level, such as Bangladesh, Cambodia, India, Indonesia, Nepal, and Viet Nam. Others, like Pakistan, Sri Lanka, the Philippines, and Malaysia would need to increase investment by ten percentage points or more of GDP. However, increasing investment will not suffice. It is a necessary condition but to arrive at the desired growth outcomes investment must be buttressed by increases in productivity.

Most Asia-Pacific economies have yet to exhaust the potential of digital technologies but now with AI spreading its wings, the technological opportunities appear more promising. Advances in AI, which build upon the wide diffusion of computers, smartphones, internet access and robotics, are raising hopes among emerging market and developing economies (EMDEs) that total factor productivity (TFP) could begin adding between two and four percentage points annually to their growth rates.[4] This expectation derives from the belief that AI has the making of a general-purpose technology (GPT) akin to electricity and computerization, spawning a wave of innovations that would boost productivity throughout the economy.[5]

These countries can catch up through capital deepening, technological assimilation and structural changes (Figure 3).[6] Given their stage of development, most of these countries should be able to increase productivity growth by approximately 2 percentage points per annum.

Figure 3 – Global labor productivity rates

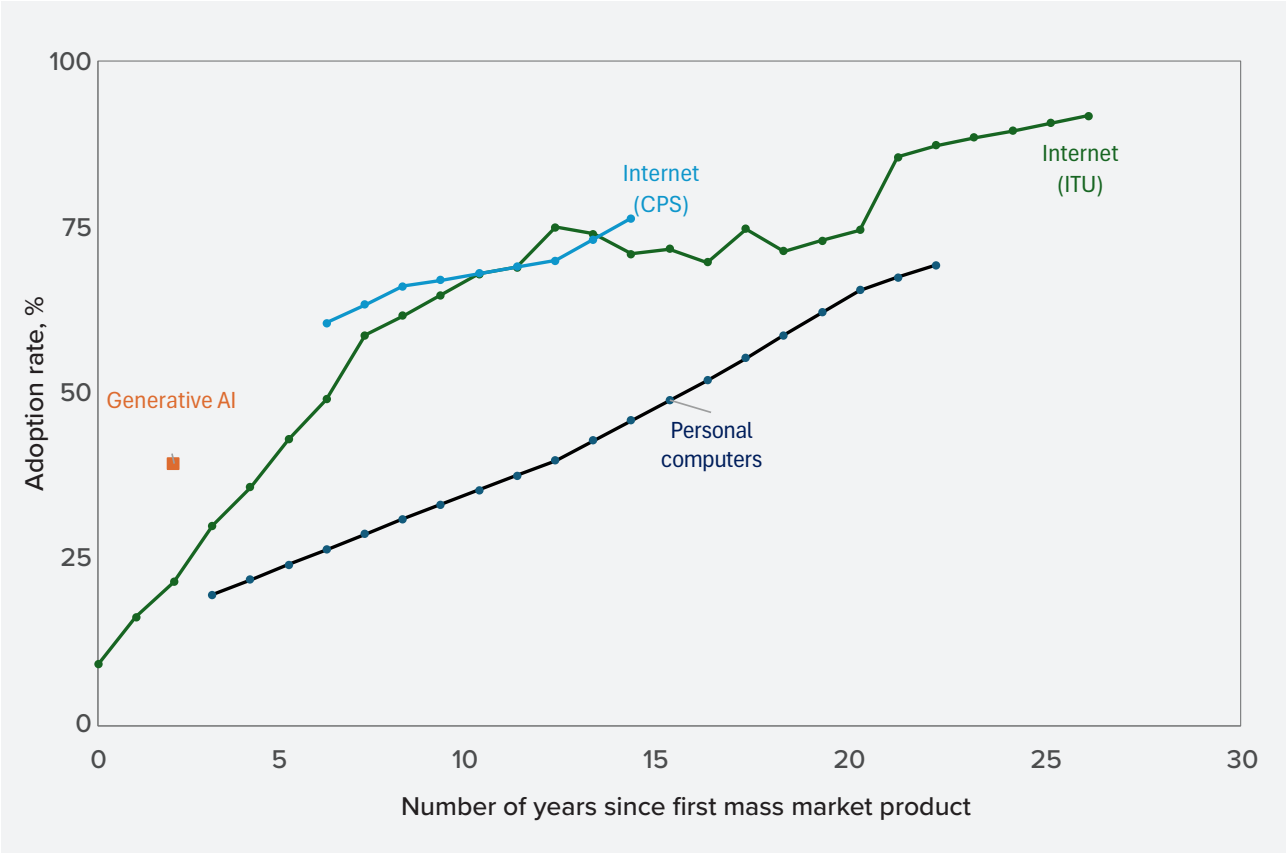


Source: The Conference Board. Data accessed Nov 2025.

As Figure 4 shows, the uptake of generative AI in the United States since the launch of ChatGPT4 in 2022 has been faster than that of mobile phones, personal computers or the internet.[7] Developers and users of this technology are understandably optimistic – triggering a flood of investment in model building, training, AI start-ups, data centers and energy infrastructure.[8 9 10] This is reminiscent of the telecom and dotcom boom of the end 1990s. Whether AI will prove to be a gamechanger is difficult to foresee. The proof of the pudding will be in the near- and longer-term trend in productivity attributable to AI. Although the economic consequences of AI have not surfaced in the macroeconomic numbers, there have been guesstimates of their impact for a handful of advanced economies, mainly the United States. The performance of the US economy since the middle of the nineteenth century has not always reflected technological boosts. The economy benefitted from a succession of GPTs – electricity, the internal combustion engine, biotech, computerization, the internet etc, but real per capita GDP grew at an almost unwavering rate of 2 percent per annum.[11] AI only began acquiring traction quite recently, so any findings are preliminary and speculative. From economic and policymaking standpoints, what matters most is: the anticipated productivity bonus; the appearance of new occupations and of specific tasks within job categories that would absorb workers displaced by AI; and the distributional consequences.

To address these issues the rest of this chapter is divided into five sections. Firstly, it briefly outlines the principal research questions and identifies the countries that will serve to illustrate the impact of AI over the medium term. Then it presents a thematic analysis examining the economic consequences of AI and how they could affect inequality within and between countries. The following section discusses recent policy initiatives by Asia-Pacific countries and their prospects. The chapter concludes offering some policy guidelines and summarizing the possible future outcomes.

Figure 4 – Adoption rate of generative AI and other technologies at home and at work in the US



Source: The Conference Board. Data accessed Nov 2025.

Research topics and issues: factor productivity and income distribution

This chapter addresses two overall questions:

(i) What is the likely impact of AI systems on total factor productivity and on economic growth in Asia-Pacific countries, primarily those in the middle-income category, and how long might it take before their effects surface in the macroeconomic data?

(ii) What would be the likely impact of AI on income distribution both within and between Asia-Pacific countries during the 2020s and the early 2030s?

Given the paucity of data and analysis on Asia-Pacific EMDEs there are no convincing answers. Moreover, given the heterogeneity of Asia-Pacific economies it is difficult to make broad regional projections. At one extreme, there are low-income, or lower middle-income, and countries in protracted crisis context, such as Afghanistan and Myanmar. At the other, there are advanced economies like Japan, the Republic of Korea, and Singapore. And the middle-income economies that lie in between cover a wide spectrum, with markedly differing levels of per capita GDP, resource endowment, state capability, industrial depth, technological readiness, and export intensity.

The region spans a vast diversity of scale and capacity. It includes the world's two most populous countries, both with significant technological and industrial capabilities, alongside several small island states with populations of a million or less.

Potential economic benefits

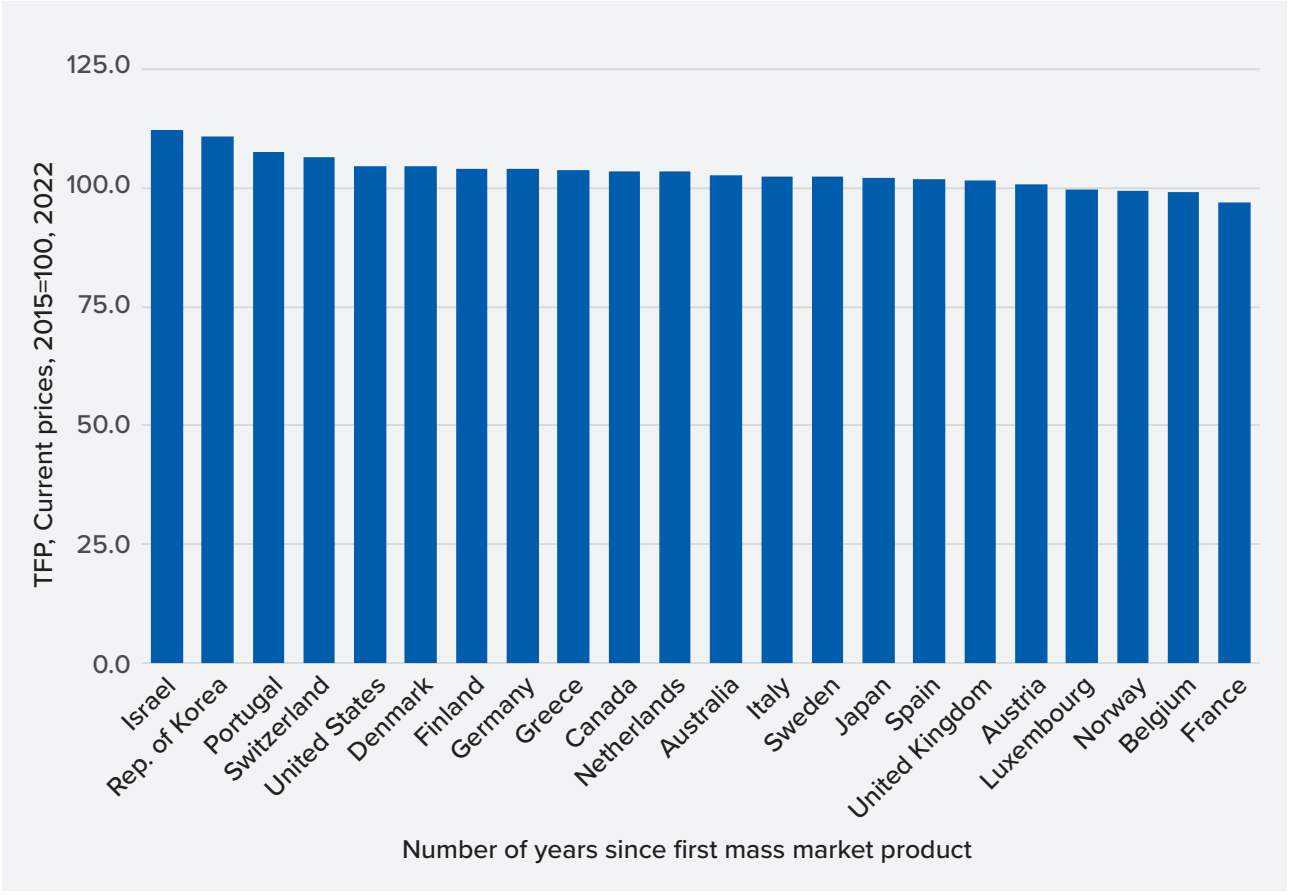
The economic benefits garnered from AI will depend on the degree to which AI ecosystems take root, the range of activities that are materially affected, and on how widely the benefits are shared. During the foreseeable future, most Asia-Pacific countries risks becoming largely reliant on AI innovations from advanced countries and will attempt to integrate them into their own production systems.

Any ensuing growth of TFP will depend on multiple factors that are difficult to disentangle. These include learning by doing from capital investment, innovation, resource allocation, the accumulation of intangibles, and the availability of managerial skills.[12] There could also be a restructuring of the economy, which could favor the more productive activities in the formal urban sector.

In the recent past, the main driver of technological change has been digitalization, and it is not a spent force; the diffusion of IT/digital technologies will continue and will be complemented and enhanced by AI, with impacts on economic structures and managerial efficiency. However, it will be difficult to isolate the AI-specific signal because in most cases during the medium term the use of AI models could be superficial and at the margin, and maybe confined to larger, more outward-oriented firms in the formal sector. Informal businesses could take advantage of AI models once smaller specialized ones (SLMs) can be accessed, but it is not clear when agentic SLMs might come into widespread use.

Figure 5 shows TFP trends in the OECD countries and Table 2 presents TFP data for selected Asia-Pacific countries. Neither suggests a recent technology-induced

Figure 5 – Total factor productivity in the OECD countries



Source: (OECD, 2024a)

acceleration in productivity. This time, with AI it could be different, with a boost in TFP, though the main impacts could lie sometime in the future and perhaps only for a few countries. Nevertheless, as AI matures, the tempo of diffusion will accelerate, and specialized models could begin to deliver tangible rewards. The signals should become stronger first in the advanced economies and after a lag, in EMDEs.

Table 2 – TFP growth in Asia-Pacific countries 2000-2024

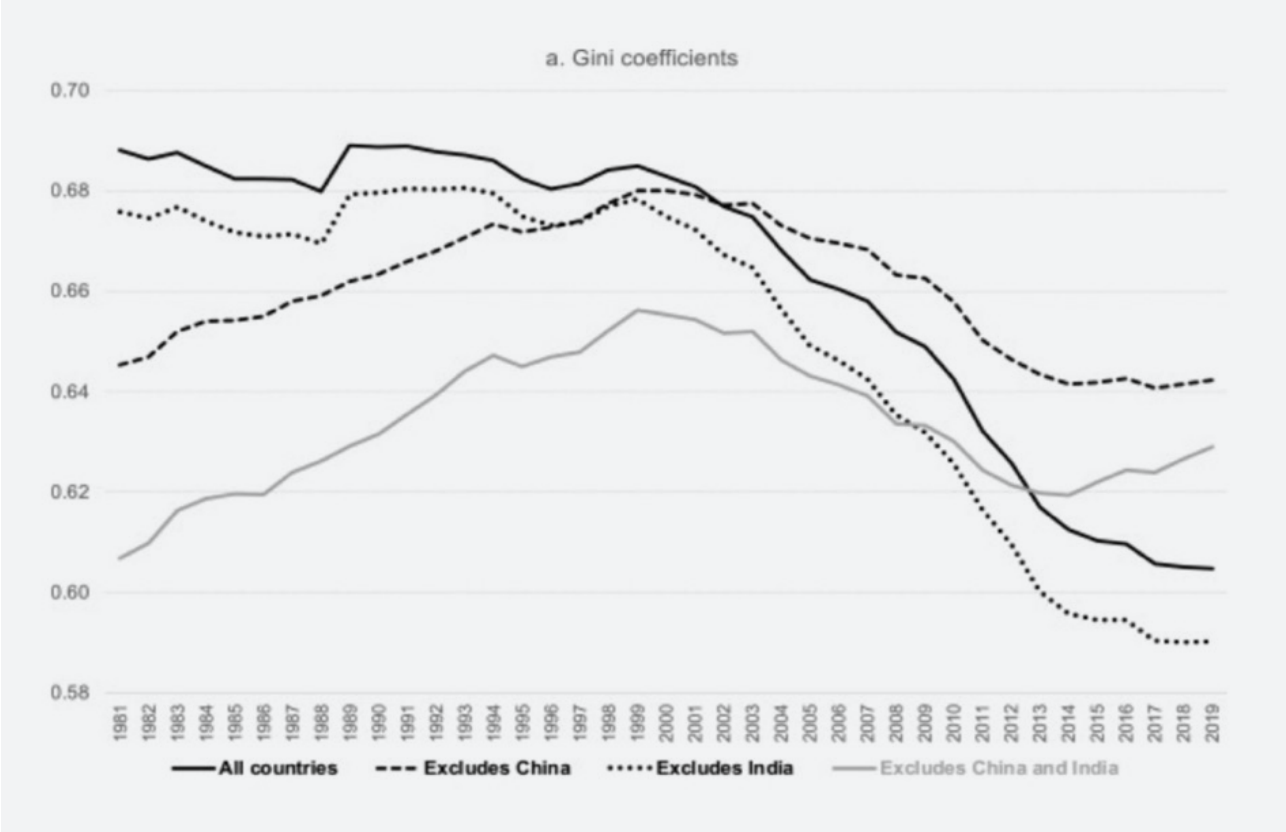
	2000-2007	2011-2019	2020	2021	2022	2023	2024 (Forecast)
Other Developing Asian Economies	**1.3**	**0.4**	**-2.7**	**-1.1**	**-0.7**	**-0.2**	**1.4**
Bangladesh	-0.1	0.6	0.7	-0.4	-0.3	0.2	0.4
Cambodia	0.5	-1.0	-8.1	-5.2	-1.8	-1.0	0.0
Indonesia	1.7	-0.1	-4.0	0.3	-0.8	-0.1	1.5
Malaysia	0.6	0.3	-4.1	-1.0	3.2	0.5	1.3
Myanmar	5.0	-1.5	1.0	-14.1	0.8	1.7	1.2
Pakistan	2.3	0.9	0.9	-1.0	-1.0	-2.0	0.3
Philippines	1.5	0.6	-3.3	-4.5	0.3	1.3	2.5
Sri Lanka	-0.2	-0.9	-2.8	-4.9	-9.6	-3.5	1.1
Thailand	1.9	1.3	-5.4	-0.1	-2.7	0.2	2.5
Viet Nam	-1.1	1.5	-1.3	0.2	-0.5	-0.7	1.3
China	2.1	0.8	-0.7	3.5	-1.2	0.8	0.4
India	1.2	1.8	-6.0	4.8	1.4	2.1	2.8

Source: (Conference Board, 2024)

The impact on income distribution

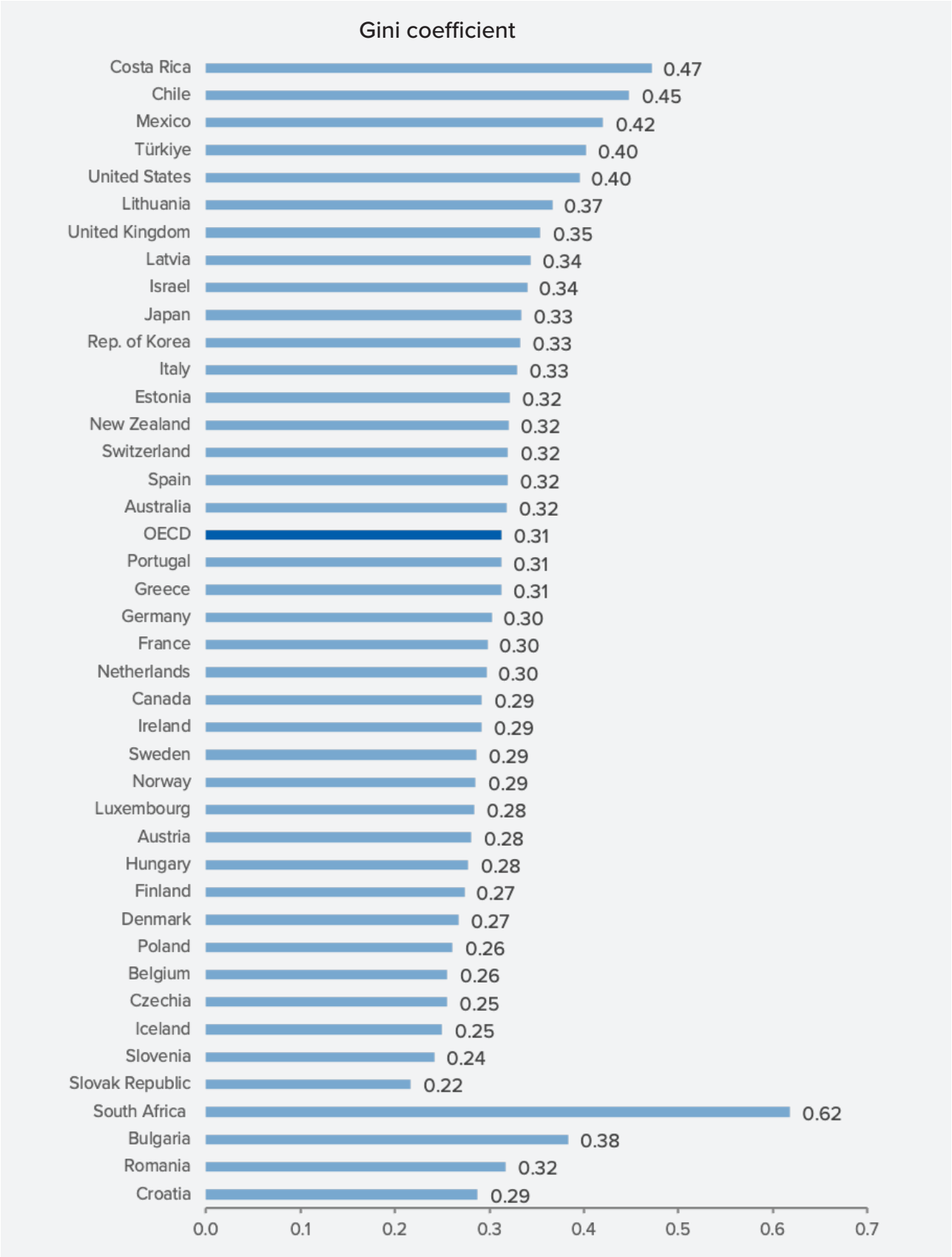
Equally challenging is gauging the distributional consequences. Measured by the Gini coefficient, global inequality declined from the late-1990s through 2015 – roughly the period during which EMDEs registered high rates of growth. Then it stagnated until 2020 (Figure 6).

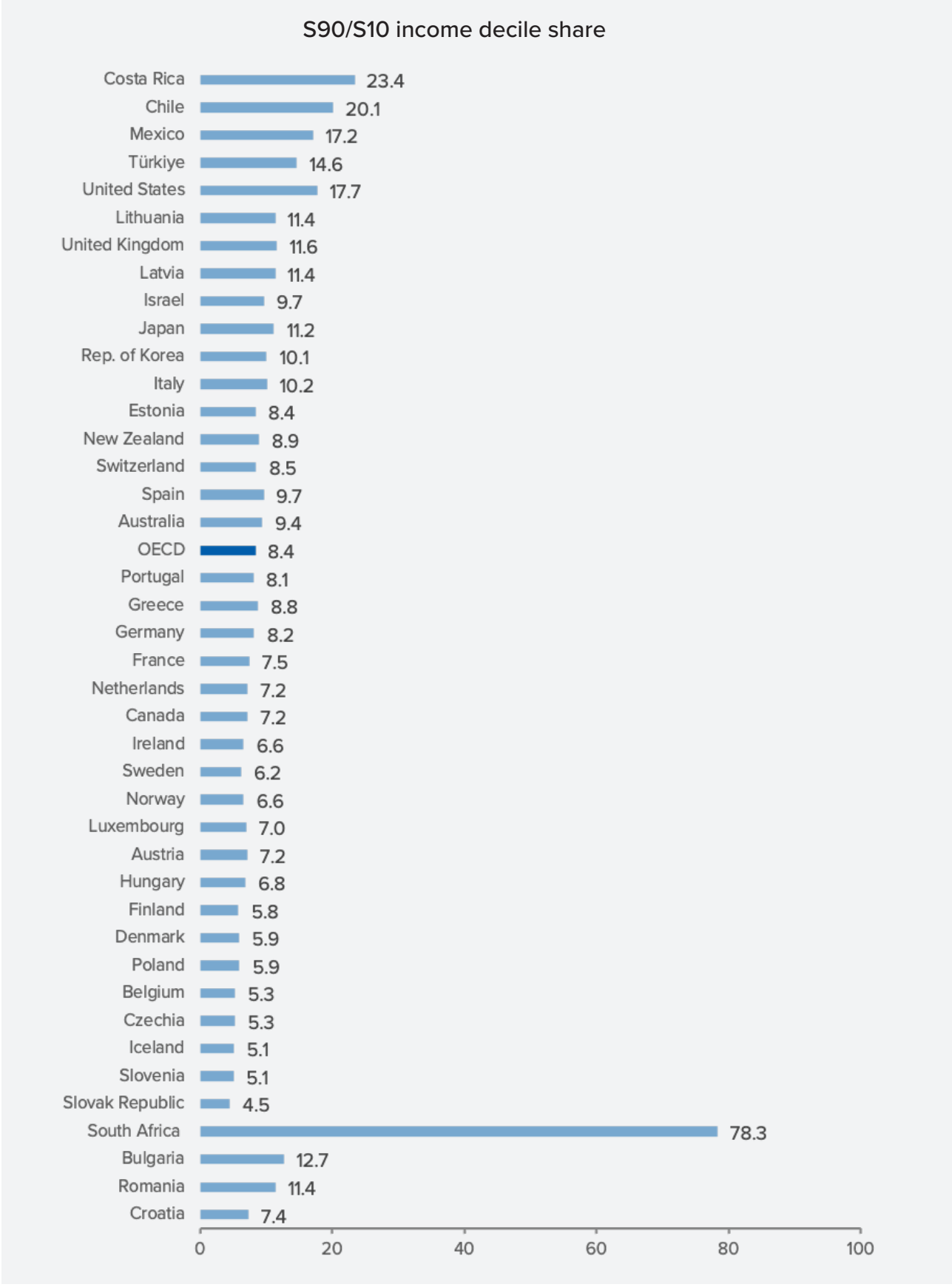
Figure 6 – Trends in global inequality



Source: Kanbur, Ortiz-Juarez and Sumner, 2024

Figure 7 – Gini coefficient of household disposable income and gap between richest and poorest 10 percent in 2021





Source: OECD, 2024b

Between 2007 and 2019, within-country inequality rose in a few European countries. Income distribution also became more unequal in the United States, China and India, but in China it has diminished since 2010.[13] However, between-country inequality fell.[14]

Like TFP, income distribution is subject to both economic and political forces. The increase in income inequality in the United States was in part the result of disruption caused by computerization and affiliated digital technologies.[15] Other important factors were trade liberalization and the offshoring of manufacturing by American multi-national companies as well as the competition from lower-priced imports which led to a loss of well-paid jobs in some manufacturing industries. At the same time, labor's share in GDP was eroded by the bargaining power of labor vis-à-vis capital and the drop in unionization, abetted by legislation.[16]

In a few European countries, on the other hand, and in Japan and the Republic of Korea, where the bargaining power of labor is stronger, the decline of manufacturing has been slower and income distribution has remained relatively stable.

Figure 8 shows the income gap between the top and bottom deciles for G20 countries, indicating how little the distribution of income changed between 2000 and 2022. During this period, from about 2012, AI models and machine learning were making their debuts. Overall, the average distribution moved only fractionally in the OECD countries – the United States was the outlier. The gap narrowed in the G20 countries, with Brazil and Mexico registering substantial declines.

Figure 8 – Income gap between the top and bottom income deciles in G20 countries

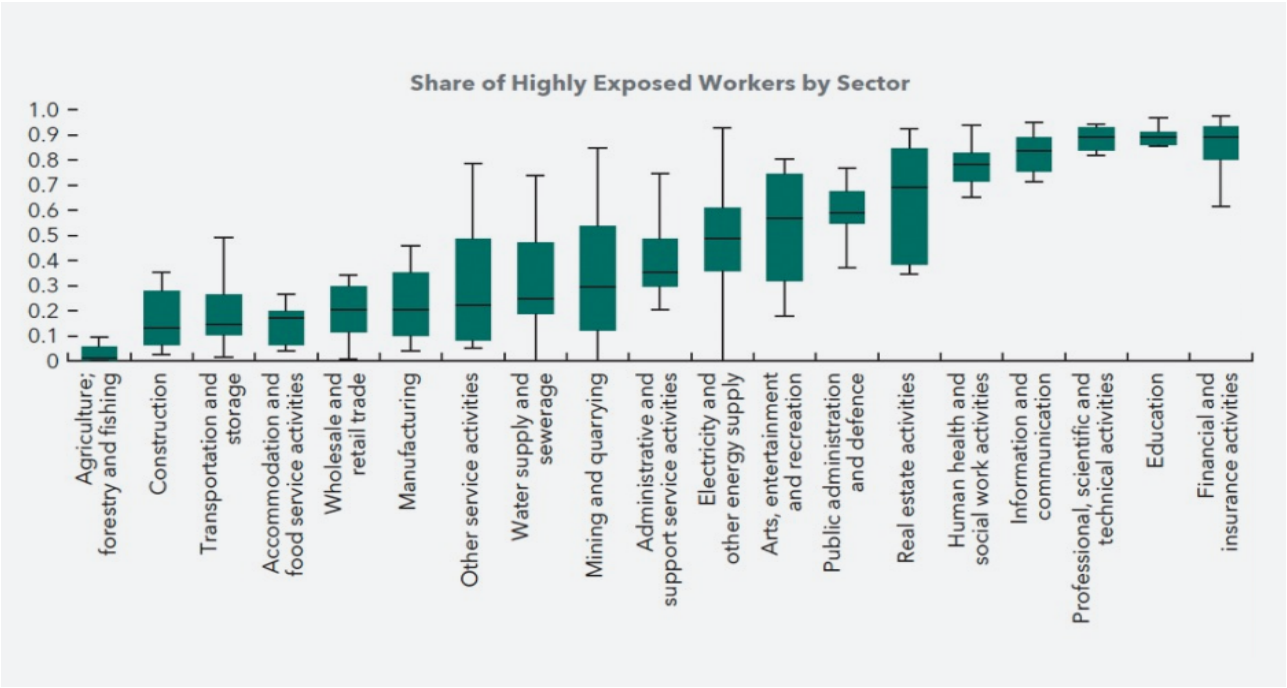
Source: (Soldani, 2024)

Income inequality in the Asia-Pacific region is relatively high, with estimates that top earners account for a significant share of total income. The inequality is greatest in South and South-East Asia with wealth inequality typically higher than income inequality. In India, Maldives, and Thailand, those in the topmost decile account for more than one half of the income. In Nepal and Bangladesh, the share of the top 10 percent is close to one-third. Pakistan, Viet Nam and Indonesia fall in between, with shares ranging from 40 to 50 percent of incomes. [17]

Clues as to how income distribution within Asia-Pacific countries might evolve in the AI era can be gleaned from their experience with digital technologies. In Cambodia, Malaysia, the Philippines and Thailand, for example, access to the internet provided greater connectivity along with financial and other services, and by reducing information barriers may have lowered income inequality.[18] Similarly in China rural households benefitted from the internet, especially those in the less developed areas and with less education.[19]

AI is expected to lead to shifts in labor demand across sectors, and this could have distributional consequences depending on which occupations and tasks are affected. If it is mostly the low-end routine jobs that are impacted, then the income distribution could become more unequal.[20] [21] If, as is likely, jobs are affected across the spectrum, the adjustment pressures could be more broadly shared (Figure 9). But as with earlier technologies, AI could create new occupations and new tasks. In which case, the distributional outcomes within and between countries in Asia and the Pacific are difficult to foresee.

Figure 9 – Impact of AI on workers across sectors



Source: (IMF, 2024)

Thematic analysis

Since 2013, numerous attempts have been made to gauge the impact of AI on jobs and on income distribution and on various occupations.[22] These suggest impacts on 25 to 40 percent of all jobs in Asia-Pacific developing economies, and on half of all jobs in the more advanced economies.[23]

In some cases, AI would augment/complement workers' capabilities; in others AI would displace workers. If the former effect outweighs the latter, within-country income distribution would become more equal. If workers are displaced and alternative job opportunities are not available, inequality could widen.

In the advanced economies, AI could complement jobs, with less displacement and more productivity gains.[24] The opposite could be the case in developing countries, with women and lower-skilled workers in sales and clerical positions to be potentially hit hardest by AI. This could lead to greater inter-country inequality.

Other scenarios are possible. The middle-income economies that are rapidly closing the gap on the high-income ones could be increasing their share of jobs that benefit from AI. This would reduce the income disparities between these fast followers and the advanced countries. In other middle- and lower middle-income countries, formal sector jobs could be negatively impacted by AI. However, countries with large informal and rural economies might also be able to absorb digital technologies in ways that broaden inclusion and narrow intra-country income gaps. Overall, intra- and inter-country income disparities will depend on how rapidly digital and AI technologies are adopted, influencing the pace of productivity coverage.

The GPT that could serve as a benchmark for AI is computerization. Like electricity, the advent of PCs proved to be revolutionary but did not transform the work environment overnight. Hewlett Packard marketed the first desktop computer in 1968, and thereafter PCs began to gradually infiltrate the workplace and find their way into households. But as Figure 10 shows, businesses adopted computers gradually and households lagged even farther behind. Even by 1987, economist Robert Solow was complaining that he "sees computers everywhere except in the productivity statistics."[25]

The experience from past GPTs.

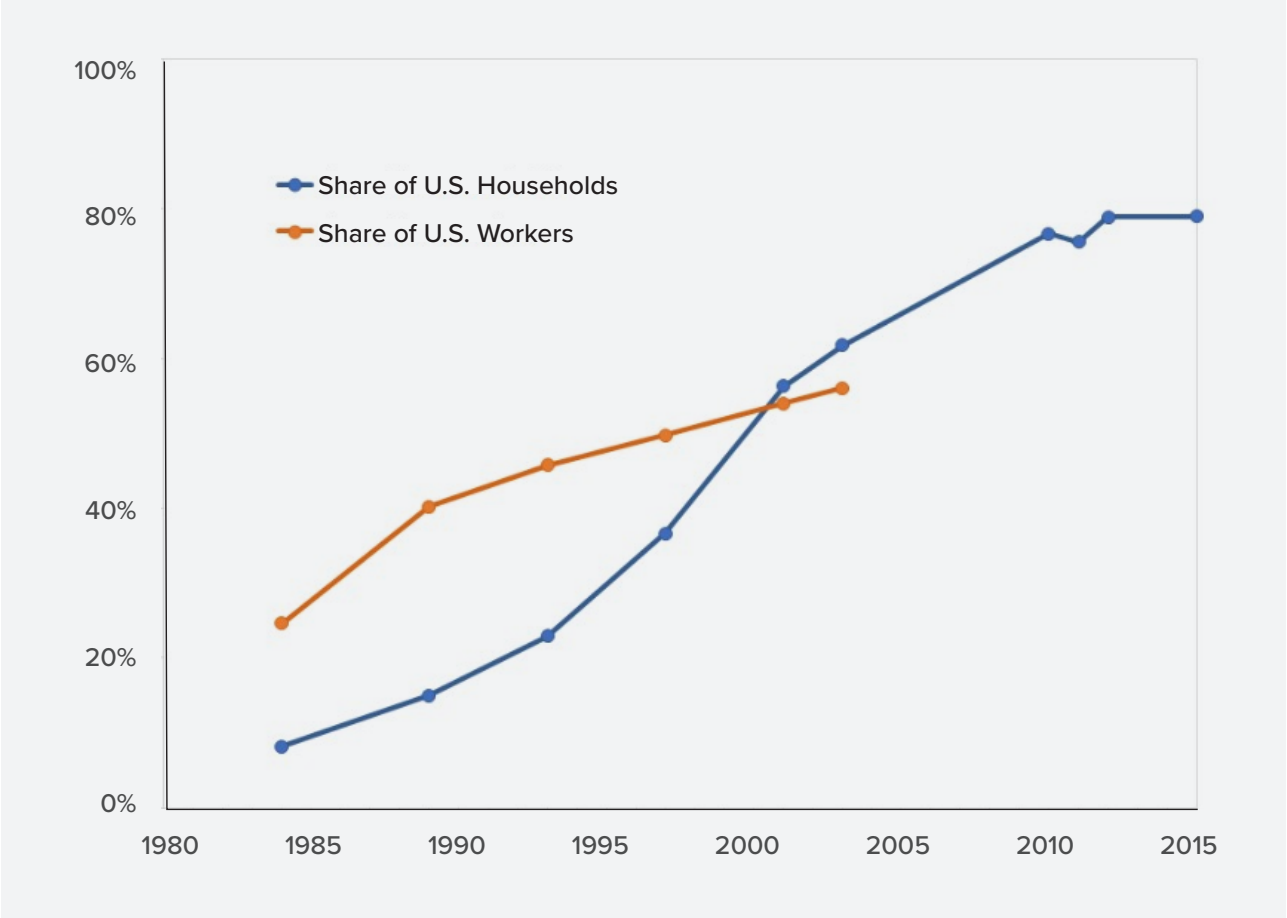
By the 1990s, however, computers had become ubiquitous and their impact was reinforced by broadband internet access and their contribution was becoming visible in the TFP data. As they were integrated into workplaces and the home environment, demand rose steeply, stimulating the manufacturing value chain. This served to raise the productivity of IT-intensive manufacturing and of IT-intensive services.[26]

By the latter part of the 1990s Solow's expectation was realized. Yet, the productivity boost imparted by computerization was short-lived.[27] Soon after the turn of the century, TFP was trending downward, and neither the internet nor the uptake of digital technologies was able to reverse that decline and the subsequent stagnation.

The standard explanation for the Solow productivity paradox is that a revolutionary new technology is bound to make slow headway because it must supplant existing technologies that represent sunk capital. For example, electricity had to displace water and steam powered equipment.[28] To address initial adjustment challenges and realize the efficiency gains businesses need to invest in complementary assets and restructure their work practices to incorporate the new technology.[29] [30] This can be a protracted process, requiring organizational change and staff upskilling, and adaptation of existing practices. Larger and younger firms are usually at the forefront of adoption.[31] [32]

Computerization displaced workers in some jobs and created new occupations and automation gradually reduced the demand for labor-intensive repetitive and routine tasks in manufacturing and services – with a shift from clerical and routine production jobs towards others, including higher-paid professional ones and low-wage jobs in services.[33]

Figure 10 – Diffusion of PCs at home and work



Source: Kalyani and Hogan (2024)

Again, this was a gradual process. Between 1999 and 2018 relatively few occupations declined by 25 percent or more per decade and in 1999 these accounted for 9 percent of jobs.The gaps left by jobs that become redundant were filled by others, some requiring different skills. In fact, six out of ten jobs in the second decade of the 21st century did not exist in 1940.[35] Employment in the manufacturing sector began to dwindle and those laid off often had either to settle for lower-paid work in the services sector – or depending on their geographical mobility and age, exit the workforce.[36] Thus far, it appears that technology has stimulated demand and has created more jobs than it has displaced.[37] [38]

The effects of computerization and digitalization on productivity and income distribution were much less apparent in the EU and Japan, and played a limited role in several Asia-Pacific EMDEs. After the spurt in productivity had died down by the mid-2000s, in Germany, Japan and the US from 2004 through 2016 the growth of labor productivity declined in virtually every subsector including in all manufacturing activities.[39]

In the EU, as of the early 2020s, for the average firm in 70 percent of sectors digitalizing had not improved productivity: only 20 percent of firms increase their TFP by 0.34 percent, though firms at the forefront of the lagging 70 percent did realize some gains.[40] Among the Asian EMDEs, rapid growth from the mid-1990s through the early-2000s was a consequence of structural change in urban industries, high rates of investment in physical and human capital, industrialization, and technological catching up. Computerization contributed

very little. Furthermore, since 2010, the spread of digital technologies anchored to this GPT has largely failed to restore growth rates to levels reached in the 1990s.

Expectations for AI need to be tempered by experience with computerization as well as with the recent introduction of AI.[41] Since the introduction of GPT-1 in 2018, there has been no uptick in TFP growth either in the United States, or in other advanced economies or EMDEs. However, it could be too soon to judge. In 2018, according to the US Census Bureau, only 3 percent of firms were using AI and by 2023-2024 the proportion was still only 4.4 percent – mostly the larger and faster-growing firms. Many more are experimenting with the technology and testing the water. Penetration has been greatest in sales and marketing, customer service (e.g. call centers), software engineering/coding, translation, data analysis, and in generating text (Figure 11). Manufacturers are also taking advantage of AI to upgrade robots/drones and electric vehicles.

Many of the pioneers are discovering that the organizational restructuring and training required is both disruptive and costly, and years can elapse before the benefits of AI appear in the bottom line. A study of 25,000 Danish workers in 11 occupations exposed to AI found that chatbots were in widespread use but noted barely any improvement in earnings and productivity.[42]

Figure 11 – Use of AI and its intensity

Low Impact — High Impact

Industry	Total Value ($ billion)	Marketing and Sales	Customer operations	Product R&D	Software Engineering	Supply Chain and Operations	Risk and Legal	Strategy and Finance	Corporate IT	Talent and Organization
Public and social sector	70–110									
Agriculture	40–70									
Basic materials	120–200									
Construction	90–150									
Chemical	80–140									
Administrative & professional services	150–250									
Energy	150–240									
Real estate	110–180									
Retail	240–390									
Travel, transport, and logistics	180–300									
Advanced electronics & semiconductors	100–170									
Consumer packaged goods	160–270									
Advanced manufacturing	170–290									
Insurance	50–70									
Media and entertainment	80–130									
Healthcare	150–260									
Education	120–230									
Telecommunications	60–100									
Pharmaceuticals & medical products	60–110									
Banking	200–340									
High tech	240–460									

Source: McKinsey Digital (2024)

Note: The indicators 'Total (%), Industry Revenue, and Total Value ($billion)' reflect estimates of generative AI's potential revenue generation across industries.

Randomized control trials show that when chatbots are not well matched to tasks, the outcomes can be negative.[43] Major firms that have introduced AI models including LLMs are at risk of low returns on significant investments.[44] As with PCs and electricity, the productivity boost may not materialize for another decade or more.

The broader productivity impact of AI will depend on how widely AI is adopted, and in which sectors. If it is limited to agriculture and manufacturing whose share of GDP declines, then TFP growth will be constrained – an example of the 'Baumol effect': sectors where productivity lags tend to become more expensive as the cost of inputs increase.[45] [46] Meanwhile many services make less use of AI and remain more human-centric.

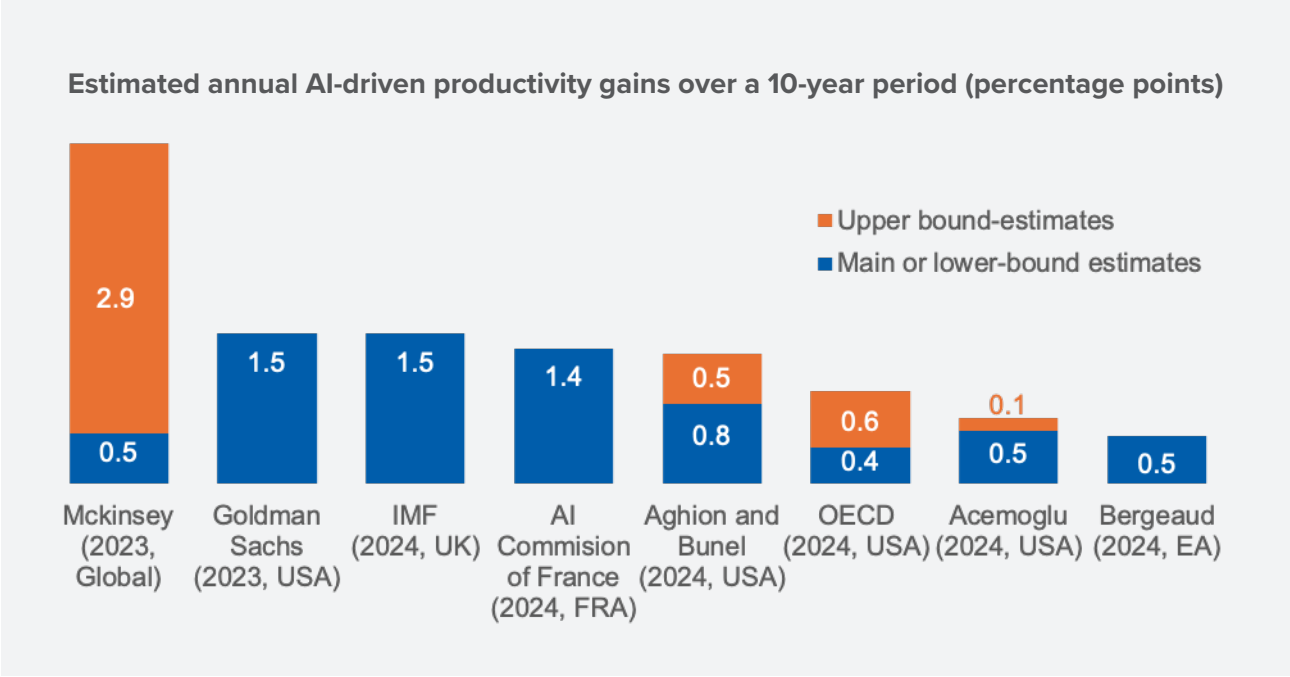
Forecasting AI gains

With so many variables and uncertainty around things to come, researchers differ in their forecasts of labor productivity and of TFP, and present their estimates with upper and lower bounds. The range is illustrated in Figure 12.[47] Others suggest an increase of between 0.4 percent and 0.9 percent, but acknowledge that "AI has a long way to go before reaching the high adoption rates that are necessary to detect macroeconomic gains."[48]

The countries that reap the maximum gains from AI will probably be those that internalize more of the AI value chain and embed AI in products and services for which there is strong demand. The smartphone is an excellent exemplar – an ingenious product that can host scores of apps. The AI value chain

As indicated in Figure 13, the AI value chain can be decomposed into six parts. At the core of the AI ecosystem is the semiconductor processing unit. AI models need massive amounts of computation and in the early years struggled to perform. Their subsequent acceleration was enabled by the use of ultrafast graphics

Figure 12 – AI-supported growth in labor productivity in the United States and European countries



Source: Filippucci and Schief (2024)

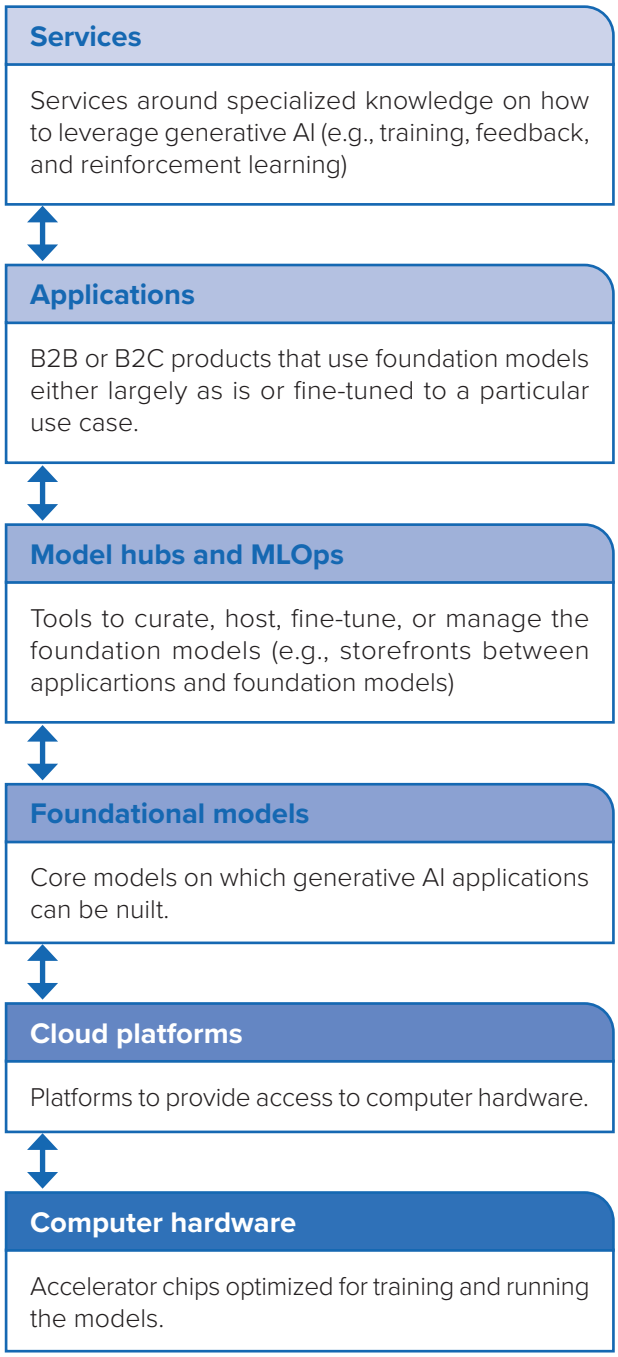
Note: Productivity gain refers to the predicted increase in annual labor productivity growth over a 10-year horizon.

processing units (GPUs) initially optimized for gaming.[49] Over the past decade, AI development has accelerated significantly with advances in GPUs, in multicore central processing units, and in 'tensor processing units' with integrated circuits designed specifically for machine learning.

As the complexity of these chips has increased, their design and manufacture have become concentrated in just a few countries – as has the production of the equipment needed to build them. This part of the AI supply chain is dominated by the most technologically advanced economies, only four of which are in Asia and the Pacific. For example, China, the Republic of Korea[50] manufacture entire chips, while Japan supplies key inputs to the manufacturing process. Among other countries in Asia and the Pacific, India could begin designing and manufacturing advanced semiconductors for AI models. Overall, participation across the region remains limited.

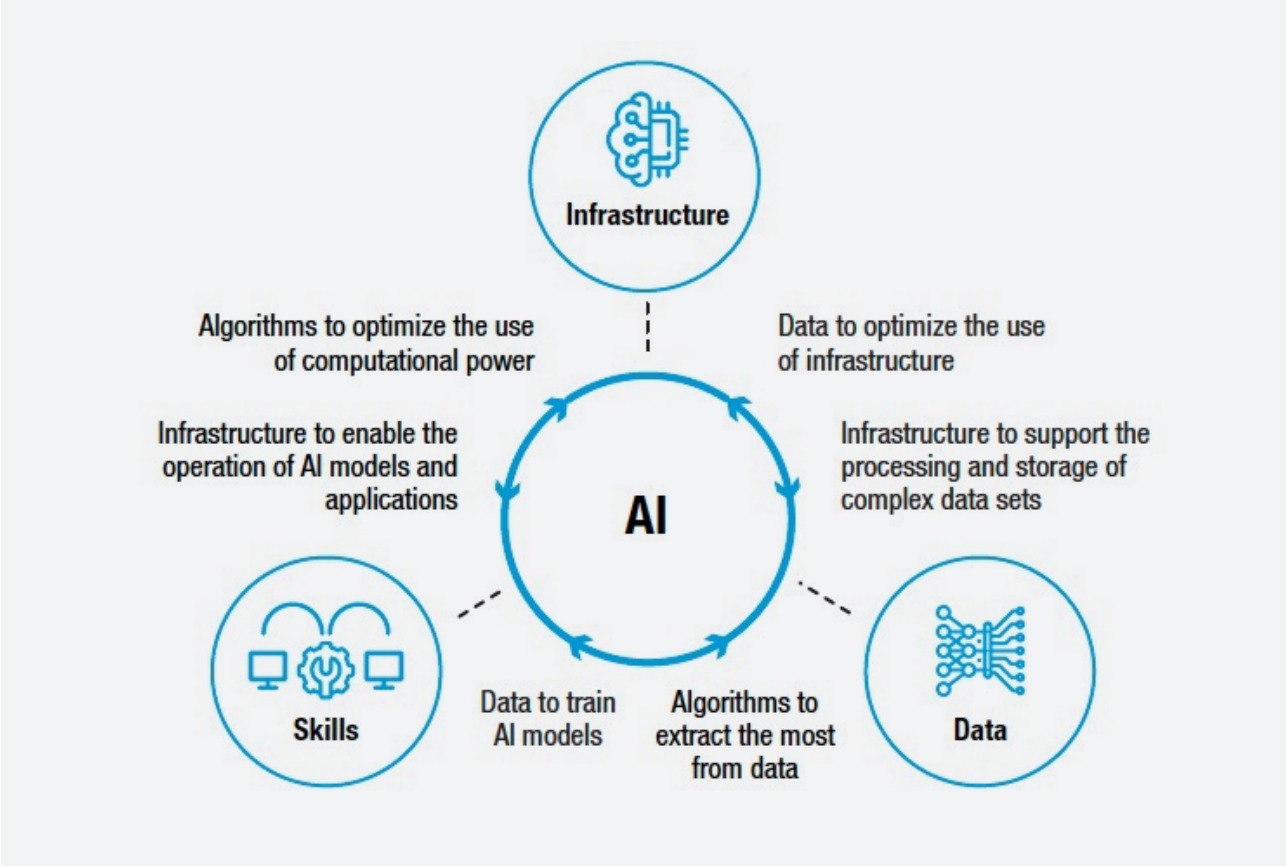
As indicated in Figure 14, progress can be assessed along three key dimensions – infrastructure, skills and data.[51]

Figure 13 – The AI value chain



Source: McKinsey Digital, 2023

Figure 14 – The AI ecosystem



Source: UNCTAD, 2025

Table 2 – TFP growth in Asia-Pacific countries 2000-2024

	Infrastructure	Data	Skills	Policy and governance
Adoption	"Electricity ICT infrastructure Digital devices"	"Access to domain-specific data Data storage and processing power"	"Basic digital sills (e.g., data literacy) Awareness and understanding of AI Technical knowledge"	"Principles Governance Policies (e.g., industrial, innovation) Strategies"
Development	"Internatioinal connectivity Data centres and high-speed networks"	"Large and fiverse datasets High quality, standardized, and interoperable data Privacy, security, and anonymization"	"Advanced digital skills (e.g., data science, machine learning) AI-specific skills and experiences Cognitive skills (e.g., problem solving)"	

Source: (UNCTAD, 2025)

Powering AI

AI models require vast amounts of computing power (compute) for both training and operations which are carried out in hyperscale data centers. Building and operating these facilities and equipping them with state-of-the-art servers requires significant capital investments. Outside China, the global market is dominated by Microsoft, Azure, Amazon Cloud Services, Equinix, and Oracle Cloud Services. Data centers consume considerable amounts of electricity and need ample supplies of water to cool the servers, so they are clustered in locations with abundant supplies of power and access to large volumes of water. And to minimize data transmission times, they generally need to be close to locations where AI usage is high, typically urban areas.[52]

In Asia and the Pacific this limits the number of potential locations. One is Malaysia which is building a cluster of data centers in the southern state of Johore which can service not only domestic users but those in neighboring Singapore.[53] These will complement 16 centers near Kuala Lumpur.

Data centers are costly to build and expensive to operate.[54] To attract foreign investment in these specialized facilities, a country has to offer significant incentives that may reduce the economic returns. After construction, managing and servicing of the facility is done by a small team of technical personnel, often expatriates, which may limit domestic employment creation. Hence, if there are no forward linkages the value added and productivity gains from hosting data centers can be meagre. And because they are capital- and skill-intensive, data clusters do not improve income distribution at the national level. Even the regionwide effects can be minor.[55]

Foundation models

A third crucial step in AI development is the foundation model, which employs deep neural networks with billions or trillions of interconnected artificial neurons. Earlier models focused on specific tasks such as playing chess or Go, natural language processing, image and pattern recognition, or data analytics. The latest models utilize generative AI and large language models (LLMs) trained for a variety of tasks.[56]

These models demonstrate a strong capacity to understand language, to respond coherently to prompts, to process huge chunks of data, to write accurate computer code, to solve mathematical problems, and to respond to queries with systematic step-by-step reasoning.

Since the advent of the transformer architecture in 2017 and the launch of BERT,[57] and of GPT1 in 2018, new LLMs have proliferated.[58] The first version of GPT4 appeared in 2022 and by January 2025 had had seven updates. LLMs have been released by 14 companies; in the United States, these are Google, DeepMind, OpenAI, Anthropic, xAI; in China they are Alibaba, DeepSeek, Tencent, ByteDance, ZhipuAi, and 01.a; and in Europe, Mistral AI. Companies are also taking advantage of open sourcing by DeepSeek, Meta and Alibaba on the foundation models to make narrower and more specialized models that perform more efficiently and are cheaper to train and operate.

Training and data requirements

The fourth step in the value chain is training the models with sufficient data, either unfiltered or curated. A model with billions of parameters must be fed tens of billions of tokens – words or sentences or pictures – scraped from the internet, including sites such as Wikipedia, Reddit, or YouTube.

Some technical data can, however, be held behind paywalls, subject to copyright, or closely held by institutions or firms. Gaining access can be difficult for all but the largest developers, which may risk that the AI ecosystem might disproportionately benefit those who have the resources to access the data and train the models.[59]

After ingesting the data, the responses must be fine-tuned using reinforcement learning and generative adversarial networks (GANs) to ensure suitable responses, minimize errors and reduce incorrect results called hallucinations. This is another expensive and time-consuming process.

Such models can, for example, enable office workers, journalists and students to write essays, answer emails, or synthesize information, and can make routine tasks less burdensome and boost productivity. Nevertheless, as with digitalization, the macroeconomic benefits could be minor. And there is a potential downside in that such assistance could erode human skills of reading, writing or in math or computer coding.

Specialized AI

The fifth element in the value chain, and the one arguably most relevant for Asian EMDEs, is the specialized AI model (Johnson, 2025). Such models distil and customize open-source foundation models so as to fulfil specific tasks. They can, for example, control robots and other production processes to make them more cost effective and move material around factories or warehouses.[60]

Decisions on investment in automation and robotization will typically hinge on two key factors: relative input costs, and the supply of labor. If capital is expensive and labor is cheap, production can be labor-intensive. If skills are scarce and loading training models onto factory equipment necessitates inputs of skilled workers, then factory owners will prefer to use the simplest technologies.

The Republic of Korea, Japan, Singapore and China possess the skills and the capital, but as a result of long-term demographic trends, their domestic labor supplies are shrinking, and in general wages are on the rise. For these economies, automation using AI may be the right choice. But the majority of Asian EMDEs need to find ways of employing large pools of low- and semi-skilled workers.[61] Many MSMEs may have limited immediate opportunities to integrate advanced AI applications. Figure 15 gives a global overview of the location of the world's top-tier AI researchers.[62] In the Asia-Pacific region they are largely in China and the Republic of Korea. As indicated in Figure 16, India is also a major source of the global AI researchers.

Specialized AI models are transforming operations across government, business, and professional fields. In China, both central and local governments have deployed customized versions of DeepSeek's R1 model to enhance public services, accelerate contract processing, and optimize management processes.[63]

In the private sector applications include:

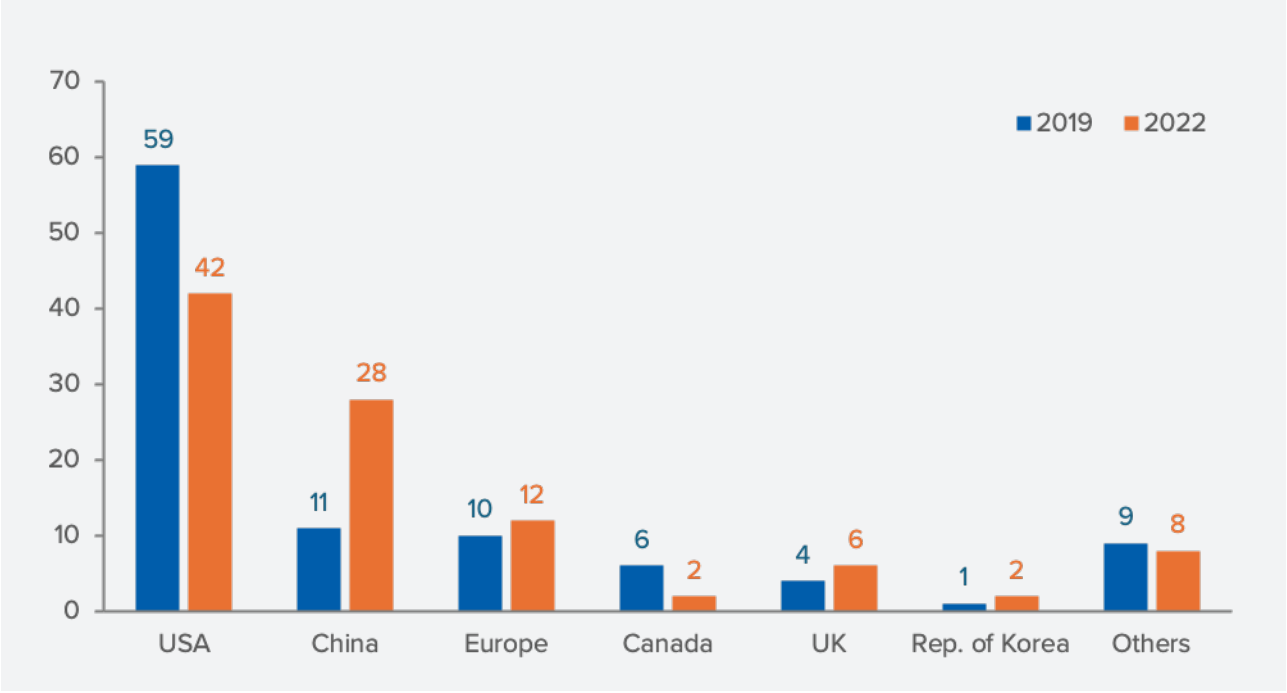
- *Customer Service* – Call centers are using AI to improve the productivity of the less experienced workers.
- *Software Development* – Engineers increasingly rely on AI for automated coding.[64]
- *Healthcare* – AI systems demonstrate growing proficiency in medical imaging and chart analysis.
- *Education* – Raising education quality through personalized tutoring, grading and feedback.
- *Finance* – AI is poised to excel at financial analysis and credit risk assessment.
- *Agriculture* – Precision farming applications that boost crop yields.
- *Environmental Management* – Enhanced weather and wildfire prediction.

Individuals and enterprises are actively experimenting with AI solutions. Widespread customization remains constrained by three critical shortages: technical skills, reliable energy infrastructure, and quality training data.

Users and propagators

A sixth node in the value chain is comprised of firms, large and small, that serve as early adopters demonstrating the utility of AI models to rapidly grow their businesses. These may be privately held startup companies, which if

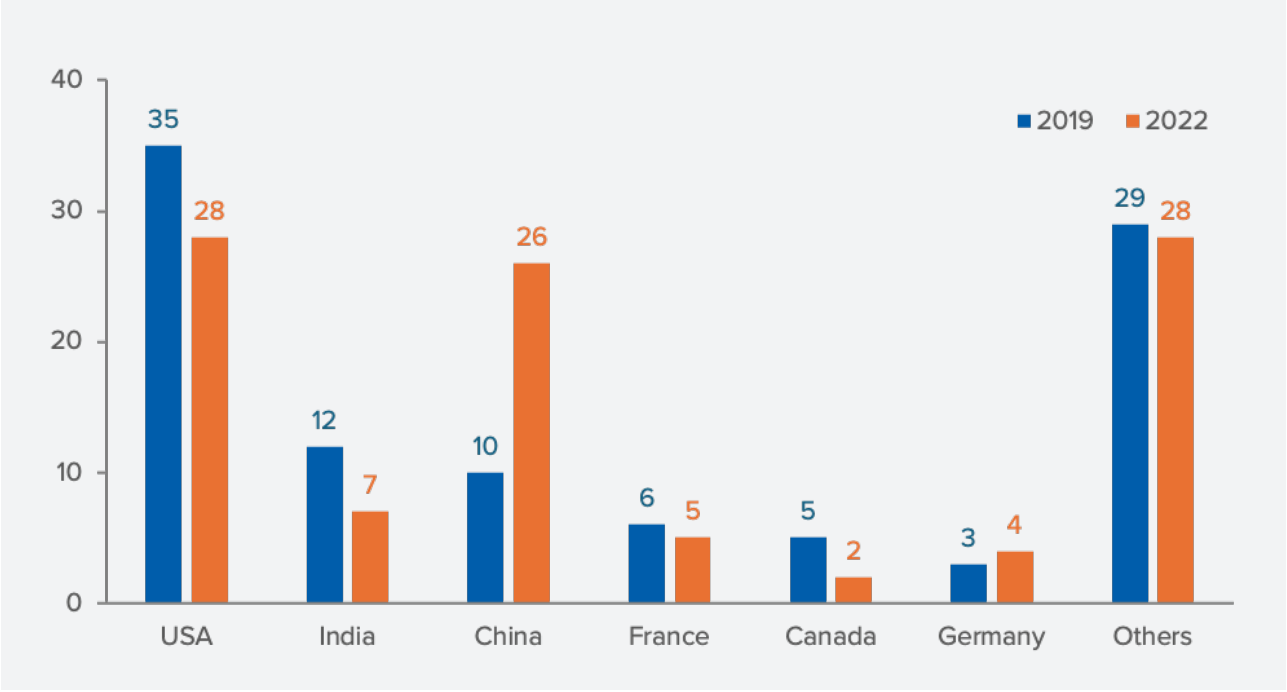
Figure 15 – Distribution of top-tier AI researchers



Note: Refers to the top 20 percent based on undergraduate degrees

Source: (MacroPolo, 2023)

Figure 16 - Countries of origin of top-tier AI researchers



Note: Refers to the top 20 percent based on undergraduate degrees

Source: (MacroPolo, 2023)

valued at more than $1 billion are referred to as 'unicorns'. Nothing is more convincing than the emergence of several unicorns that have clearly established expanding markets for AI-based innovations. Such enterprises are sprouting in the United States,[65] China and Europe,[66] with a few in the Republic of Korea, India and Singapore.

The final node in the value chain is an entrepreneurial ecosystem supported by venture financing. For Asian EMDEs, this might be the starting point, initiating the gradual assimilation of the technology and beginning to build the skills and infrastructure needed to move up or down the value chain.

The technological change occurring in Asia and the Pacific thus far is largely driven by diffusion of digital technologies and countries have made extensive use of online search engines aided by the cloud and data analytics. However, it can be argued that this has yet to make a major difference in the capabilities of Asia-Pacific governments or the ways in which education, government, finance, healthcare and other information-intensive activities are conducted. Nor have there been major improvements reflected in macroeconomic or other indicators.

Malaysia, China and India, for example, have deepened their financial systems and increased their technological sophistication, but this has not moved their productivity needles. Educational outcomes in parts of South and South-East Asia continue to face persistent challenges.[67]

In some respects, AI is being positioned as a pathway to strengthen growth and advance structural transformation. Many Asia-Pacific countries are embracing AI though discussions of potential productivity gains, the time needed for these gains to emerge, and longer-term distributional effects are still evolving.[68] Current policy approaches set a generally sound direction, and further clarity on objectives across the AI value chain, along with roadmaps with waypoints for assessing progress, would help guide implementation more effectively.

Country-level policies

To consider the possible medium-term consequences this chapter looks at four countries that broadly represent Asia's diversity.

- Republic of Korea – an advanced economy with a large high-tech sector.
- Malaysia – an upper middle-income South-East Asian economy which is a technological pacesetter.
- Pakistan – a populous, slow-growing, lower-middle-income country.
- Fiji – a leading Pacific Island economy.

Developed country – Republic of Korea

The Republic of Korea is a developed, technologically advanced economy with a large high- and medium-tech manufacturing sector, and a skilled, tech-savvy labor force and a highly developed energy and telecommunications infrastructure.

Although the country is well endowed with STEM skills it needs to nurture more high-quality researchers and designers. It has only 2 percent of the top 20 percent of AI researchers, and graduates from Korean universities are not included in the top 20 percent of AI researchers. Nevertheless, the Republic of Korea is investing 5.2 percent of GDP in R&D and is responsible for a third of the AI patents filed between 2010 and 2021, and Korean researchers have published over 68,000 papers on AI -related topics.[69]

Along with China, the Republic of Korea is considered well placed to achieve productivity gains from AI. It has the capacity to design and manufacture the chips that power advanced AI models, as well as the combination of research capabilities, data, start-up ecosystem, and large corporations that can design and train foundation LLMs.[70] The Republic of Korea is home to over 30 unicorns in areas such as retail, fintech, gaming, software and others.[71]

Although the Republic of Korea invests the equivalent of 32 percent of GDP, growth has settled at a 2 percent rate. The contribution of TFP has fallen to 0.6 percent per annum as against 2.3 percent per annum between 1980 and 2010.[72] AI-enabled improvements in allocative and production efficiencies could partially restore TFP growth though this may be offset by a drag on productivity from a rapidly ageing workforce.[73] [74]

Emerging market developing economy – Malaysia

The Malaysian economy has expanded at a 4-5 percent per annum rate since 2010 and TFP growth has levelled out at about 1 percent per annum or lower. The World Bank projects a slowing of both TFP and GDP growth rates, with the IMF pegging Malaysia's growth at 4 percent through 2030.[75]

Malaysia is rapidly moving up the AI learning curve, with a slew of programs and funds that might enable it to become a regional AI hub.[76] It has a Ministry of Digital and a National AI Office, an action plan for the second half of the 2020s, a National LLM strategy and an AI Sandbox.

Malaysia is seeking strategic partnerships with the AI MNCs even as it is constructing their datacenters. Because Malaysia is aiming to become a datacenter hub, it also has corresponding plans for power and water supplies. In addition, Malaysia has hopes of creating a homegrown semiconductor ecosystem. These initiatives are expected to spur economic activity and multiply the number of jobs for the highly skilled.

These initiatives are expected to spur economic activity and multiply the number of jobs for the highly skilled. Whether they will deliver their targeted $115 billion in additional productive capacity by 2030 is less certain. It may be many years before they can independently produce specialized models that impact productivity and growth.

Developing country – Pakistan

The Government has expressed a commitment to ethical and inclusive AI development backed by investment in skills, research, tech parks, and a start-up ecosystem. It has established a national task force on AI and its implementation.

A handful of start-ups have materialized for digital technologies e.g. Vyro (content creation), Traversaal AI (B2B AI solutions), Xylexa (digital health), Adlytic AI (retail analytics), and Farmdar (sustainable agriculture).[77] They may be able to adopt models developed elsewhere, but the country would benefit from developing research capabilities in universities or institutes.

Pakistan faces ongoing institutional and operational challenges in ensuring effective implementation. Constraints related to limited capital and a shortage of specialized skills weigh on progress; the country's the human capital index (HCI) score stands at 0.41.

The scope for utilizing AI to improve industrial productivity is constrained by the small share (14 percent of GDP) and the low-tech composition of most manufacturing activities. Absorption of AI may also be hindered by the size of the informal sector. Pakistan has excess generating capacity, mostly fossil fueled, but its distribution network is weak, and water resources are under stress.

Pacific Island State – Fiji

Several Pacific Island States are incorporating AI into their development plans as they proceed with the building and hardening of the ICT infrastructure and the digitalization of services. Fiji has its sights on the Fourth Industrial Revolution to galvanize industry and agriculture and is making AI a cornerstone of its development plans.

A focus on research is expected to promote technological adoption and absorb more Fijians in high-value jobs.[78] Skill and data constraints will hamper efforts to leverage AI (the HCI index score is 0.51).

Other countries in Asia and the Pacific

Overall, countries in Asia and the Pacific differ greatly in their absorptive capacity for AI (Figure 17). Those in the upper- and upper middle-income groups are better positioned to take advantage of the technology,

to introduce the desirable governance and regulatory institutions, and to collaborate productively with international bodies.

Policy recommendations

Countries at all levels of development should be able to take advantage of customer-facing applications using small, customized AI models, either adapted from freely available ones or built using open-source foundation models trained with additional data from local sources. These developments are within the capabilities of most countries.

The adoption of AI models could be facilitated by seven measures derived from experience to date in Asia and the Pacific and elsewhere:

1. *Policies* – Design policies promoting training by public and private providers in digital and coding skills.
2. *Infrastructure* – Strengthen the physical/cloud infrastructure underpinning the use of AI models. This might be adequate for the AI usage likely during the second half of the 2020s in most upper-middle-income countries but would need to be augmented to accommodate more widespread application and movement up the AI value chain in the 2030s.
3. *Fiscal measures* – Support for tax/financing schemes that encourage entry by providers of AI services. Start-ups are emerging throughout Asia and the Pacific as AI becomes more user friendly and such firms serve as the bedrock for future development.
4. *Start-ups* – Leverage start-up vehicles for introducing practical applications with intuitive interfaces that are inclusive and easy to use, including on mobile devices.
5. *Government adoption* – Promote public sector initiatives for government agencies to use AI models to respond to queries and reduce the cost of doing business and the conduct of routine transactions. A distilled version of the AI model DeepSeek is already in use by central and subnational entities in China. By taking the lead, the government can accelerate diffusion and stimulate innovation by others.
6. *Trust* – Enhance trust in the use of AI through increasing data privacy, and consumer and copyright protections.
7. *Governance* – Proactively work with other countries to define AI governance- related standards, guidelines and rules. This is ongoing with limited participation by developing economies.[79]

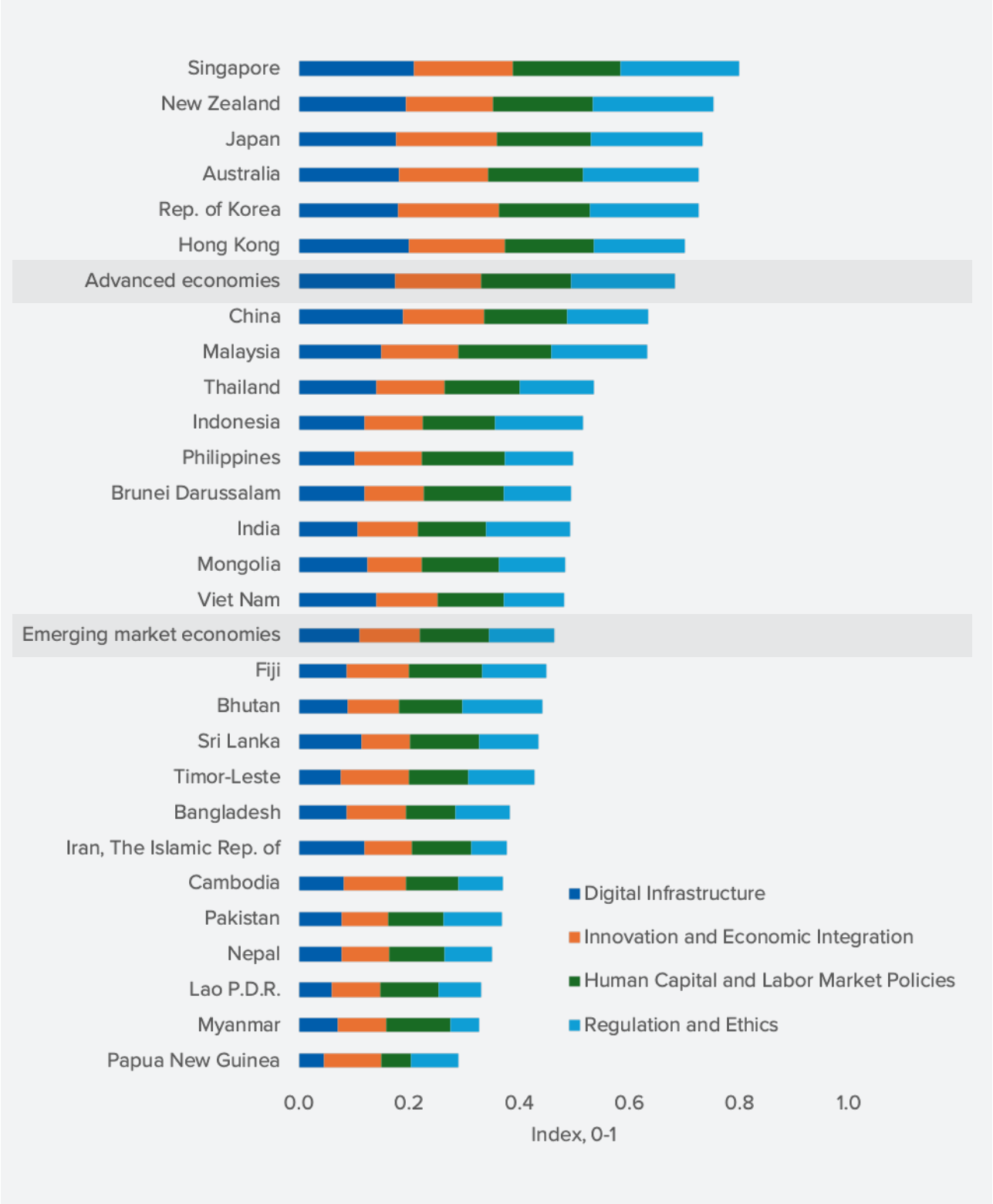
Possible outcomes, positive and negative

AI systems are expected to become more adept at systematic reasoning and planning, and at interacting with other AI systems and facilitating automation. In particular, there is a subset of tasks in which AI tends to perform best, such as coding or synthesizing a large volume of information. Other tasks are somewhat messy and unstructured, and functions calling for creativity and innovation are beyond their capabilities.[80] [81] It is too early to claim with any confidence that AI will be a gamechanger, but its role will grow.

By harnessing digital technologies, the middle-income countries can improve the performance of healthcare and education services, manufacturing and finance. Digitalization can also benefit agriculture. In other words, the low-hanging fruit for most of the Asian EMDEs is not AI models but plain vanilla digitalization. As of now, AI is just a thin layer of icing on the cake of usable technologies. If past GPTs are a guide, Solow's observation will resonate in Asia and the Pacific throughout the 2020s and well into the 2030s. AI will in all probability have a minimal impact on TFP and on income distribution within and between Asia-Pacific countries.

Whether the AI revolution spreads throughout Asia and the Pacific, which innovations take root, and the pace of assimilation, will depend upon a variety of factors specific to individual countries. Lower-middle-income, and some middle-income ones, will also have to contend with the massive energy and water consumption of the

Figure 15 – Distribution of top-tier AI researchers



Note: Refers to the top 20 percent based on undergraduate degrees

Source: (MacroPolo, 2023)

vast server farms that support LLMs.[82] Another restriction will be the availability of high-quality training data for which synthetic data might not be adequate. Usage will also be inhibited by any tendency of models to hallucinate.[83] A further bottleneck for middle-income Asia-Pacific economies will be the supply of engineers and scientists who can build cutting-edge algorithms and architectures.[84]

A successful outcome will depend upon widespread and growing demand for products and services incorporating AI so that providers begin making profits. There are plenty of users, but earnings of the leading AI companies are not covering the costs of building, training and updating models. And it could be even harder for companies to turn a profit if open sourcing makes AI products more like commodities.

Back in the day when semiconductors were all the rage, it was the demand for these products that generated profits and sustained investment in the semiconductor/consumer electronics/cloud computing boom. The Moore's law trajectory was triggered initially by demand from the military followed in quick succession by demand for mainframes, for consumer electronics like pocket calculators, radios, recorders, PCs, and smartphones and for cloud computing.[85] After more than three decades, this IT revolution eventually led to a spurt in productivity.

In the United States this technological revolution also led to a concentration of market power and an increase in inequality – and perhaps also in China. But elsewhere in Asia and the Pacific it is difficult to pin the blame on technology for changes in income distribution.[86]

This time it may be different. The belief taking hold is that AI is offering a cornucopia of innovations, which could speedily revive productivity throughout the economy – of manufacturing, of many services and of agriculture as well. As these innovations achieve scale, productivity gains would begin to surface in the macroeconomic data, the pace of GDP growth would begin to accelerate and there would be jobs old and new for all.

The most optimistic forecasters expect tangible improvements in productivity and consumer welfare in this decade.[87] [88] The more temperate ones believe that Asia-Pacific economies could benefit by the early 2030s and beyond.

Undoubtedly, the gains will be unevenly distributed both within and between countries. Artificial intelligence is likely to benefit high- and upper-middle-income countries that possess the necessary physical and human capital, data, and leading technology firms. On the other hand, the economies that have relied on an elastic supply of low-cost labor could fall behind; unless they can leverage the technologies that will raise productivity and sustain competitiveness, income disparities among Asia-Pacific countries could widen.[89]

END NOTES

1. (Krugman, 1990)
2. (Greenberg, Padhi and Smit, 2024)
3. (Conference Board, 2025)
4. (Cerutti et al., 2025) looks at the impact on macroeconomic variables, including GDP, for different countries and groups of countries, such as advanced economies and emerging economies with a 10-year horizon. Most of the estimates of AI impact on GDP focus on global or advanced economies (Davidson, 2021; Goldman Sachs, 2023; McKinsey Digital, 2023), while a few focus on Asia-Pacific countries, including (Johnson et al., 2016) ILO, 2025b, Goldman Sachs, 2025, CoinGeek (2025), Malaysia Center for the Fourth Industrial Revolution (2023) and AI for Vietnam Foundation (2025).
5. (Trajtenberg, 2018; Goldfarb, Taska and Teodoridis, 2022; Smith, 2024)
6. (Asian Productivity Organization, 2022)
7. This quickening of the uptake is facilitated by the wide availability of computers and access to the internet. Fan and Qiang (2024)
8. The concept driving this investment is called the scaling laws. The name dates to a 2020 paper posted by open AI titled scaling laws for neural language models. The gist is that when we combine more data and compute we get better results, that is, less loss. This was one of the core ideas that helped Open AI make the GPT Series a reality.
9. (WID, 2023)
10. (Irwin-Hunt, 2025)
11. (Jones, 2023)
12. (Van Reenen, 2022)
13. (WID, 2023)
14. (Filauro, Parolin and Valetto, 2025)
15. (Berkeley Economic Review, 2018; Autor et al., 2024)
16. (Manyika et al., 2019; Green, 2024; Karabarbounis, 2024)
17. (UNDP RBAP, 2022; WID, 2023)
18. (Ningsih and Choi, 2019)
19. (Huang and Quan, 2025; Tian et al., 2025)
20. (Cornelli, Frost and Mishra, 2023)
21. (Cornelli et al., 2023) conclude based on data from 86 countries that income distribution could become more unequal because it is the upper decile that stands to benefit at the cost of those lower down the food chain more exposed to displacement by AI.
22. (Frey and Osborne, 2017, no date)
23. (Tavares et al., 2025)
24. (Hennig and Khan, 2025)
25. (Solow, 1987)
26. (Acemoglu et al., 2014)
27. A significant share of the increased productivity was contributed by a single industry – electronics and electrical machinery, improvements in the quality of products and inclusion of new products. (Atalay et al, 2025).

28. (Fressoz, 2024)
29. In (Denning, 2021) Denning writes that "A key to solving the Solow Paradox lies in recognizing that bureaucracy and computers are a marriage made in hell: computers generate a great deal more work, but not necessarily more useful work. In a bureaucracy, there is often no net gain [and absent a bureaucratic overhaul, computers can make matters worse].
30. (Denning, 2021)
31. (Brynjolfsson, Mitchell and Rock, 2018; Bonney et al., 2024)
32. (Gordon, 2014) is of the view that recent GPTs (e.g. IT) are not as revolutionary or as "general" as the ones that emerged in the late nineteenth and early twentieth centuries.
33. (Autor et al., 2024)
34. (Handel, 2022)
35. (Autor et al., 2024)
36. (Braxton and Taska, 2023)
37. (Somers, Theodorakopoulos and Hötte, 2022)
38. (Rotman, 2024) rehearses past fears of unemployment resulting from technological advances and believes that prevailing fears regarding AI are also likely to be misplaced. From an analysis of data from 24 developed countries during 2005-2021, (Guliyev, 2023) finds a negative relationship between AI and unemployment. "AI has the potential to revolutionize the workforce by creating new job roles, automating routine tasks, and increasing productivity."
39. (Bailey et al., 2019)
40. (Anderton, Botelho and Reimers, no date)
41. Other technologies like 3D printing and cloud computing have been slower off the mark. Amazon Web Services began marketing a cloud computing platform in 2002 and 3D printers became available from 1988 but as of 2019, cloud computing was included in only 50 percent of urban job postings and 3D printing in 1 percent.
42. (Humlum and Vestergard, 2025)
43. (Dell'Acqua et al., 2023; Otis et al., 2024)
44. (Council, 2024)
45. When productivity gains are unevenly distributed while wages rise more or less in step across sectors, then the sectors where productivity lags tend to become more expensive as costs of inputs increase. This is known as the Baumol effect.
46. (Filippucci, Gal and Schief, 2024)
47. OECD, 2024
48. (Filippucci, Gal and Schief, 2024)
49. The transition from CPUs to GPUs (with multiple cores but less memory storage) and TPUs was one key step however, companies are now looking beyond e.g. at Neural Processing Units, AI accelerator chips and hybrid architectures that combine different kinds of processors.
50. Samsung has manufactured GPUs for Nvidia and builds others using AMD's RDNA architecture. It is planning to increase investment in such chips.
51. (UNCTAD, 2025)
52. Between the time a signal is initiated and when it is received, there is a brief delay because it takes a few seconds to transmit the packet, propagate it through the medium, for the packet to work its way through the queue at the other end, and for it to be processed before it can be accessed by the receiver. (, 2024)

53. Thirteen are operational with another three in the pipeline. The investors are Nvidia, GDS international, Microsoft, YTL Power, and Princeton Digital. Bytedance and Equinix have also received approval. (Ruehl, 2024; See, 2024) How much scope there is to expand capacity is debatable because, Johore was plagued by water shortages in 2019, and the electricity demand has strained the state's power supplies resulting in power outages.
54. The pace of technological change is such that data centers can become obsolete in seven years.
55. Although this is merely suggestive, Ireland, which has attracted 98 data centers, has experienced a decline in its Gini ratio from 33.5 in 2013 to 30.1 in 2021.(World Bank, 2025)
56. Generative pretrained transformer (GPTs) are among the most capable LLMs.
57. BERT stands for bidirectional encoder representations from transformers.
58. The LLMs constituted a significant advance over natural language processing models (NLPs) because unlike the latter they did not need to be trained using manually labeled data. Training of LLMs is initiated with unlabeled data and the parameters created adjusted during the finetuning stage when the model is put through its paces.
59. (Gambacorta and Shreeti, 2025)
60. With robots, it is the hardware and not the software that will be hurdle.
61. (Hémous et al., 2025) using data from 41 countries find that as wages of low-skilled workers rise, automation innovation is stimulated with an elasticity of 2 to 5.
62. (MacroPolo, 2023)
63. (Thome, 2025)
64. (Brynjolfsson, Li and Raymond, 2023; Saeedy, 2025)
65. The largest number are in the United States followed by China. The number grew by 110 globally in 2024, 65 of which were in the US. (Teare, 2025)
66. (Jackson, 2024)
67. The PISA test scores of students in most Southeast Asian countries fall short of the OECD average. (Hayashi, Yamakawa and Ohneda, no date; West, no date)
68. (Anzolin et al., 2024)
69. (McFaul et al., 2023)
70. (McFaul et al., 2023)
71. (Tracxn, 2025a)
72. (IMF, 2024)
73. (Kim & Chang, 2023)
74. An ageing workforce is an issue for both China and Japan.
75. (Devadas et al., 2020; IMF, 2024, 2025)
76. (Silapan, 2024)
77. (Tracxn, 2025)
78. (Wise, 2024; Fourrage, 2025). Fiji National Development Plan 2025–2029 and Vision 2050 stress economic resilience, people empowerment, and good governance and Fiji aspires to be a high-income economy by 2050 and touches upon ICT and digital trade but AI gets no mention. (Goverment of Fiji, 2024)
79. (LaForge, 2024)
80. (Thomson Reuters, 2025)

81. Generative AI (LLMs) are becoming expert at mixing and recombining training data. But too often they can respond by fabricating content and inventing references. Real creativity and breakthroughs require human ingenuity. More compute, more data (already being exhausted) and better algorithms could reduce hallucination until artificial general intelligence is achieved, humans will not be sidelined. (Frey and Osborne, no date)
82. The 200 million daily users of ChatGPT consume at least half million kilowatts of electricity. The Chinese company Deep Seek has demonstrated that LLMs (Deep Seek V3) can be made more energy frugal while using earlier model Nvidia H800 processors by inventing superior algorithms, architectures and training strategies. Schneider et.al. (2024). (Schneider, Shen and Zhang, 2025)
83. Model hallucination in AI, especially in large language models (LLMs), refers to the phenomenon where the model generates information that is factually incorrect, misleading, or entirely fabricated, even though it may sound plausible or confident.
84. (UNDP, 2025b)
85. Gordon Moore the former CEO of Intel projected a doubling of transistors on an integrated circuit every two years. This extraordinary pace of technological change was sustained for decades and has become a benchmark for other technologies.
86. (Abdela and Steinbaum, 2018; Efstathiou, 2019; Ma, 2022)
87. Digital technologies have enhanced welfare in ways that are not easily captured by GDP and productivity data. AI boosters are of the view that it could confer tangible and intangible benefits well in excess of the downsides. The race between the goods and the bads is ongoing.
88. (McKinsey Digital, 2023; Frost et al., 2024)
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