ASIA-PACIFIC PERSPECTIVES

UNDP

THE NEXT GREAT DIVERGENCE

Why AI may widen inequality between countries

Background Papers

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Background Papers

United Nations Development Program

One United Nations Plaza New York, NY 10017, USA

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This report compiles the nine background papers that underpin *The Next Great Divergence?* These papers were authored by leading scholars and practitioners from across the Asia-Pacific region and beyond, whose research and insights form the analytical foundation of the report.

- Catherine Tucker and Nan Clement (MIT Sloan School of Management), *Seeing the Unseen – Avoiding Data Deserts and Algorithmic Exclusion*
- Shen Zhou (School of Humanities and Social Sciences, AI Fusion Institute, University of Science and Technology of China) and Xufeng Zhu (Institute for Sustainable Development Goals, Tsinghua University), *AI and Human Security*
- Xian Hu and Chen Fang (School of Economics and Management, Tsinghua University), under the guidance of Jian Zhang (Institute of Climate Change and Sustainable Development, Tsinghua University), *AI and the Climate Crisis*
- Sara Beery (Department of Electrical Engineering and Computer Science, Massachusetts Institute of Technology), *People-Centric AI for Conserving Biodiversity*
- Michael Muthukrishna (London School of Economics and Political Science) and Iyad Rahwan (Max Planck Institute for Human Development), *AI for Productivity and Empowerment – in Agriculture, Health, Education and Transport*
- Shahid Yusuf (The Growth Dialogue, George Washington University), *The Macroeconomic Consequences of AI*
- Sarayu Natarajan, Kunal Raj Barua, Supratik Mitra, Nighat and Sagnik Sanyal (Aapti Institute), *Lessons from Online Gig Work in India and Indonesia*
- Urvashi Aneja, Aarushi Gupta, and Sasha John (Digital Futures Lab), *Exploring the Potential of AI to Usher in a New Governance Paradigm in Asia and the Pacific*.
- Zheng Liang, Shuyang Sheng, Zhenming Huang, and Shangrui Wang (Institute for AI International Governance, Tsinghua University), *AI for the Next Generation of Public Services*

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Philip Schellekens
Chief Economist
Regional Bureau for Asia and the Pacific
United Nations Development Program

CONTENTS

PART 1

PEOPLE: HUMAN CAPABILITY AND SECURITY ON A HEALTHY PLANET

CHAPTER 1 — SEEING THE UNSEEN: AVOIDING DATA DESERTS AND ALGORITHMIC EXCLUSION

Catherine Tucker and Nan Clement (MIT Sloan School of Management)

AI can make predictions that help promote human development and social inclusion, but it can also widen inequalities. Lack of local infrastructure and data gaps can lead to 'algorithmic exclusion' of vulnerable communities such as women, informal workers, displaced persons, and rural communities. As each country's economic and social system becomes more AI-driven, people who find themselves isolated in `data deserts' risk exclusion from public services such as health or disaster assistance as well as from employment opportunities or financial services. There can also be widening gaps between countries when lower-income nations lack the financial or technical resources to take full advantage of AI systems.

For many years, economists tended to see the goal of AI research as being to create useful and somewhat sentient robots. Now however, many see AI as a technology for something that was previously difficult and costly to do: making accurate, and customized predictions. AI is already being deployed to reduce the costs of predictions in many areas including:

- *Radiology* – AI can examine unstructured data in a radiology image and suggest whether someone is likely to be healthy or have a disease that needs to be treated.
- *Writing and predictive text* – AI now tracks text messages typed into cell phones and predicts what might come next. If the user agrees, the prediction becomes the message.
- *Self-driving cars* – AI examines real-time camera images to assess the immediate environment. If it predicts a hazard ahead, for example, it can steer the car to avoid the hazard or come to a stop.
- *Fraud detection* – AI can monitor bank and other transactions and predict whether they are likely to be fraudulent.
- *Customer-service chatbots* – Faced with a customer service query, AI can make a prediction about what information will best resolve the issue.
- *Agriculture* – AI can predict what crops will produce the best yield for a particular piece of land.

Short and long-term impacts

In general, when economists consider the impact of cost-saving technology that can be deployed across the economy, they know two things. First, that as a 'general-purpose technology,' it is likely to have profound effects on how the economy works. Second, that for the new technology to be deployed effectively, there will need to be large changes in how the economy works, so full deployment will take a long time.

The canonical example is electricity. This cost-saving technology revolutionized economic and social life in the modern era. However, this transformation took many decades. Initially, electricity was mainly used for illumination, and particularly for enabling houses to be lit after dark. Its use in factories that had been built for steam power was tentative and piecemeal. It was only after factories had been rebuilt for electrification that economies gained the full benefits.

Policy-makers in the Asia-Pacific region could therefore consider these two timescales. First, in the short term, countries can use AI to reduce the cost of prediction and improve human welfare. Second, over a longer period, countries can reorganize industrial production around

AI. However, both transformations require stronger and more extensive digital infrastructure.

Relying on equitable data

AI can be thought of as a production function where one input is algorithmic technology and the other input is data. Science is widely available and often open, at least to those with the necessary knowledge and capacity, and the technology is in principle widely accessible. However, for AI to work well for each person, or each type of person, there needs to be enough data about them. Even in countries or areas well served by physical infrastructure, some groups are regularly excluded, including women, informal workers, displaced persons, and other marginalized groups.

AI systems trained on datasets that omit these groups are likely to perpetuate and even amplify existing economic disparities. For instance, digital health datasets that do not fully represent rural populations will make AI-powered diagnostic tools less effective, potentially widening disparities in healthcare. Such citizens are likely to suffer from 'algorithmic exclusion.'

If AI technologies are to fulfil their promise of helping to create more inclusive and equitable societies, there should be full data representation. This chapter examines what this would mean for access to credit and health services, but similar concerns about digital deserts or invisibility extend across the whole human development landscape. This chapter discusses in depth some of the challenges for the Asia-Pacific region posed by missing data, using two motivating examples – inclusive finance and healthcare.

The use of national ID systems to resolve data fragmentation and promote financial inclusion via AI

Traditional models of financial inclusion have been hindered by the high marginal cost of serving low-income and remote populations, especially when identity documentation is fragmentary or non-existent.

AI can be used to promote inclusion and is particularly helpful for people without formal credit records. In general, access to credit requires some form of security, which is a challenge for those without wealth, or at least a financial record which gives the lender comfort that the person is a good credit risk. In countries without a single, universally accepted identifier, such as the United States or the UK, data brokers must piece data together about an individual using names, addresses, telephone numbers and email addresses. However, this is fraught with challenges, because the stability and accuracy of these digital identifiers are affected by underlying inequality. Lower-income households are more likely to move frequently and change telephone numbers, and are less likely to use an email address consistently. And if they are members of minority groups their names are more likely to be misspelled. Records of prior businesses owned or prior education or training obtained may not exist at all, or may not exist digitally, making it hard for lenders to assess risk before providing a loan.[1]

AI tools offer the ability to sift through and integrate multiple alternative, non-conventional data points relating to the borrower, such as online purchasing behavior or satellite data on crop production on a small farm, and combine many different records – and predict future behavior. This improves the accuracy of lenders' credit risk scoring systems. However, such data still needs to be accurately matched to an individual.

Financial providers are already highlighting the usefulness of AI in the credit allocation process: a mid-2024 McKinsey survey of 24 senior credit risk executives found that 19 of them expected to have implemented AI within the next 12 months.[2]

National ID systems can serve as identifiers around which government services, such as disaster relief, can be delivered. But they can also be used as the core of digital profiles that companies or other organizations can use, for example, to allocate credit. In data science, such an identifier is referred to as a 'key.' For a key to be effective, it is ideally an immutable alphanumeric string which is attached to multiple different types of data on an individual. Then, these different data sources can be effortlessly merged to form a single data profile.

Fully digital national ID systems may provide benefits ultimately to citizens if they allow a complete digital profile that can then be used by an AI algorithm to make accurate predictions about the needs and behaviors of similarly situated people. The government of India, for example, with Aadhaar in place, will be straightforwardly able to build AI tools on top of the infrastructure layer, such as by using non-financial activities to improve predictions for credit-scoring systems, complemented by human review.[3 4] For financial inclusion, it also in the interests of the citizen to have successful and accurate predictions made about them.

Most countries in the Asia-Pacific region have mandatory national ID cards, generally digital with biometric chips (Table 11). These ID cards have typically been created for national security purposes or for controlling access to government benefits.

Table 1 – National ID systems in selected Asia-Pacific countries

Country	National ID System Name	Mandatory?	Digital/Biometric Component
Brunei	*Kad Pengenalan (Smart Identity Card)*	*Yes*	*Yes – chip with photo & fingerprints*
Cambodia	*Khmer Identity Card*	*Yes*	*Yes – biometric (photo & fingerprints)*
Indonesia	*e-KTP (Kartu Tanda Penduduk)*	*Yes*	*Yes – biometric chip card*
Lao PDR	*National ID Card*	*Yes*	*Yes – photo and fingerprint biometrics*
Malaysia	*MyKad*	*Yes*	*Yes – smart card with photo & fingerprints*
Myanmar	*National Registration Card (NRC)*	*Yes*	*Transitioning to biometric smart card*
Philippines	*PhilSys ID (PhilID)*	*Yes*	*Yes – biometric (photo, fingerprints, iris)*
Singapore	*NRIC (National Registration ID Card)*	*Yes*	*Partially – biometric data held, not on chip*
Thailand	*National ID Card*	*Yes*	*Yes – biometric smart card*
Viet Nam	*Citizen Identification Card*	*Yes*	*Yes – biometric chip card*
Japan	*My Number Card*	*No*	*Yes – chip card with photo and digital cert*
China	*Resident Identity Card*	*Yes*	*Yes – biometric smart card (photo, fingerprints)*
Tonga	*TongaPass*	*Yes*	*Transitioning to biometric smart card*

This table suggests significant commonalities across countries, probably because most are using the same suppliers such as the Thales Group, a French multinational, or the Modular Open-Source Identification Platform (MOSIP). MOSIP, established in 2018, was inspired by the scale and success of India's Aadhaar project. Launched in 2009, MOSIP was conceived and initiated by the International Institute of Information Technology Bangalore (IIIT-B), with initial funding from the Bill & Melinda Gates Foundation. MOSIP is an open-source platform upon which identity systems are built using modules, such as national registration or personal authentication. In Asia and the Pacific, the largest implementation is in the Philippines, though Sri Lanka and Indonesia are also thought to be interested.

Universal Trusted Credentials

While these single identifiers attach to individuals, there have also been initiatives to support access to credit for medium and small enterprises, notably the Universal Trusted Credentials initiative launched by UNDP in partnership with the Monetary Authority of Singapore.[5] Traditional credit scoring models systematically disadvantage businesses operating in informal economies or those with limited banking histories. The UTC system validates alternative data points, such as consistent utility payments, supplier relationships, and mobile money transaction patterns, to create financial identities for businesses previously excluded from conventional lending processes – with the potential to increase loan approval rates for women-owned businesses and rural enterprises.[6]

At a digital disadvantage

AI for financial inclusion would typically link with government digital national ID systems. However, allocating credit on this basis is likely to further exclude some groups who do not have ready access to digital services. Lao PDR, using World Bank funds, has invested heavily in trying to ensure that the national ID system can reach remote communities.[7] Broader constraints on internet affordability and connectivity continue to shape how effectively these systems can be linked with digital service delivery.[8] As a result, rural rates of adoption of broadband are less than 1 percent in some communities.[9]

For example: In many countries, people facing gendered, livelihood or displacement related barriers may be under-represented in available datasets, creating 'data deserts' in which some populations become less visible to algorithmic decision-making systems.

This algorithmic exclusion is concerning in the Asia-Pacific region, where both within and between countries there are often large disparities in digital data readiness.[10]

Even in a developed economy, for infirmed or disabled people an existing physical disadvantage may translate into a data disadvantage if the AI used for predictions depends on how that individual has used the physical My Number Card.

The risks of bias and digital exclusion.

While some Asia-Pacific countries have extensive national ID systems, they are nevertheless not universal, and each has its own weaknesses and gaps.

India – Launched in 2009 by the Unique Identification Authority of India (UIDAI), Aadhaar assigned a 12-digit number to residents, linked to biometric and demographic data. As of 2024, over 1.3 billion residents had been enrolled, making it the largest biometric ID system globally. Given the complexity, its roll-out has seen different iterations and challenges. Earlier data shows that marginalized populations were at times unable to verify biometrics in the system, leading to possible risk of exclusion. Later evidence suggest that gaps in connectivity access and literacy remain obstacles hindering full access to benefits in certain cases, such as rural communities.[11]

Japan – Japan has well-established digital infrastructure. The My Number Card is deployed broadly for access, for example, to national pensions and to government services. Although the card is digital, to renew it people must visit a physical office.[12] Such physical verification may reduce fraud, but it may also pose a challenge to infirmed or disabled people, or anyone for whom leaving their house is difficult.

Philippines – The rollout of the PhilSys national ID system, built on MOSIP, was accelerated during the COVID-19 pandemic. Communities without formal identity documents—including some indigenous groups—faced difficulties enrolling. Efforts were subsequently made to expand registration outreach and improve accessibility.[13] The Government explicitly tried to tackle this by, for example, organizing registration efforts of citizens living in geographically isolated and disadvantaged areas. For example, on 30 November 2021, more than 100 individuals residing in remote areas of Nueva Ecija were registered.[14] Universal registration could imply more effort by governments to involuntarily register people who live remotely or in indigenous communities.

Myanmar – Myanmar's national ID system has uneven coverage, and some population groups — including long-standing communities in Rakhine State — face barriers to obtaining official identity documents. These documentation gaps predate the development of digital ID systems, but they shape who can access digital services and who may be excluded when identification is required.[15]

China – The national ID is required for most interactions of daily life. Now China has proposed expanding this national ID system to include all aspects of internet life by complementing it with a national internet ID system.[16] Such expansive data collection and infrastructure owned by the Government, is useful for AI development, but increases the risks of government surveillance. This raises broader concerns about balancing data-driven innovation with rights and privacy protections.[17]

Although national ID cards are on balance helpful, it is important to note different views. Many people are unhappy with the notion of mandatory, national, digital IDs. The principal objection concerns privacy. A dataset that includes a national ID number and a photo is one thing; a dataset that links these to the person's medical record, voter registration, driving record, phone number and record of purchases, all of which are possible with digital IDs, is quite another. Such a profile poses a far greater threat to individual privacy, while a more valuable tools for hackers.

As the 2022 OHCHR report Privacy in the Digital Age notes, "States should [when adopting new biometric systems,] consider risks of abuse, function creep and repurposing, including risks as a result of future political changes." [19]

AI for financial inclusion

If countries do decide to enable national IDs and attached profiles as the basis for financial inclusion, they will need to incorporate detailed data on vulnerable and excluded populations, while doing so in ways that do not expose every aspect of residents' lives to exploitation by data holders.

Without consultation, governments risk deploying AI in harmful ways, for example by unfairly denying access to benefits or services. AI systems could be used to automatically flag people for negative governmental actions, such as shutting down individuals' or communities' access to banking, train systems, or the internet.

Decisions around what AI to deploy should not simply happen top-down. Instead, mechanisms of consent and consultation should permit thorough discussion of both the possible benefits and the potential adverse consequences. Not every community or individual will weigh up the risks and decide that they wish to participate in AI-driven government processes that fail to offer a net benefit.

AI-driven predictions for healthcare

A second example where AI can significantly benefit residents of the Asia-Pacific region is AI-driven healthcare. In this section, we use the very specific illustration of a device for diagnosing diabetic retinopathy

– a serious complication of diabetes which damages blood vessels in the retina, which in turn leads to partial vision loss or blindness. The Asia-Pacific region is predicted to become the largest contributor to the economic burden of diabetes by the 2030s, with a total cost of approximately $800 billion annually, due to a combination of diet, genetics and a lack of diagnosis.[20]

Traditionally, to diagnose diabetic retinopathy, a doctor would take images of the eye that would be then examined by specialist for a variety of markers – a long, complex and potentially expensive process. By contrast, AI-enabled devices can detect the markers within minutes, and can be deployed at scale even in areas and regions without trained specialists. The new device takes an image, and submits it to an online algorithm, receiving results within 60 seconds.[21] Initial evidence suggests that such systems are better than humans at detecting diabetic retinopathy.[22] They are also low-cost and easy to deploy at scale.

Unlike the use of AI to make financial predictions, these AI-embedded devices do not require the person to have a pre-existing data profile. Instead, the data for the AI prediction is created in real time and should not be distorted by that person's economic status. The clinical features used in retinal screening do not differ inherently by socioeconomic status. This means that, if these features are well represented in the training data, AI models can perform accurately across diverse populations even when screening access varies.. Furthermore, the AI device requires only electricity and the internet, and a link to a data center somewhere in the world.

This is less demanding than the infrastructure needed for UTC, for example, or for Aadhaar. There are nevertheless, potential sources of inequality. First, the technology only makes a prediction about who should be referred to a specialist, or who is at risk for vision loss and blindness from diabetes. This is less useful in countries or regions that lack access to specialists. Second, the technology is intended for those who are already known to have diabetes. In South-East Asia, for example, more than half of diabetes cases are undiagnosed.[23] So while AI can make some forms of diagnosis cheaper and more scalable, it will have limited applicability unless complemented by basic forms of healthcare.

Moreover, as with any AI-enabled device there are potential inequalities in training data. One such device, EyeArt has been developed using data from the United Kingdom and the United States. Another device, SELENA, originally developed in Singapore, was trained on a Singaporean population.Such training misses out large populations,[24] for whom predictions will be inaccurate. If devices do not get properly deployed in such groups because of uncertainty over their efficacy, more inclusive data for fine-tuning will never be created. Though some of the risks of algorithmic exclusion can be mitigated using standalone devices, there is thus nevertheless the potential for indirect algorithmic exclusion via an absence of relevant training data.

Different approaches to data governance

To help counter algorithmic exclusion and other data concerns, some Asia-Pacific economies are implementing risk-based data frameworks, based on a recent European Union methodology which applies progressively more stringent requirements for higher-risk systems. Others are taking a more development-oriented approach to AI data governance seeing it as a means of reaching economic objectives, but often without robust safeguards against algorithmic exclusion or bias in AI outputs (Table 2).

- *Bangladesh* – The draft National Artificial Intelligence Policy incorporates principles of social equity and fairness, and also emphasizes the potential for AI to increase welfare, and establishes a National AI Council to drive innovation and industry development.
- *China* – The New Generation Artificial Intelligence Development Plan takes a development-oriented approach.

- *Fiji* – The National Digital Strategy framework primarily addresses the cybersecurity aspects of AI.
- *India* – The Digital Personal Data Protection Act strengthens the privacy framework around the use of personal data in digital and algorithmic systems, though broader AI governance mechanisms continue to evolve through complementary policies and initiatives.
- *Japan* – Japan has a distinctive hybrid model, combining innovation priorities with its AI Strategy 2022 while actively participating in international governance initiatives through the G7 and OECD.
- *Republic of Korea* – The Basic Act on Artificial Intelligence adopts a risk-stratified approach, distinguishing between high-impact AI systems requiring human oversight and generative AI applications subject to transparency requirements and content labelling.
- *Thailand* – The draft Royal Decree on AI-Based Service Businesses establishes a tiered regulatory system with distinct requirements for different risk categories of AI systems.

As these examples suggest, AI regulatory frameworks in the Asia-Pacific region do not specifically consider the problem of algorithmic exclusion. Though policies cover AI as a technology, they do not address directly the issues of data readiness or disparities in inclusion or exclusion of particular groups of populations, or how those issues might affect AI outcomes.

Table 2 – AI governance in selected Asia-Pacific countries

Country	Policy Name	Status	Key Focus Areas	Regulatory Approach	Features
Bangladesh	National Artificial Intelligence Policy[26]	Draft 2024	AI research, education, industry development, governance	Establish National AI Council with emphasis on innovation	Six principles: social equity, equality, and fairness; transparency and accountability; safety, security, and robustness; sustainability
China	New Generation Artificial Intelligence Development Plan[27] Opinions on Deepening the Implementation of Artificial Intelligence Plus Action, for implementation starting from the 15th Five Year Plan (2026-2030)	Implemented 2017	AI development, industry applications, talent cultivation, ethics and security	Government-led development with industrial policy focus; Comprehensive legal and ethical framework including Cybersecurity Law, Data Security Law, Personal Information Protection Law, Anti-Monopoly Law, and various AI-specific regulations	The Plan: Three-step strategic objectives with milestones for 2020, 2025, and 2030, including on ethical frameworks. The AI+ Initiative includes penetration targets; defines six action areas; establishes foundational support capabilities.

Country	Policy Name	Status	Key Focus Areas	Regulatory Approach	Features
Fiji	A framework to safeguard internet users against AI threats as part of National Digital Strategy[28]	Implemented 2024	Safeguarding internet users from AI-related threats		
India	IndiaAI Mission[29]	Implemented 2024	AI research, innovation, healthcare, education, agriculture, smart cities, infrastructure, and mobility	Pro-innovation governance with ethical guidelines; voluntary principles for responsible AI	Three distinct pillars: economic opportunity, social development/ inclusive growth, and "AI garage for 40 percent of the world"
Japan	AI Strategy 2022[30]	Implemented 2022	Digital transformation, industrial competitiveness, ethical AI usage	Co-regulatory approach balancing innovation and risk management	Emphasis on human-centered AI; social implementation focus; ELSI (Ethical, Legal and Social Issues) considerations
Lao PDR	National Digital Economy Development Strategy[31]	Implemented 2021	20-Year National Digital Economy Development Vision (2021–2040) and the 10-Year National Digital Economy Development Strategy (2021–2030)		Part of broader digitization efforts; early-stage focus on AI education and infrastructure
Papua New Guinea	No AI Policy	N/A	N/A	N/A	No official AI-related policies as of 2025
Thailand	Royal Decree on the Operation of AI-Based Service Businesses[32]	Implemented 2023	Risk-based	Tiered regulatory approach based on risk levels of AI systems	Classification of AI systems by risk; registration requirements for high-risk AI

Country	Policy Name	Status	Key Focus Areas	Regulatory Approach	Features
Republic of Korea	Basic Act on Artificial Intelligence[33]	Implemented 2024	Ethical AI usage, innovation promotion, and user protection	Risk-based framework differentiating high-impact and generative AI systems	Transparency requirements; human oversight for high-impact systems; labelling for generative AI outputs; enforcement begins January 2026

Other issues hindering algorithmic inclusion

There are many other potential causes of data deserts and algorithmic exclusion. One is multiple languages. Asia and the Pacific is the most linguistically diverse area in the world. Papua New Guinea alone has more than 800 languages; Indonesia has more than 700. There are likely to be more digital records in the national lingua franca, offering larger training sets. Those who know the lingua franca will therefore be more algorithmically included than those who only know a minority language, because there will be more digital records on them.

In societies affected by conflict or marked by long-standing social divisions, data collection has at times been misused, contributing to understandable mistrust among marginalized communities. It is therefore important that these communities are meaningfully informed and engaged in decisions about how data and AI systems are used, with transparent communication and safeguards that reflect their rights, perspectives, and priorities.

A further issue is the lack of complementary digital infrastructure. If the country itself is to take responsibility for the process of designing and training for AI rather than leaving it to other countries it will need sophisticated computational resources, data storage architectures, and high-bandwidth networks. Countries or regions lacking these digital resources cannot participate in the self-reinforcing needed for ongoing fine-tuning.

Policy implications and recommendations

Policymakers in the Asia-Pacific region may consider how AI can improve welfare in the short term by reducing prediction costs, accompanied by measures to assist workers and companies in the transition. In the longer term, they can think about ways AI can improve welfare through efficiency gains in industry. They should therefore identify sectors where reducing the costs of prediction can generate welfare improvements.

As a core principle, AI policies should mitigate algorithmic exclusion. Policymakers can pro-actively consider what groups within their country may be excluded from the benefits of AI, as a result of being less present or visible within pre-existing commercial and governmental data systems and social structures.

Ensuring that everyone can access services, benefit from AI-enabled systems, and be appropriately represented in data should not depend on the volume of data collected about them. At the same time, policymakers may wish to recognize that some individuals and groups—including privacy-conscious communities or certain minorities—may prefer to limit their visibility in official data systems. Approaches to digital inclusion should therefore balance the need for effective service delivery with respect for diverse preferences, rights, and expectations around data use.AI has already proven its use in specific areas like diabetic retinopathy scans.

Strategies to promote AI in healthcare need to be grounded in strong health systems that ensure people can access timely diagnosis and treatment. ; AI tools still depend on a robust healthcare system that routes people to the right diagnosis and treatment of conditions. AI systems demand vast computational resources, data storage architectures, and high-bandwidth networks. Policymakers can help make sure these resources are available, reliable and affordable.

In settings affected by linguistic diversity, past conflict or low levels of institutional trust, deploying AI enabled services may require additional time and engagement to ensure they are inclusive and responsive to local needs. Clear communication and participatory design processes can support equitable adoption.

END NOTES

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CHAPTER 2 — AI AND HUMAN SECURITY

Zhou Shen (School of Humanities and Social Sciences, AI Fusion Institute, University of Science and Technology of China) and Zhu Xufeng (Institute for Sustainable Development Goals, Tsinghua University)

This chapter examines the impact of AI on human security and inequalities, presenting significant use cases of the application of AI in Asia and the Pacific — for rural healthcare in Viet Nam, agriculture in Bangladesh, manufacturing in Thailand and climate prediction in Indonesia. The chapter categorizes countries in terms of their AI capacities and suggests corresponding policies that build from community needs through regional cooperation to global engagement.

Human development is about people, about expanding their opportunities and choices, and improving their well-being.[1] Human security complements this framework by addressing vulnerabilities and protecting people from critical threats.

The concept of human security emerged from the 1994 United Nations Human Development Report – as a deliberate effort to broaden and deepen the security agenda beyond the traditional nation-state paradigm of national security. The report characterizes human security as a universal issue that prioritizes people. It is primarily divided into two key areas: freedom from fear; and freedom from want. For the United Nations, these issues are addressed across seven interrelated dimensions: economic, food, health, environmental, personal, community, and political security.[2]

Human insecurity arises when individuals face threats such as poverty, hunger, disease, environmental degradation, violence, social exclusion, and political repression – which undermine their dignity and well-being. In the digital age, human security can also be undermined by digital divides and by digital-related risks to privacy that affect personal security.

AI can exacerbate these risks. In terms of freedom from want, new technologies are reshaping economic structures and labor markets, in both positive and negative ways. On the positive side there are opportunities for enhanced productivity, wellbeing, and new forms of employment – improving food security through precision farming, for example, crop yield prediction, and supply chain optimization. At the same time, there are concerns about potential job displacement and widening skill mismatches, which may disproportionately affect certain groups if not addressed proactively.

AI has a similar dual impact on matters related to freedom from fear. AI-enhanced surveillance and protection systems can improve public safety, but on the negative side they can also infringe on personal privacy and be open to misuse. Similarly for political security, there are positive applications for improving services and governance, yet also risks to democratic processes, including information manipulation and excessive digital surveillance.

These concerns are particularly acute for vulnerable groups, including for some vulnerable women. AI can enhance women's security by offering access to services, economic opportunities, and to protection systems. However, this could also reverse progress in women's workforce participation, as jobs disproportionately occupied by women due to social and gender norms—such as clerical, administrative, and service roles—are highly susceptible to AI-driven automation. There are also concerns for other socioeconomic groups: rural communities, ethnic minorities, and economically disadvantaged populations, who may see fewer benefits from AI while being more vulnerable to associated risks.

The Asia-Pacific region offers diverse contexts that provide insights into the varied ways AI interacts with development and human security. Countries in the region demonstrate varying capacities, from advanced AI innovation hubs to those still strengthening foundational infrastructure.

These differences create both challenges and opportunities: while AI may risk widening between-country disparities, they also open avenues for regional cooperation and shared progress. The actual outcomes will depend on effective policy design and implementation – on the ways that countries incorporate AI into their human security strategies.

Analysis and methodology

This study explores the multiple implications of AI for human security – focusing primarily on the Asia-Pacific region and on the key dimensions of economic, health, food and environmental security – paying special attention to cross-border issues. First it provides an analytical framework that systematically evaluates both the positive and negative effects of AI. Second, it considers inequality between countries in the context of AI adoption and human security. Third, it develops evidence-based policy recommendations that take into account varying technological and institutional capacities across the Asia-Pacific region. The overall aim is to offer more effective and nuanced ways of leveraging AI for human security while minimizing potential adverse effects.

At the core of the methodology is a 2×2 matrix that considers impacts along two dimensions: directness of impact (direct/indirect); and nature of effect (positive/negative).

These four possibilities can be used to identify the immediate benefits, spillover effects, direct challenges, and systemic issues (Table 1). For analyzing inequality, it provides a structured way to understand how AI affects disparities between countries, considering both immediate and long-term implications (Table 2). For policy recommendations, it enables the development of targeted interventions that address specific impacts and challenges (Table 3).

Table 1 – Impact implications

Dimensions	Impact Implications
Directly positive	Immediate benefits of AI implementation
Indirectly positive	*Secondary and spillover benefits*
Directly negative	*Immediate challenges and drawbacks*
Indirectly negative	*Amplified challenges from systemic and structural flaws*

Table 2 – Inequality implications

Dimensions	Inequality implications
Directly positive	Inequality in districts or countries' capacity to implement AI solutions
Indirectly positive	*Inequality in districts or countries' ability to leverage spillover effects*
Directly negative	*Inequality in districts or countries' resilience against immediate AI-related disruptions*
Indirectly negative	*Inequality in districts or countries' capacity to prevent vulnerabilities in infrastructure, organizational structure and AI governance.*

Table 3 – Policy Implications

Dimensions	Policy implications
Directly positive	*Policies promoting immediate AI benefits*
Indirectly positive	*Policies supporting beneficial spillover effects*
Directly negative	*Policies addressing immediate challenges*
Indirectly negative	*Policies tackling systemic and structural flaws*

The data collection focuses on Asia-Pacific cases, which are supplemented by information from media, governments, international organizations, consulting companies and academic literature. This approach can embrace the complexity of AI's role in human security while remaining sensitive to the region's diverse contexts. It can also help identify both common features and context-specific factors that influence outcomes.

Impacts on human security

Artificial intelligence demonstrates significant potential for enhancing human security. The positive impacts emerge most prominently in healthcare delivery, agricultural productivity, disaster response, and the creation of economic opportunities, though the distribution and scale of the impacts vary considerably between countries.

Directly positive cases

Indonesia and healthcare – The Social Security Agency for Healthcare is developing AI tools on its national health insurance platform to bring better services to the public. It focuses on improving data analysis, streamlining processes, and preventing fraud by integrating AI in three key areas: user experience, process improvement, and insights and prediction. This includes utilizing natural language processing for chatbots to enhance user interactions and robotic process automation to reduce repetitive tasks and minimize errors. Since its launch in 2014 the JKN (Jaminan Kesehatan Nasional, National Health Insurance) program the has collected 442 billion data points which can be analyzed using AI. The JKN can use this to detect fraud and improve service delivery to forecast patient behavior and disease, allocate resources and improve healthcare outcomes. JKN also launched Healthkathon 2024.[3 4]

Viet Nam and food security – Viet Nam is Asia's largest producer and exporter of dragon fruit. The AI Plant Doctor app, created by BOM Software in 2021, has been introduced to provide smallholder farmers with a user-friendly tool for diagnosing pests and diseases that threaten dragon fruit, thereby enhancing crop protection and food security and improving farmers' livelihoods. The initiative integrates AI with agriculture, supporting Viet Nam's agricultural transformation and innovation goals.[5]

Malaysia and food security – Under an initiative spearheaded by Mimos Berhad, a government agency under the Ministry of Science and Technology, farmers are set to benefit from SKYFLD a digital agriculture platform provided by HELM AG, a German crop protection and fertilizer group that also provides satellite services. This digital agriculture initiative includes the use of HELM's mobile crop doctor Plantix, through which farmers can upload photos of sick plants for analysis. Utilizing AI, the app diagnoses plant diseases, pests, and nutritional deficiencies and offers instant feedback and treatment recommendations, making it user-friendly and accessible even for those with limited technical skills, as well as contribute to improved food security.[6]

Indirectly positive cases

Lao PDR, governance – The Government is integrating AI into governance and public administration, including launching 37 digital government systems and developing a national digital identity system.[7] Building on these digital governance advancements, in March 2025, the Lao National Assembly and the Parliamentary Assembly of the Francophonie, an association of the parliaments of Francophone countries around the world, discussed AI's role in parliamentary work, focusing on digital tools for governance, policy assessment, and combating misinformation. These parliamentary AI adoption efforts support democratic participation and social cohesion by enhancing legislative efficiency and informed policymaking.[8]

Thailand, combating gender-based violence – Many gender-based violence cases go unreported due to social norms, fear of judgment, and constraints in accessing justice. Sis Bot is an innovative AI-powered chatbot that can help survivors access justice and support services. Sis Bot operates 24/7 and can be accessed via platforms like Facebook Messenger, offering immediate responses to inquiries on how to report incidents, preserve evidence, and understand legal rights, including information about shelters and services. By demystifying the legal process and empowering survivors with knowledge, Sis Bot helps women make informed decisions about seeking help. The project has garnered support from UN Women, emphasizing the importance of access to justice as a critical component of gender equality.[9]

India, supporting the Aadhaar system – The Aadhaar biometric ID system is managed by the Unique Identification Authority of India (UIAI) and is linked to the Unified Payments Interface that is used, for example, for distributing benefits. AI is now being incorporated into Aadhaar – aiming to bolster security, enhance user experience, streamline service delivery,[10] and improve fraud prevention, personalized customer service, and regulatory compliance.[11] AI can for example, detect cloned fingerprints and issue real-time fraud alerts during authentication requests.[12 13] To improve user experience, Aadhaar has partnered with the Bengaluru-based company Sarvam AI to include voice interactions in Hindi, English, and other languages.[14] To ensure data privacy and security, Sarvam AI's GenAI stack is hosted within UIDAI's infrastructure. Nevertheless, some risks remain – with or without AI – of leaving many vulnerable people behind. These include people with low levels of digital financial literacy, senior citizens, and the poor especially in remote rural communities that have weak ICT infrastructure.[15 16 17] Errors in Aadhaar enrolment and biometric failures can also cause anxiety and exclusion.[18]

The implementation cases above typically combine technological sophistication with careful attention to local context and user needs, and are being deployed as part of broader development strategies rather than as standalone solutions. They can also benefit from strong partnerships between government agencies, technology providers, and local organizations and build on existing community structures and cultural practices. Successful implementation for any system typically requires strong feedback mechanisms that enable continuous adaptation and improvement.

While AI technologies offer significant potential for enhancing human security, they can also create new problems such as job replacement, digital divides and opportunities for cybercrime. AI implementation directly disrupt livelihoods and services, and also have indirect systemic effects that deepen structural inequalities.

Directly negative cases

Job losses – According to one survey, about half of all jobs in Asia-Pacific advanced economies are exposed to AI, compared to only about a quarter in its emerging market and developing economies. Concerns about job losses to automation are hindering consumers' acceptance of AI in the workplace. However, worries about AI-driven job losses differ markedly across the region. India and Singapore show the highest levels of concern, with 97 percent of consumers in both markets being slightly to very concerned about AI replacing their jobs.[19]

Income inequality – While AI can enhance productivity and economic growth, it can also exacerbate income inequality both between and within countries. For instance, women and low-skilled workers are more likely to be affected as they are often employed in roles that are easily automated.[20]

Cybercrime – AI can enhance threat detection, automation, and incident response, strengthening protection against cyberattacks that threaten personal and national security. On the other hand, AI technologies can also be exploited for sophisticated cybercrimes, deepfakes, and identity fraud, posing new challenges for personal security and trust in digital systems.[21] Cases of deepfakes and identity fraud have surged across Asia and the Pacific notably in Singapore, Thailand and Indonesia – threatening personal security and undermining consumer trust.[22]

Indirectly negative cases

Healthcare – Across Asia and the Pacific, AI adoption in healthcare can improve diagnostics and service delivery, but also raises concerns over privacy, data security, and equitable access especially in less developed countries with limited digital infrastructure.[23]

Agriculture – AI-driven agritech innovations can improve crop monitoring and pest control, but smallholder farmers face hurdles in adoption due to a lack of investment or subsidies, or weak digital capacities.[24]

Environment – AI's rapid expansion demands huge data centers which consume large amounts of energy.[25] A survey among 1,000 UK adults commissioned by CloudNine PR found that 54 percent of people familiar with GenAI recognized that its expansion could have environmental impacts, and 45 percent supported legislations requiring GenAI companies to be transparent about their environmental costs.[26] At the 20th Indonesia-Japan Policy Research Forum in February 2025, 150 policymakers convened in Jakarta to examine AI's environmental impacts and opportunities. Attendees identified increased power consumption and carbon emissions as the primary ecological concerns requiring attention. These issues are particularly relevant in South-East Asia, where fossil fuels generate over 80 percent of the subregion's electricity.[27]

Human rights – AI may also be used in ways that inadvertently contribute to misinformation, increased social monitoring, or biased decision-making. These dynamics can raise concerns for democratic participation and civic freedoms, particularly in contexts where governance and regulatory frameworks are still developing.[28]

Instances where challenges arise often reflect limited engagement with affected communities or insufficient consideration of existing power dynamics. These issues underscore the value of maintaining a diversity of approaches to human security and ensuring that technological tools complement—rather than replace—traditional methods and knowledge systems that contribute to resilience.

Impact on inequality

The diffusion of AI technologies across the Asia-Pacific region may lead to varying levels of opportunity and access within and between countries. These differences can reflect existing socioeconomic patterns and in some cases, may widen them, resulting in uneven experiences of benefit and risk.

- *Technological capacity* – Countries and areas differ in their capacities to harness AI's direct positive impacts. This includes disparities in technological infrastructure, data resources, and technical expertise. Some countries or districts can deploy sophisticated AI systems for precise service delivery and social welfare distribution, but others lack the basic technological foundations.

- *Absorptive capacity* – Countries or areas differ in their capacities to recognize, assimilate, and leverage beneficial spillover effects from AI advancement, or translate AI-driven productivity gains in one sector into broader economic benefits. Hampered by institutional and structural limitations, they struggle to create beneficial linkages across their economies.

- *Protective capacity* – Some countries or areas have strong social safety nets and retraining programs to help communities navigate AI-related changes, while others face more limited institutional capacity to support their populations in adapting to shifts such as changes in employment or access to digital tools.
- *Development capacity* – While some countries are well positioned to influence their long-term development trajectory in an AI-driven economy, others may face greater challenges in addressing structural changes and could have less influence over how technological shifts affect them.

Capability categories

Based on performance across these dimensions, countries in Asia and the Pacific could fall into the following broad capability categories.

1. *Comprehensive implementation* – Countries or areas with high capabilities across all four dimension are able to implement AI solutions effectively, leverage indirect benefits, and protect populations from negative impacts. The Republic of Korea for example, has AI-driven initiatives in elderly care that aim to provide sophisticated monitoring and support services. Singapore has the SkillsFuture Initiative which provides subsidized access to training courses and job transition support for citizens and residents. These countries can successfully leverage AI for human security while simultaneously maintaining strong worker protection programs.
2. *Active implementation, with scope to enhance safeguards* – Strong implementation capabilities and the potential to leverage indirect benefits are evident, although resilience against certain negative impacts and preventive measures remain areas for further strengthening. Examples include India, Indonesia, Malaysia and Thailand. In India, AI-powered financial inclusion initiatives have reached millions of citizens, yet challenges persist in supporting workers affected by technological change and in ensuring long-term technological autonomy. In Malaysia, the rapid adoption of foreign AI systems in the manufacturing sector has contributed to productivity gains, while also highlighting the need to carefully manage reliance on external technological decisions and market fluctuations.
3. *Strategic planning with scope to expand implementation* – These countries demonstrate strong strategic foresight, though implementation capacities are still developing. Examples include Viet Nam, the Philippines, and Lao PDR. Lao PDR shows strategic foresight and governance in preparing for AI integration, while improvements are needed in scaling AI applications across sectors such as agriculture, healthcare, and industry, due to the constrained technical resources and investment. The Philippine Development Plan 2023–2028, along with the National Innovation Agenda and Strategy Document 2023–2032, positions AI as a driver of sustainable development, with targeted sectoral initiatives supporting application in crop mapping, disaster resilience, and water and grid efficiency.
4. *Emerging capabilities with scope to strengthen operational execution* – Countries facing fundamental challenges across all dimensions, severely limiting their ability to benefit from AI while leaving them vulnerable to its disruptive effects. Constraints in digital infrastructure can hinder effective AI deployment in agriculture, and limited social protection systems may increase vulnerability to technological disruption. High reliance on external technologies can pose risks if solutions are not sufficiently adapted to local conditions and needs.

These allocations between capability groupings are at a high level of generalization and it should be pointed out that similar disparities in capacity can also be observed between areas or regions within countries.

China, for example, could be placed overall in category 1 but presents a complex landscape of AI-related development. In Category 1 are eastern coastal cities like Beijing, Shanghai, Guangdong, Shenzhen, and Hangzhou, where sophisticated smart city initiatives integrate with strong districts research capabilities.[30] These districts have successfully deployed AI solutions across multiple security dimensions while maintaining strong protective measures for affected populations. In contrast, rapidly developing inland provinces such as Hubei, Henan, Anhui, and Sichuan align with Category 2 –AI deployment in manufacturing and agriculture have supported productivity growth, though social support systems are still evolving to accompany communities through technological transitions. Provinces in Categories 3 or 4, including the Northeastern and Western regions, have begun establishing AI policy frameworks and digital infrastructure, with opportunities to further strengthen local talent and scale AI applications over time.[31]

Achieving Category 1 status requires coordinated development across all dimensions, demanding significant resources and careful policy coordination. Countries typically progress from Category 4 to either 3 or 2. For Category 2 countries, the priority is to strengthen social protection systems and develop domestic AI capabilities. For Category 3 countries, it is to build stronger digital infrastructure and implementation capacity while maintaining existing protections. Category 4 countries require comprehensive action assistance across all dimensions.

Table 4 presents a policy matrix organized along the four dimensions of impact – direct positive, indirect positive, direct negative, or indirect negative – and the four capability categories. This integrated approach suggests targeted interventions that address specific challenges while building on existing strengths.

Table 4 – Policy matrix for AI interventions that affect human security

	Category 1: Comprehensive implementation	**Category 2: Implementation without protection**	**Category 3: Strategic planning but limited implementation**	**Category 4: Low capacity and implementation**
Direct positive	Develop next-generation AI applications for complex security challenges; establish regulatory sandboxes for innovative applications; create incentives for AI solutions targeting underserved populations.	Develop sector-specific AI adoption roadmaps with clear security objectives; establish specialized implementation units in key ministries; create incentive structures for domestic firms to adopt security-enhancing AI.	Identify high-impact security domains for initial AI deployment; develop context-appropriate applications that build on community strengths; create technology demonstration centers in underserved regions.	Establish basic digital infrastructure in key security service domains; develop simplified AI applications for immediate security needs; create technology adaptation programs for local contexts.

	Category 1: Comprehensive implementation	**Category 2: Implementation without protection**	**Category 3: Strategic planning but limited implementation**	**Category 4: Low capacity and implementation**
Indirect positive	Establish knowledge-transfer mechanisms to share expertise regionally; create centers of excellence for security applications; develop open-source platforms for security-focused AI solutions.	Develop supplier programs connecting AI-enabled firms with local businesses; create technology diffusion networks; establish cross-sectoral working groups to identify spillover opportunities.	Strengthen traditional security systems while gradually integrating AI components; develop community-based technology adaptation programs; create knowledge networks between traditional providers and tech experts.	Build basic technical literacy among security service providers; establish simplified knowledge-transfer mechanisms adapted to local contexts; create demonstration programs showing benefits in familiar contexts.
Direct negative	Establish comprehensive AI risk assessment methodologies; develop rapid response mechanisms for implementation failures; create robust oversight frameworks for high-risk applications.	Develop worker transition programs for sectors facing displacement; create emergency response mechanisms for system failures; establish oversight frameworks for high-impact applications.	Integrate AI awareness into existing social protection systems; develop hybrid response mechanisms combining traditional and AI approaches; create context-appropriate risk assessment methodologies.	Establish fundamental safeguards before deploying AI in critical domains; create simplified risk assessment approaches; develop community-based feedback mechanisms to identify challenges.
Indirect negative	Develop adaptive regulatory frameworks evolving with technological advancement; create forward-looking education systems; establish inclusive governance models ensuring diverse stakeholder representation.	Develop domestic AI research and development capabilities; create data sovereignty frameworks protecting critical security information; establish long-term workforce transformation programs.	Create development pathways integrating AI with traditional security systems; establish education programs blending technical and traditional knowledge; develop governance frameworks maintaining community voice in decisions.	Develop basic technological sovereignty protections; create fundamental data governance frameworks; establish simplified but effective regulatory approaches for initial applications.

These categories can also guide regional cooperation and development support. Category 1 countries have technical expertise and policy frameworks. Category 4 countries require holistic support of AI adoption, addressing both technological and social dimensions. Regional cooperation mechanisms can then support countries in their development trajectories and ensure that AI helps enhance human security.

A phased approach

Countries will follow different trajectories based on their specific contexts and priorities. For Category 4 countries, the initial emphasis will be on building basic infrastructure and institutional capabilities, establishing the foundation for subsequent advancement. Category 3 countries can leverage their existing social protection strengths while strategically expanding AI implementation in priority domains. Category 2 countries can urgently strengthen protection mechanisms while maintaining implementation momentum. This approach acknowledges both the benefits of existing implementation strengths and the risks of continued advancement without corresponding protection measures. Category 1 countries can pioneer integrated approaches that balance continued innovation with comprehensive protection, serving as regional models while supporting other countries' advancement.

The matrix indicates a structured approach for identifying priorities and sequencing interventions. By emphasizing both implementation and protection, it supports balanced development that enhances security outcomes while minimizing potential harms. It should be recognized, however, that development can often be non-linear and countries may leapfrog certain stages or develop hybrid systems. This pragmatic approach acknowledges the reality of limited resources while supporting meaningful progress toward more equitable and beneficial AI engagement.

Infrastructure and literacy – the hard and soft levers

Addressing AI-related inequality requires a two-lever approach focusing on infrastructure and capacity. Without adequate infrastructure, even the most basic AI applications remain only theoretical possibilities. At the same time, without widespread digital literacy, infrastructure investments are more likely to deepen rather than diminish existing inequalities. AI infrastructure represents a ‘hard’ lever, providing the technical foundation for AI implementation, while AI literacy serves as a ‘soft’ lever, enabling populations to participate in and benefit from AI advancement.

AI infrastructure includes both foundational elements and specialized capabilities

- *Core connectivity* – The essential foundation, including both fixed and mobile broadband networks that can reach everyone.
- *Data infrastructure* – Including both repositories and processing capabilities.
- *Secure data storage* – With appropriate classification and access controls to ensure that sensitive security information remains protected while enabling authorized analysis.
- *Common standards* – For data collection, classification, and sharing to support cross-border cooperation on transnational security challenges while respecting sovereignty. For example, Indonesia utilizes the Disaster Information System and the Early Warning System to enhance public safety and mitigate risks associated with natural disasters.[32]

AI literacy encompasses the knowledge, skills, and attitudes necessary for meaningful engagement with AI technologies. Rather than technical expertise alone, comprehensive literacy includes understanding of potential applications, awareness of limitations and risks, and ability to participate in governance discussions. By enabling informed participation, technological advancement should reflect community needs and priorities. But there can also be initiatives to engage broader population groups. For example, the AI Ready ASEAN initiative aims to equip 5.5 million individuals in South-East Asia with essential AI skills.[33] In Singapore, AI Singapore and the United Nations Development Program are collaborating to expand access to AI learning to marginalized groups in South-East Asia and the Pacific Islands.[34]

These hard and soft levers can be deployed for inclusive AI development – though the digital divide remains a persistent concern. It may be unrealistic for many countries to leapfrog traditional infrastructure development stages to become AI ready, especially when decades of development have failed to close persistent gaps. A balanced approach must acknowledge the theoretical complementarity between technical systems and human capabilities, but also recognize the practical constraints and the potential asymmetries that could further entrench disparities.

Finally, the financial burden of the expansive infrastructure required – from reliable electricity to high-speed connectivity and computational resources – will demand innovative funding models that thus far have proved elusive.

A local approach to regional and global cooperation

Effective engagement with AI in the context of human security requires acknowledging that communities hold valuable knowledge about their own security challenges, which should complement rather than be displaced by external expertise. Rather than imposing standardized solutions, both technical features and deployment processes should be modified to align with local contexts. For example, in the Arctic, community-based monitoring programmess integrate indigenous knowledge with conventional scientific approaches to monitor environmental changes, adapting technologies to community information needs and infrastructure inequalities.[35]

Building on these local foundations, regional cooperation mechanisms enable coordinated action on shared challenges while respecting national and community sovereignty. These multi-level frameworks recognize that many security challenges transcend borders while solutions require adaptation to specific contexts. Effective regional collaboration balances shared standards and coordinated action with respect for local implementation approaches and governance models.

The ASEAN Digital Masterplan 2025 for example, establishes shared objectives and technical standards while acknowledging diverse implementation pathways based on member states' specific conditions.[36] This framework aims to transform ASEAN into a leading digital community and economic bloc, powered by secure and transformative digital services, technologies, and ecosystems. Achieving all its goals faces significant hurdles. Digital readiness is very uneven across ASEAN, with wide disparities in internet access, digital skills, and infrastructure.[37] Singapore and Malaysia are among the leading countries in the bloc. Progress is influenced by varying levels of coordination capacity and the absence of a dedicated regional implementation authority, the complex regional dynamics, socioeconomic differences, disparate regulatory regimes, cybersecurity risks, and firms' adaptability to technological changes.[38]

ASEAN is also working with Australia and Japan to harmonize their greenhouse gas accounting methodologies through the Asia Zero Emissions Community.[39] Deeper regional integration and cross-border carbon pricing will maximize AI's potential to advance the green transition.

These specialized regional cooperation mechanisms complement broader frameworks. The Mekong Basin Disease Surveillance Network (MBDS), established in 2001, demonstrates this approach by creating shared data systems and response protocols for health security threats affecting Cambodia, China, Lao PDR, Myanmar, Thailand, and Viet Nam.[40] The MBDS focuses on improving cross-border infectious-disease outbreak investigation and response through data sharing and joint responses, developing expertise in epidemiological surveillance, and enhancing communication between member countries. This domain-specific collaboration enables deeper integration in areas of clear mutual benefit while maintaining broader sovereignty in other domains.

Knowledge exchange networks connecting practitioners across the region facilitate learning and adaptation without imposing hierarchical relationships. For example, the Asia-Pacific Migration and Environment Network serves as an internet-based resource for sharing analysis, insights, and experiences on the interaction between the environment and migration.

These horizontal networks enable peers facing similar challenges to share implementation experiences and adaptation strategies, creating valuable learning communities. For instance, the Asia-Pacific Telecommunity Capacity Building Program provides training in ICT, telecommunication management, and network security.[41] These programs recognize that countries in different categories require distinct forms of support, from basic infrastructure development to advanced governance models.

Global engagement

Local and regional approaches establish the foundation for productive engagement with global frameworks and standards. By developing approaches suited to their regional contexts, Asia-Pacific nations can actively contribute to global governance.[42] Their engagement ensures that international frameworks reflect the region's diverse experiences and priorities, supporting solutions that are meaningful and effective locally.

This multi-level approach – building from local foundations through regional cooperation to global engagement – ensures that AI development for human security remains anchored in actual needs and conditions while benefiting from broader collaboration. By respecting local knowledge and priorities while creating mechanisms for productive cooperation, it supports technological advancement that enhances security for all populations across the diverse contexts of the Asia-Pacific region.

END NOTES

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18. (Shankarias, 2017)
19. (TNGlobal, 2025)
20. (Hennig and Khan, 2025)
21. (Corrigan, 2024)
22. (TNGlobal, 2025)
23. (Goover, 2025)
24. (Burwood-Taylor et al., 2023)
25. (Stuart, 2025)
26. (Cloudnine, 2024)
27. (Correia et al., 2025)
28. (Feldstein, 2019)
29. (Lung, 2024)
30. (Xiao, 2024)
31. (Ives and Holzmann, 2018)
32. (UNFPA, 2020)
33. (Van, 2025)
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CHAPTER 3 — AI AND THE CLIMATE CRISIS

ZHANG Jian, Institute of Climate Change and Sustainable Development (Tsinghua University) and HU Xian and FANG Chen, School of Economics and Management (Tsinghua University)

Powering AI will require huge quantities of natural resources, from energy to water to minerals. This chapter assesses the potential opportunities and challenges of AI deployment to support countries' Nationally Determined Contributions. It considers AI's dual role as both an enabler of climate action and a contributor to resource depletion. It also addresses the implications of uneven AI readiness across countries, showing how disparities in technological capacities can may exacerbate existing inequalities in climate mitigation and adaptation capability. Through case studies, the chapter zooms in on climate change areas that have a high priority across Asia and the Pacific: net-zero transitions, climate adaptation, and risk reduction.

Climate change is one of the most pressing and complex global challenges of our time. While it is a shared threat, countries and regions differ significantly in both their contributions to climate change and their capacity to mitigate emissions or adapt to its impacts. These disparities are particularly pronounced in Asia and the Pacific, where countries face markedly different climate risk exposures, institutional capacities and financial resources.[1]

Asia and the Pacific, home to over half the world's population and a number of large and rapidly growing economies, accounts for more than 50 percent of global CO_2 emissions and is among the regions most vulnerable to climate change. Over the past 60 years, temperatures in Asia and the Pacific have risen faster than the global average, with devastating consequences for food systems, economies, and social structures.[2] Over the period 2000 to 2022, Asia and the Pacific experienced more than 60 percent of global climate disasters, displacing 225 million people and costing $1.3 trillion.[3] Six of the top ten countries most affected by climate-related disasters are located in this region.[4]

If the world is to achieve the targets of the Paris Agreement, to limit global warming to well below 2°C, and preferably to 1.5°C, the large emitters in the region will need to accelerate decarbonization efforts. At the same time, the socioeconomic impacts of climate change are becoming more severe. More than four out of five people in the region are exposed to multi-hazard risks associated with both slow-onset and sudden-onset climate events.[5] Under high-emissions scenarios, developing economies in the region could see their GDPs decline by up to 17 percent by 2070, and by as much as 41 percent by 2100.[6] Without urgent and coordinated action, climate change is likely to remain a significant driver of poverty and inequality across the region, with particularly profound impacts on countries facing multiple structural vulnerabilities.

The need for digital solutions in climate action

As the window for meeting climate targets narrows, and the urgency for resilience grows, it is important to understand how advanced digital technologies – particularly AI – can accelerate climate action. This would be part of coordinated and timely action across multiple fronts. Governments and stakeholders need to access up-to-date climate data, build accurate and dynamic models, conduct rapid and high-quality analysis, and translate insights into actionable policies. In addition, policy design and evaluation must reflect the diverse needs of regions, communities, and stakeholder groups – particularly in areas where climate vulnerability is highest.

However, progress is hindered by a number of factors. Many countries have limited access to granular climate data and face constraints in analytical and response capacities, particularly in remote or under-resourced settings. There is also a shortage of skilled personnel trained in climate science, data analytics, and systems modelling. At the same time, levels of public and private investment in digital solutions vary considerably..

The potential of AI to support climate action

AI technologies – encompassing machine learning, computer vision, natural language processing, and geospatial analytics – are increasingly being applied to fill these gaps. On the mitigation side, AI supports low-carbon transitions through smart grid management, energy efficiency improvements, and real-time emissions monitoring. On the adaptation side, AI powers early warning systems for floods and heatwaves, improves agricultural decision-making, and strengthens food security in the face of rising climate risks. AI technologies also present promising opportunities to improve climate resilience by making climate-related information more accessible, timely, and cost-effective, particularly for marginalized communities.

When designed and implemented in an inclusive way, AI tools can enhance adaptive capacity and even contribute to reducing climate-related inequality. UNESCO has highlighted the potential of AI in forecasting, monitoring, and mitigating climate impacts.[7] One notable example is the Asia-Pacific Risk and Resilience Portal 2.0. This digital platform leverages AI and machine learning to map localized climate vulnerabilities and guide evidence-based adaptation planning.[8] Crucially, it prioritizes capacity building by training rural government officials and community leaders to interpret and apply AI-generated risk data in local preparedness and response planning.

By improving data availability, accelerating analysis, and enabling adaptive decision-making, AI has the potential to transform how climate action is planned, implemented, and evaluated. Innovation is urgently needed across the Asia–Pacific region, from driving low-carbon transitions in major emitting economies to strengthening resilience in climate-vulnerable countries.

The limitations and risks of using AI

While AI holds significant promise for accelerating climate action, its deployment also comes with environmental costs. At the core of AI operations are data centers whose energy intensity far exceeds that of conventional buildings – consuming 10 to 50 times more energy per square foot than typical commercial spaces. Currently, data centers are estimated to account for 1–2 percent of global electricity consumption. In the Asia-Pacific region, according to IEA, data center energy use in 2024 reached 105–180 TWh – led by China (70–130 TWh), Japan (10–20 TWh), and Australia (8–12 TWh). In Singapore in 2023, data centers consumed approximately 9 percent of national electricity.[9]

These facilities also require vast amounts of water for cooling. Global water consumption for data centers is currently estimated at around 560 billion litres per year and could rise to about 1,200 billion litres per year by 2030, further straining natural resources, particularly in water-scarce regions.[10]

At the same time, the production and disposal of AI hardware also brings serious ecological risks. Mining for metals such as cobalt and silicon, essential for the manufacturing of servers and high-performance processors, can lead to soil erosion, habitat destruction, and contamination of water sources. At the other end of the product lifecycle, the improper disposal of e-waste poses additional threats to both ecosystems and public health – a problem being exacerbated by the pace of technological advancement in AI which is shortening hardware lifecycles.

Sustainability principles need to be embedded into the full lifecycle of AI systems – from design and deployment to decommissioning. Without proactive measures, broader climate benefits may be compromised by the environmental externalities, particularly in the Asia-Pacific region where digital expansion and climate vulnerability are accelerating in parallel.

Beyond the climate and environmental costs of AI, there are potential social costs. Uneven access to AI infrastructure, limited data availability, and unequal digital literacy across gender and urban-rural lines will exacerbate existing disparities and exclude the populations most vulnerable to climate change – especially in remote or under-resourced areas.

Vulnerability to climate disruptions and the capacity to cope with them are far from uniform, reflecting a complex landscape of socioeconomic, geographic, and institutional inequalities.[10] This diversity is reflected in the ND-GAIN index which measures a country's exposure, sensitivity and capacity to adapt to the negative effects of climate change across six sectors – food, water, health, ecosystem services, human habitat, and infrastructure (Table 1). In this index, higher scores indicate greater climate vulnerability and lower readiness to adapt. The Asia-Pacific region has some of the world's most resilient countries and some of the most vulnerable. For example, New Zealand (0.304) and Australia (0.316) have strong infrastructure, governance, and adaptive systems and thus high levels of resilience. In contrast, Bangladesh (0.568), Myanmar (0.514), and Pakistan (0.515) are much more vulnerable due to their high exposure to climate hazards, limited institutional capacity, and socioeconomic constraints.

Table 1 – The inequality of climate vulnerability: Ranking by ND-GAIN Vulnerability (2023)

Asia-Pacific Rank	Global Rank	Country	Income Group	Score
1	10	New Zealand	Upper	0.304
2	18	Australia	Upper	0.316
3	18	Kazakhstan	Upper middle	0.316
4	39	Republic of Korea	Upper	0.357
5	41	Uzbekistan	Lower middle	0.359
6	46	Kuwait	Upper	0.362
7	48	Mongolia	Lower middle	0.365
8	50	Jordan	Lower middle	0.366
9	51	Malaysia	Upper middle	0.367
10	54	Japan	Upper	0.369
11	65	Iran	Lower middle	0.376
12	70	China	Upper middle	0.382
13	71	United Arab Emirates	Upper	0.383
14	75	Singapore	Upper	0.389
15	80	Azerbaijan	Upper middle	0.404
16	80	Brunei Darussalam	Upper	0.404
17	85	Saudi Arabia	Upper	0.408
18	92	Oman	Upper	0.420
19	97	Indonesia	Lower middle	0.430

20	103	Thailand	Upper middle	0.435
21	104	Bahrain	Upper	0.436
22	109	Philippines	Lower middle	0.444
23	116	Fiji	Lower middle	0.453
24	119	Dem. People's Rep. of Korea	NA	0.460
25	122	Viet Nam	Lower middle	0.468
26	125	Sri Lanka	Lower middle	0.475
27	126	Cambodia	Low	0.481
28	128	India	Lower middle	0.485
29	130	Laos	Lower middle	0.486
30	134	Nepal	Low	0.490
31	141	Nauru	Lower middle	0.509
32	143	Palau	Upper middle	0.513
33	143	Samoa	Lower middle	0.513
34	145	Myanmar	Low	0.514
35	146	Bhutan	Lower middle	0.515
36	146	Pakistan	Low	0.515
37	157	Timor-Leste	Lower middle	0.538
38	162	Maldives	Upper middle	0.550
39	162	Papua New Guinea	Low	0.550
40	165	Kiribati	Low	0.557
41	168	Vanuatu	Low	0.563
42	170	Bangladesh	Lower middle	0.568
43	172	Tuvalu	Low	0.576
44	176	Afghanistan	Low	0.588
45	177	Marshall Islands	Lower middle	0.590
46	180	Tonga	Lower middle	0.607
47	184	Micronesia	Low	0.621
48	185	Solomon Islands	Low	0.629

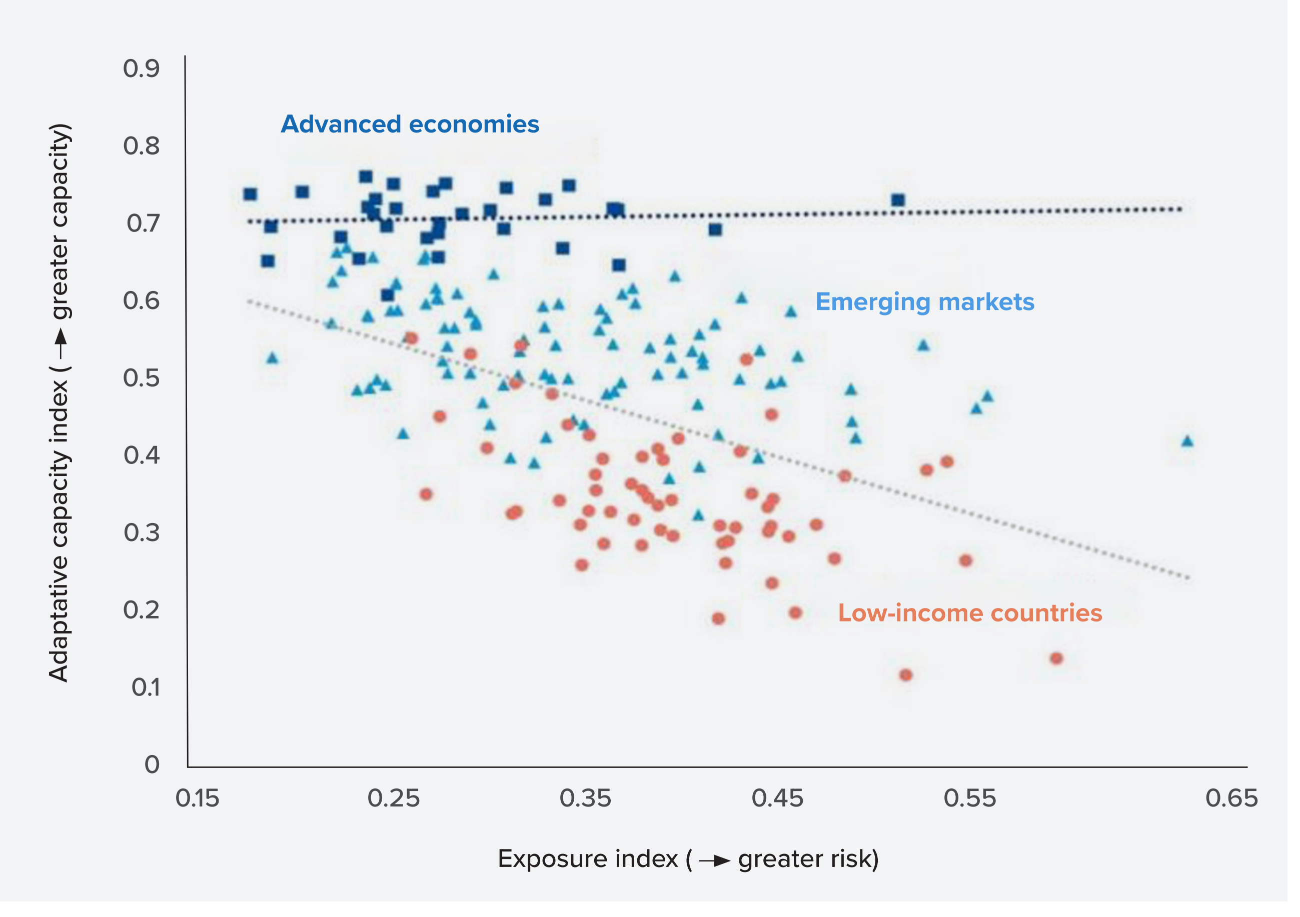
Source: ND-GAIN, 2025[12]

There are similar disparities in adaptive capacities. Typically, there is a negative correlation between climate risk exposure and adaptive capacity – and one which is stronger in low-income countries (Figure 1)). Similar patterns of inequality emerge at the micro level. For example, sea-level rise is likely to intensify socioeconomic disparities in already unequal coastal areas: wealthier individuals may relocate to safer, higher ground, increasing land values and displacing poorer populations to more hazardous zones.[13]

This chapter examines the dual role of AI in the climate crisis in Asia and the Pacific, and asks the following questions:

- *Distributional impacts* – How might the benefits and risks of AI-driven climate action be distributed across countries, sectors, and communities, and what are the implications for equity and justice?
- *Effectiveness and trade-offs* – In what ways can AI accelerate the implementation of NDCs, while managing its own energy and emissions footprint?
- *Sustainability and system integration* – What are the integrated strategies that can align AI deployment with low-carbon development goals – such as those involving green computing, renewable-powered data infrastructure, and lifecycle-conscious design.

Figure 1 – Unequal costs of climate change



Notes: This figure is based on IMF staff calculations using 2015–2018 data from the European Commission, the United Nations University Institute for Environment and Human Security, the University of Notre Dame, and the April 2020 World Economic Outlook. Dotted lines represent the estimated linear relationships for advanced economies and for emerging-market and low-income countries combined, respectively.

Source: IMF [14]

- *Policy and inclusion* – What targeted policy interventions are needed to ensure that the most climate-vulnerable and digitally underserved populations can access and benefit from AI applications, such as early warning systems, adaptive planning tools, and clean energy access?

AI's role in addressing climate challenges

AI can contribute to climate change mitigation in many ways, in particular through energy optimization, climate modelling, and sustainable agriculture.

- *Energy optimization and renewable energy integration* – AI facilitates demand-side management, predictive maintenance, and grid optimization. Machine learning algorithms forecast energy demand and renewable energy output, enhancing the integration of solar and wind resources. Reinforcement learning optimizes energy storage and distribution systems. AI-driven smart grids minimize energy wastage, with studies indicating up to 15 percent reduction in energy efficiency in optimized systems.[14]By improving energy efficiency and accelerating the transition to renewables, AI technology can help reduce greenhouse gas emissions and enhance the economic viability of renewable energy through cost-effective load balancing.

- *Climate modelling and prediction* –AI deep-learning techniques enhance the resolution and accuracy of climate models. Neural networks process vast datasets from satellites, sensors, and historical records to predict climate trends, extreme weather events, and long-term shifts, helping to reduce economic and human losses. Sophisticated models can compare multiple projections and scenarios and refine the predictive capabilities and granularity of climate models – providing precise projections and enabling early warning systems for extreme weather. For instance, AI-improved models have enhanced hurricane path predictions, decreasing evacuation costs.[15]

- *Disaster response and risk assessment* – AI can integrate computer vision and natural language processing to analyse real-time data from drones, social media, and satellite imagery. Predictive models assess risks of floods, wildfires, and droughts, while AI-powered chatbots streamline disaster communication and resource distribution. These applications can reduce vulnerability in high-risk regions, for example through early wildfire-detection systems that achieve up to 90 percent accuracy in identifying ignition points based on explainable machine-learning models. In doing so, AI technologies can help optimise humanitarian aid delivery and support more rapid, resilient recovery.[16 17]

- *Sustainable agriculture and land use* – AI optimizes crop yields through precision agriculture, utilizing IoT sensors and machine learning to monitor soil health, water usage, and pest activity. Computer vision identifies deforestation and land degradation, while predictive analytics guide reforestation efforts. FAO's AIM4Forests program, for example, uses AI to improve forest monitoring and carbon verification, aiding governments in deforestation risk assessment.[18] A case study from Australia showcased the effectiveness of intelligent irrigation systems, which led to a 40 percent decrease in water losses during rice cultivation through optimized canal management.[19] Thus, AI could promote food security and reduce land-based emissions and enhance adaptive capacity in agriculture-dependent communities.

- *Carbon capture and emissions monitoring* – AI optimizes carbon capture and storage processes by modelling geological reservoirs and predicting capture efficiency. Machine learning tracks emissions through satellite data and industrial sensors, identifying leakage and monitoring compliance with emissions regulations in real time. AI-enhanced monitoring systems have detected methane leaks with up to 95 percent accuracy.[20]

Table 2 – Summary of AI applications in climate change

Domain	AI techniques	Key applications	Benefits
Energy optimization	Machine learning, reinforcement learning	Smart grids, renewable integration, energy forecasting	Reduces emissions, enhances energy efficiency, supports renewable energy adoption
Climate modelling	Deep Learning, generative adversarial networks	Climate trend prediction, extreme weather forecasting	Informs policy, enables early warnings, optimizes adaptation strategies
Disaster response	Computer vision, natural language processing	Risk assessment, real-time disaster monitoring	Enhances resilience, reduces losses, optimizes aid delivery
Sustainable agriculture	IoT, machine learning, computer vision	Precision agriculture, deforestation monitoring	Promotes food security, reduces emissions, supports sustainable land use
Carbon capture & monitoring	Machine learning, predictive analytics	CCS optimization, emissions tracking	Accelerates decarbonization, ensures regulatory compliance, mitigates greenhouse gases

AI-driven smart grid systems

Through smart grid systems AI can orchestrate dynamic energy distribution and facilitate seamless integration of renewable energy sources, addressing critical inefficiencies in traditional energy infrastructure. By employing machine learning and predictive analytics, AI mitigates systemic challenges such as energy wastage, grid instability, and over-reliance on fossil fuels, enabling real-time demand forecasting and load balancing. These capabilities resolve some of the challenges related to intermittent renewable energy supply and peak load management, contributing to more resilient energy ecosystems. This could substantially reduce greenhouse gas emissions, enhance grid reliability, and optimize resource utilization – though there are still many implementation barriers.

CASE IN CHINA, AI-DRIVEN SMART GRID SYSTEMS[21]

The rapid increase in China's renewable energy capacity embeds a fundamental shift, moving its power grid from a traditional, single-function system toward a smarter, greener, and more adaptive energy model. China Southern Power Grid has been actively applying AI technologies to accelerate the construction of a new-type of power system and a clean, low-carbon energy structure. It launched China's first AI-based, system-wide load forecasting platform, improving forecast accuracy from 97.6 to 98.3 percent. In parallel, by combining AI with meteorological data, the company has achieved second-level supply–demand matching across more than one million square kilometers. Since 2025, its renewable energy utilization rate has remained around 97 percent. Beyond grid operation, the company is also expanding AI applications in virtual power plants, spot market trading, microgrid energy management, carbon monitoring and tracking, and electric vehicle charging infrastructure planning. Through large-scale AI models and reinforcement learning, the company is addressing the "energy trilemma" – achieving a system that is clean and low-carbon, secure and reliable, and economically efficient.

AI-driven smart manufacturing

AI transforms smart manufacturing by optimizing production workflows and energy-intensive processes and tackling inefficiencies inherent in industrial operations. Utilizing predictive maintenance, reinforcement learning, and real-time monitoring, AI addresses systemic challenges such as high energy consumption, equipment downtime, and carbon emissions. These interventions enhance operational precision and reduce resource waste, aligning industrial activities with environmental imperatives. The positive impacts encompass diminished industrial carbon emissions, increased production efficiency, and reduced operational costs, fostering sustainable industrial practices and reinforcing the viability of low-carbon manufacturing paradigms.

AI-driven smart buildings

In the realm of smart buildings, AI can optimize control systems, including heating, ventilation, and lighting. Through advanced data analytics and adaptive algorithms, AI addresses key operational inefficiencies by dynamically adjusting resource allocation based on occupancy and environmental variables. This alleviates the carbon-intensive nature of building operations and mitigates urban heat-island effects. The positive outcomes include significant reductions in energy demand, lower carbon footprints, and improved occupant well-being, contributing to sustainable urban development and scalable frameworks for energy-efficient infrastructure.

CASE IN HONG KONG (SPECIAL ADMINISTRATIVE REGION OF CHINA) – AI-DRIVEN SMART BUILDINGS

In Hong Kong (Special Administrative Region of China), AI-driven smart buildings are pivotal for mitigating climate change and reducing carbon footprints by optimizing energy consumption and enhancing operational efficiency.[22] Buildings are the dominant source of carbon emissions in Hong Kong, responsible for approximately 90 percent of the city's total electricity consumption. The electricity generation required to power these buildings consequently accounts for over 60 percent of Hong Kong's total carbon emissions. This significant share substantially exceeds the global average, where buildings contribute about 39 percent of energy-related carbon emissions, highlighting the acute challenge faced by high-density urban centers like Hong Kong.[23]

Traditional building management systems (BMS) lack the intelligence to effectively balance computational demands with energy efficiency, resulting in performance degradation and excessive cooling costs. A next-generation, AI-powered building-management platform harnesses an integrated framework of semantic models, digital twins, the internet of things, and mixed reality to offer scalable solutions for energy efficiency, supporting emissions-reduction planning and helping to avoid carbon-intensive system lock-in. Empirical data from long-term pilot studies confirm average energy savings of over 20 percent.[24]

Climate resilience: applications in disaster adaptation and agricultural sustainability

AI can support Asia-Pacific countries in managing climate-related disasters – such as floods and typhoons – by improving the accuracy of predictive models, strengthening coordination across emergency-response systems, and expanding access to climate-smart advice for farmers. In this context, AI can enable:

- Enhanced forecasting – machine-learning and real-time data analytics enable earlier, more precise disaster predictions.

- Smarter resource allocation – AI optimizes evacuation planning and helps ensure that aid reaches the right places faster.
- Data-driven decision-making – by analysing vast datasets, AI improves risk assessment and enables timely interventions.
- Lower human and economic losses.
- More resilient communities and ecosystems."

CASE IN INDIA: AI FOR FLOOD FORECASTING AND WATER MANAGEMENT

India, which is highly susceptible to monsoon-driven floods, has leveraged AI to bolster disaster preparedness and water management.[25] The Indian Meteorological Department, for example, is using AI-based flood forecasting models that integrate real-time data on rainfall, river levels, and soil moisture to deliver early warnings. Approximately 66 percent of India's population is at risk of extreme flood events, yet only one-third of those exposed are covered by flood early warning systems. In response, India is actively strengthening its Early Warning Dissemination Systems (EWDS) by leveraging new-era technologies such as the IoT, cloud computing, and artificial intelligence, enhancing EWS by enabling the sensing, cleansing, processing, and analysis of environmental data, thereby improving capabilities in monitoring, forecasting, and alert generation. Several states – including Andhra Pradesh, Odisha, Goa, Karnataka, Kerala, and West Bengal – have taken the lead in establishing cyclone warning systems, positioning themselves at the forefront of building disaster resilience.[26]

CASE IN THE PHILIPPINES: AI-DRIVEN DISASTER ADAPTATION

To enhance disaster preparedness and response, the Philippines has increasingly adopted big data and AI to gather and analyze localized vulnerability information for local government units.[27] One notable application involves mobile big data, such as call detail records and mobile positioning data, which can be used to track population movements and inform evacuation planning and resource allocation strategies.

The Philippine Atmospheric, Geophysical and Astronomical Services Administration operates the Flood Information and Warning System (FIWS), a web-based platform integrating multiple data streams, including rainfall and river-level monitoring, satellite imagery, and even social media content.[28] The system produces real-time flood forecasts and warnings during typhoon events. Using machine-learning models, FIWS analyzes historical flood patterns and post-disaster assessments to support rapid resource mobilization and relief coordination. For example, it can identify areas at highest risk of severe flooding and prioritize the deployment of rescue operations and aid supplies accordingly. To address these technical bottlenecks and enhance the role of AI in building disaster-resilient communities, increased international cooperation and policy support are essential.[29]

AI-driven agricultural sustainability

Adaptive agricultural strategies can support food security and long-term ecological stability in climate-vulnerable regions. Leveraging predictive analytics, IoT integration, and automated decision-making, AI addresses weaknesses of conventional farming practices such as inefficient water and fertilizer use and yield variability. AI is, for example, being harnessed to optimize resource management and bolster crop resilience, countering climate change-induced challenges such as erratic precipitation and soil degradation.

CASE IN VIET NAM: AI-DRIVEN AGRICULTURAL SUSTAINABILITY

In Viet Nam's Mekong Delta, with support from international donors, the deployment of cutting-edge technologies – such as integrating AI for carbon-farming applications, leveraging geospatial systems to deliver real-time crop data, and establishing digital traceability and certification platforms – supports nearly 40 million smallholder farmers.[30 31] Positive impacts include lower greenhouse gas emissions from reduced fertilizer use and enhanced food security in a region critical to global rice supply. Positive impacts include lower greenhouse gas emissions from reduced fertilizer use and enhanced food security in a region critical to global rice supply.

These initiatives can generate economic gains for farmers, but they represent only one technical pathway within a broader enabling architecture for sustainable agriculture and long-term climate resilience. Their effectiveness depends on supportive governance arrangements, clear policy and legislative frameworks, institutional capacity, enforceable standards, long-term financing, and coordination among farmers, cooperatives, agribusinesses, and public agencies. Replication in other contexts – particularly in small or resource-constrained economies – will require adaptation to local conditions, regulatory and policy readiness, robust data-governance mechanisms, and institutional ownership anchored in national systems.

AI's environmental load

AI can bring many benefits through advancements in smart grids, climate modelling, and sustainable agriculture. Yet these gains could be offset by its resource intensity. The ecological impacts of AI include the energy and water demands of data centers, greenhouse gas emissions, mineral extraction, and electronic waste generation.[32]

If unmanaged, these energy and other demands could pose challenges for countries seeking to advance their Paris Agreement commitments.[33] Strategic and context-appropriate measures may help align AI deployment with the Sustainable Development Goals and countries' Nationally Determined Contributions.

Energy consumption

AI systems, particularly training and operating large-scale models, can be energy-intensive. the computational intensity of AI, particularly in training and operating large-scale models. A single query to a GenAI model can consume ten times the electricity of a standard internet search.[34]

Globally, AI alongside cryptocurrency and data-center operations is projected to account for around 4 percent of electricity use by 2026, equivalent to the annual demand of a major industrialised nation. The Asia–Pacific region is expected to account for roughly 28 percent of this global total, driven primarily by hyperscale facilities in India, Japan, the Republic of Korea, and Australia.[35]

In 2023, data centers in the Asia-Pacific region consumed an estimated 55 TWh of the 200 TWh global total. Between 2023 and 2028, the rapid proliferation of AI infrastructure, is projected to drive a 30 percent increase in data centers and by 2030 to add roughly 15 GW of computing capacity in Asia and the Pacific – 8 percent of regional electricity demand.[36] Environmental impacts are higher in contexts where the electricity grid relies heavily on coal.

Water consumption

Although public debate has focused mainly on AI's energy consumption, its significant water consumption has received far less scrutiny. The operation and maintenance of AI infrastructure require large quantities of water for chip production, server cooling, and non-renewable electricity generation.[37] As AI deployment accelerates, the associated water demand risks intensifying competition over limited freshwater supplies and exacerbating water stress in vulnerable regions. By 2027, AI-driven data-center water consumption could reach between 4.2 billion and 6.6 billion cubic metres, equivalent to four to six times the total annual water consumption of Denmark, or roughly half that of the United Kingdom.[38]

Mineral resources

The environmental costs are compounded by the manufacture of AI hardware. AI systems rely on critical minerals, including rare earth elements, copper, aluminum, and silicon, which are essential for manufacturing semiconductors, magnets, and other components. The extraction of these minerals often results in deforestation, water pollution, and habitat loss.

The problem is intensified by the rapid obsolescence of AI hardware, driven by accelerating technological advances, generating electronic waste that is growing five times faster than recycling systems can absorb. This expanding e-waste stream presents long-term ecological risks as hazardous materials leach into surrounding ecosystems."

To reconcile AI's resource consumption with climate objectives, a multifaceted approach is required. Beyond transitioning data centers to renewable energy sources, it is equally critical to implement sustainable mining practices and enhance waste management strategies for the minerals essential to AI infrastructure. Addressing these interconnected challenges will reduce environmental degradation and support the broader climate commitments outlined in NDCs.[40]

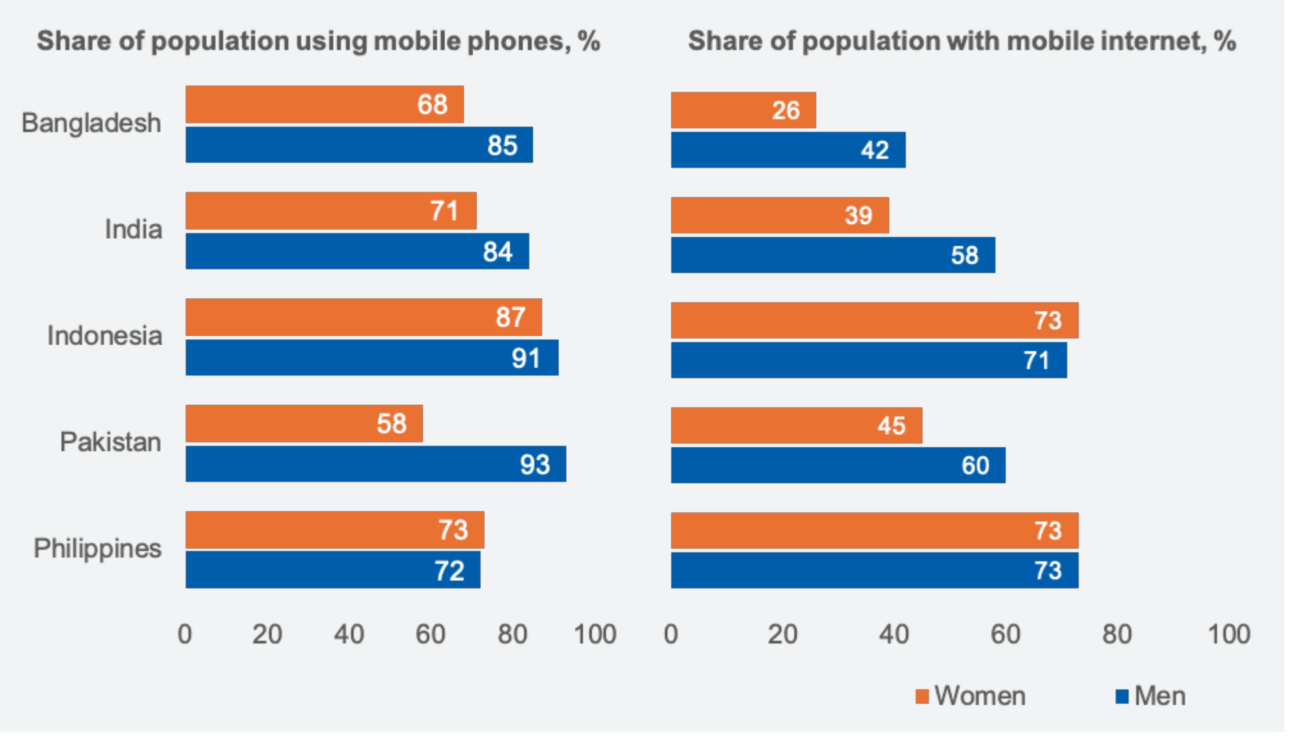
Inequality within countries

Climate impacts disproportionately affect women and marginalized groups like indigenous peoples, further deepening societal inequalities.[40] The ways in which different social groups cope with climate change are now also being shaped by deep disparities in AI access. Women, rural populations, and low-income communities may face systemic barriers to technology access and climate information, which can limit their ability to fully benefit from digital tools for resilience.

Gender gaps: women's unequal access to AI and information

In many contexts, gendered social norms, affordability barriers, and unequal access to technology can limit women's ability to benefit from climate information

Figure 2 – Mobile ownership, smartphone ownership and mobile internet adoption among men and women



Source: GSMA, The Mobile Gender Gap Report 2025 –GSMA Consumer Survey (2024), country estimates for Bangladesh, India, Indonesia, Pakistan and the Philippines services. The extent of gender disparities in 2024 has been analyzed by GSMA for five Asia-Pacific countries: Bangladesh, India, Indonesia, Pakistan, and the Philippines.[42] Mobile internet gender gaps are widest in India, Bangladesh and Pakistan – and they are still widening, Across South Asia, the smartphone ownership gap increased from 34 to 40 percent between 2023 and 2024. In India, this widening gap reflects a modest rise in men's smartphone ownership while women's ownership levels remained largely unchanged over the same period. In Indonesia and the Philippineson the other hand, the gaps were narrower: women were as likely as men to use mobile internet and smartphones.

Multiple factors drive this gendered digital divide. According to GSMA, the principal barriers for women include weak literacy and digital skills and high handset/data costs, along with concerns for safety, information security and the risks of scams and fraud. Research confirms that women often lack timely warnings of hazards "through a lack of equal access to technology, communication, and services", especially in rural or isolated areas.[42] Climate information delivered via smartphone apps, SMS alerts, or online platforms is thus far less likely to reach women. Social norms and safety concerns also play a role – in some communities, technology is seen as "for men," and women face greater online harassment, creating additional barriers to digital access.[43]

Rural communities: the climate-tech divide

Rural populations often find themselves on the wrong side of the digital divide. In Asia and the Pacific, rural areas are frequently more exposed to climate hazards yet less served by the information and telecommunication infrastructure that could help protect them.

Without connectivity, farmers cannot receive up-to-the-minute weather forecasts or pest outbreak alerts on their phones.[45] Villagers cannot participate in online climate training or access digital platforms that share drought-resistant farming techniques. "As climate patterns grow increasingly erratic, the isolation of many rural communities underscores the need for more timely, accessible, and actionable climate information to complement and strengthen traditional knowledge systems. AI-powered climate apps or early-warning SMS services that reach city dwellers may otherwise never reach a remote farming village.

Households with access to digital connectivity and financial services may find it easier to mobilize resources and recover in the aftermath of disasters. Regional data indicates that rural individuals without internet access or higher levels of education report greater challenges in raising emergency funds during crises; in one survey, around 8 percent of respondents in this group were able to mobilize resources quickly, compared with nearly 60 percent of men with higher education and internet access.[46] Communities with limited connectivity or financial access may depend more heavily on informal networks, existing savings, or external support during emergencies. Improving rural access to AI and digital tools is not a luxury but a necessity for equitable resilience. As the UNFCCC warns, without deliberate efforts to bridge these gaps, emerging climate tech could deepen existing social divides.[47]

CASE STUDIES: BRIDGING THE URBAN-RURAL DIVIDE FOR CLIMATE RESILIENCE

China – AI is helping farmers adapt to climate change by improving precision in agriculture. Using AI, drones can detect plant issues early and reduce excessive use of water and chemicals. Since 2017, AI-powered drones from XAG, a Chinese smart agriculture technology company, have helped save over 5 million tonnes of water and cut more than 368,000 tonnes of CO_2 emissions. In Sichuan's Ruoergai grasslands, AI-guided drones have been reseeding and restoring 700 hectares of degraded land, supporting climate resilience and sustainable farming.[47]

India – AI weather forecasting has been applied as the first initiative of the Agriculture Innovation Mechanism for Scale (AIM for Scale), a partnership launched in 2024 by the United Arab Emirates and the Gates Foundation. Such services have helped thousands of smallholder farmers make more informed decisions about planting and harvesting schedules. The benefits are tangible: some communities have cut their debts in half and increased their household savings by up to 10 percent as a result of using AI-generated climate insights.[48] These gains are particularly significant given the high debt burden and climate sensitivity of small-scale agriculture in the region.

Inequality between countries

AI can also contribute to inequality between countries. The hubs of AI and climate research are primarily in the United States, China, and a few countries in Europe. This concentration can contribute to talent migration patterns and may affect the ability of some countries to participate fully in AI-driven innovation.

As a result, these dynamics may result in uneven distribution of benefits, particularly for countries facing barriers to digital transformation. the benefits of AI are unevenly distributed, and many developing countries remain on the periphery of technological advancement. In this section, we analyze cross-country inequality from two key perspectives: the divide in AI infrastructure and the disproportionate environmental impacts of AI deployment, which may place greater strain on countries with constrained resources or limited digital infrastructure.

Low-income regions, particularly the least developed countries (LDCs) and Small Island Developing States (SIDS) in the Asia Pacific region, face significant infrastructural barriers that hinder the deployment of AI for climate adaptation. Many of these countries lack the foundational systems required for advanced climate analytics – such as widespread weather stations, reliable electricity grids, and adequate computing capacity. Without these enabling conditions, AI forecasting tools may depend on regional or incomplete datasets in contexts where localized, high-resolution data is limited. g tools often rely on coarse, non-localized data, limiting their relevance and effectiveness in addressing local climate risks.

The problems are exacerbated by financial constraints. Many developing countries lack the resources for crucial elements of climate-resilient AI systems – high-resolution satellite/hyperspectral imagery, geospatial data, or cloud computing infrastructure. Addressing these gaps in infrastructure is a prerequisite for ensuring that the benefits of AI technologies are accessible to the communities most vulnerable to climate change.

The backbone of effective AI applications in climate adaptation and mitigation is high-quality, context-specific data. In many contexts, data collection systems remain under-resourced or unevenly distributed, which can limit the availability of climate-relevant data. Limited data availability can reduce the precision of AI-generated insights, affecting their relevance for local decision-making.

Furthermore, the availability of data can correlate with demographic and socioeconomic status – compounding other sources of bias.[50] When AI models are trained on incomplete or biased datasets, they risk producing outputs that do not reflect the needs of underrepresented communities – particularly in areas such as disaster preparedness, resource allocation, and infrastructure planning. Equally important is the issue of data access and security: climate data must be openly accessible to local governments, communities, and NGOs while ensuring that sensitive information – such as community vulnerability profiles – is protected from misuse. To prevent climate AI from reinforcing existing inequalities and to empower communities with the information needed to adapt and thrive, it is vital to have equitable data governance, inclusive data-sharing mechanisms, and local data ownership.

Unequal environmental impacts

Across Asia and the Pacific, countries experience varied environmental implications from AI infrastructure depending on energy mix, water availability, and regulatory frameworks. Countries with access to cleaner energy grids, abundant water resources for cooling, and robust environmental governance are better positioned to support the deployment of resource-intensive AI systems in a climate-resilient and environmentally responsible way. In contrast, developing nations – many of which are still navigating the complexities of green transitions and face water scarcity – may bear disproportionate environmental and socioeconomic costs when hosting such facilities. This unequal distribution of environmental impacts underscores the urgent need for coordinated international efforts to promote equitable and sustainable AI deployment.

Most leading AI companies – such as Microsoft, Meta, and Google – are headquartered outside the Asia-Pacific region, but they have established extensive data infrastructure within the region. This can result in environmental impacts occurring in countries that may not directly capture the full economic value of the broader AI ecosystem.

Marked disparities in environmental impact exist across regions. In 2023, Google's data centers in Finland operated using up to 97 percent carbon-free energy, while comparable facilities in parts of Asia relied on only 4 to 18 percent carbon-free sources. This divergence stems largely from differences in national energy endowments, levels of renewable-energy integration, and the capacity of governments to implement and enforce sustainability measures.[52]

Water consumption is another growing area of concern. In Malaysia in 2025, for example, the National Water Services Commission reported that it had approved fewer than 18 percent of water-usage applications submitted by the 101 data centers operating in the southern peninsula, citing concerns over the risks of treated water intended for public use. As demand for digital infrastructure grows, both governments and industries are under increasing pressure to identify solutions that balance technological advancement with environmental stewardship.[52] Compounding the problems, many data centers tap into underground aquifers in major urban areas, further stressing fragile hydrological systems and increasing the risks of environmental degradation and water scarcity for surrounding communities.

Despite these risks, halting the expansion of AI and data infrastructure in developing countries is neither feasible nor desirable: digital transformations are increasingly vital for enabling economic diversification, and creating jobs. Recognizing the environmental trade-offs associated with large-scale AI infrastructure, several technology companies have begun implementing measures to influence and accelerate the decarbonization of regional power grids.[53] Similarly, Google has introduced urban greening programs, such as its Urban Forest Plan, as part of its broader strategy to address atmospheric emissions associated with data center construction and operation.[54]

CASE STUDY – SINGAPORE: MICROSOFT SOLAR ENERGY INVESTMENT

In 2024, the Portuguese utility company EDP won Phase 8 of Singapore's SolarNova programme – the country's largest solar initiative – to install up to 200 MWp of rooftop solar across more than 1,000 public-housing blocks and over 100 government buildings. Microsoft has entered into a 20-year renewable-energy agreement to purchase the electricity generated, supporting both EDP's decarbonisation goals and Microsoft's own 100-percent clean-energy target. The company is also collaborating with energy providers to expand access to solar and wind power in under-invested communities and investing in next-generation storage and water-replenishment initiatives.

This example illustrates how large technology firms can help de-risk renewable-energy investments, but it is only one part of the picture. Across Asia and the Pacific, smaller utilities, city governments, and local innovators are also experimenting with AI-enabled renewable-energy projects that are tailored to local grid conditions and financing constraints. From a UNDP perspective, the priority is to embed such technological initiatives within robust governance and regulatory frameworks, equity-focused policies, and long-term capacity-building so that sustainable AI use advances environmental and social goals rather than depending solely on the actions of a few global corporations."

Policy implications and recommendations

Embedding sustainability in AI infrastructure

To mitigate its environmental footprint and align with NDCs emission reduction targets, AI infrastructure must have sustainability embedded as a core principle – addressing specific challenges related to energy, water, mineral resources, and social inequalities. Sustainable AI infrastructure requires significant upfront investment in renewable energy and efficient technologies, which may strain public budgets but yield long-term economic and ecological benefits.

- *Energy* – For their energy-intensive operations, AI data centers must transition to renewable energy sources, such as solar, wind, and hydroelectric power. Policy mechanisms to ensure this can include tax credits, such as 30 percent investment tax credits for renewable-powered data centers. There could also be mandatory renewable energy quotas – such as 50 percent renewable sourcing by 2030 for data centers above 10 MW.

- *Water consumption* – Consumption can be reduced by advanced cooling technologies, such as direct-to-chip or immersion cooling. This can be enforced through regional water usage caps aligned with local hydrological capacities. The necessary investments can be supported by grants covering 20–30 percent of retrofit costs.

- *Critical minerals* – Ethical sourcing of critical minerals, like cobalt and lithium, should be regulated through supply chain transparency laws. Companies should be required to disclose sourcing origins and adhere to international standards, such as the OECD Due Diligence Guidance, with penalties for non-compliance of up to 5 percent of annual revenue.

- *Electronic waste* – Waste management can be strengthened by implementing extended producer responsibility regulations, mandating AI hardware manufacturers to fund recycling programs, and achieving 70 percent recycling rates by 2030.

- *Digital literacy* – Policies should prioritize digital literacy and skill development programs – with targets, for example, for the numbers of women and rural farmers trained in AI tool usage for climate adaptation. These initiatives should be funded through public-private partnerships with a minimum 20 percent private sector contribution.

Promoting open-source AI for cost-effective climate solutions

Open-source AI models offer a cost-effective and inclusive mechanism for democratizing access to advanced technologies, enabling resource-constrained nations to address climate challenges efficiently while aligning with NDCs. Pilot programs, such as Viet Nam's AI-driven irrigation systems, demonstrate the scalability of open-source AI solutions.[55] These adaptable models can be tailored for example for optimizing renewable energy integration – aiming to 50 percent renewable energy penetration by 2030. They can also enhance climate modelling accuracy and improve disaster forecasting reliability.

Recognizing the diversity of fiscal and institutional capacities across Asia and the Pacific, one possible avenue would be for interested governments and partners to co-finance the development and maintenance of open-source AI repositories. In some contexts, these could be managed by multi-stakeholder task forces comprising government agencies, technology firms, and academic institutions, with periodic progress reporting to support transparency and learning. Illustrative costings suggest that a regional hub might require on the order of $50 million over a five-year period, though actual needs would vary.

Open-source AI platforms could also be designed to leverage voluntary private-sector contributions, for example through tax incentives or recognition schemes for firms that share models, datasets, or computing resources for public-interest climate applications. Where appropriate, governments may choose to set targets for e-waste collection and recycling – such as substantially increasing recycling rates for AI-related hardware by 2030 – aligning these efforts with regional initiatives like ASEAN's Digital Masterplan 2025 to enhance equitable access to climate-focused AI tools across developing nations.[57]

Mobilizing public-private cooperation for sustainable AI investment

To encourage private investment in renewable-powered AI infrastructure and high-impact applications, such as disaster risk reduction and energy optimization, governments can offer financial incentives, such as tax breaks, subsidies, and green bonds. Experience in PPP projects in Japan and India, for example, offers insights and lessons on how disaster and climate risks could be managed under PPPs in emerging markets and developing economies.[57 58]

Corporate accountability can be further heightened by regulatory frameworks that reward energy-efficient and environmentally responsible AI deployment. In China, for example, in June 2025, under the guidance of the Ministry of Industry and Information Technology (MIIT), the Government officially implemented its first national standard titled Green Data center Evaluation. The standard was led and administered by the China Electronics Standardization Institute. Driven by the MIIT and other relevant authorities, China's data center development is increasingly moving toward high-efficiency, low-carbon, and low-resource intensiveness. As of 2025, a total of 246 national green data centers had been established across sectors such as telecommunications, internet, energy, finance, and intelligent computing.[59]

Strengthening regional collaboration for equitable AI deployment

Regional collaboration is pivotal for ensuring equitable access to climate-focused AI solutions. At present, such cooperation faces a number of barriers due to varying technological capacities and policy priorities. To harmonize governance standards policymakers can prioritize:

- *Cross-border energy integration* – Such as through the ASEAN Power Grid, to provide renewable energy for AI infrastructure.
- *Robust AI governance frameworks* – Building on initiatives like the ASEAN Guide on AI Governance and Ethics.
- *Regional knowledge-sharing platforms* – Supported by institutions such as the Asian Development Bank, these can facilitate technology transfers, capacity building, and the empowerment of marginalized communities. A collaborative framework fosters a cohesive regional strategy, aligning AI deployment with collective Nationally Determined Contributions and promoting inclusive, climate-resilient development.
- *Regional AI innovation hubs* – An initial investment of $50 million per hub could provide low-income countries with access to shared computing resources, open-source AI tools, and high-resolution climate data.

Depending on country context, such measures could be operationalised through national AI task forces coordinated by relevant ministries (for example, environment and technology), with periodic progress reports to support transparency and accountability. By embedding these targeted, enforceable policies across the AI lifecycle – from design and deployment to decommissioning – governments can align technological advancements with low-carbon development objectives, minimize ecological degradation, and promote equitable access to AI-driven climate solutions. This integrated approach will advance sustainable development and strengthen regional resilience to climate challenges in Asia and the Pacific.

Conclusion

AI's integration into climate solutions offers significant benefits, including substantial reductions in greenhouse gas emissions, improved resource efficiency, and enhanced resilience to climate-induced disasters. However, these advancements come with considerable costs, such as the high energy, water, and mineral demands of AI infrastructure. Differences in access, connectivity, and digital readiness mean that AI tools may not benefit all communities equally, and without inclusive approaches, existing digital and socioeconomic inequalities could be reinforced.

To balance AI's transformative potential with its environmental and social costs necessitates a paradigm shift in policy frameworks – with policies that prioritize sustainability, equity, and regional cooperation. Proactive, coordinated policy interventions can ensure that AI serves as a net-positive force in achieving sustainable and equitable climate outcomes, aligning technological innovation with global climate imperatives.

END NOTES

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3. (ADB, 2022)
4. (UNESCAP, 2023c)
5. (UNESCAP, 2023b)
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CHAPTER 4 — PEOPLE-CENTRIC AI FOR CONSERVING BIODIVERSITY

Sara Beery, MIT Department of Electrical Engineering and Computer Science

Asia and the Pacific is one of the most biologically diverse places on Earth, but this richness is steadily being lost. To mitigate this loss, countries across AP are racing to better understand and monitor their existing biodiversity and take action to protect and rehabilitate ecosystems. AI has been shown to be a powerful tool in this pursuit, reducing the cost and expanding the scale of biodiversity monitoring and analysis. However, fully realizing this promise across the region will require a fundamental shift from technology-centric to people-centric design. AI systems must be carefully tailored to local user needs and capacities, ensuring that technological solutions benefit Indigenous Peoples and Local Communities (IP and LCs) and respond to ecological realities. This chapter offers a people-centered AI roadmap for biodiversity that aligns with regional development goals and empowers those most affected by environmental change.

Asia and the Pacific has seven of the world's 17 'megadiverse' countries that house the majority of the Earth's species – across many complex ecological interfaces including tropical forests, near-shore marine ecosystems, and mountain landscapes.[1 2] This diversity directly supports the livelihoods of many hundreds of millions of people and helps sustain sustainable food security. The value of this biodiversity to the region has been estimated at over $2.19 trillion, including ecosystem services, medical research potential, and economic gains from ecotourism.[3]

Biodiversity monitoring has traditionally been carried out by species inventories, field surveys, and manual habitat assessments – labor-intensive and expensive exercises that are often infeasible at large scales or in remote regions.[4] Relatively few countries have the necessary infrastructure, technological capacity, or funding to monitor the decline in biodiversity – especially Indigenous Peoples, who typically stand to lose the most.[5]

To address the accelerating decline of biodiversity, the world needs new tools and approaches.[6] AI can play an important part by processing vast quantities of data from multiple sources such as camera trap images, acoustic recordings and hyperspectral satellites – which can be used to monitor ecosystems, detect species, and track changes in land cover, deforestation, and habitat fragmentation with unprecedented precision.[7 8] AI image analysis can also monitor marine systems tracking reef health, for example, and bleaching events.[9]

Nevertheless, the intricate web of relationships between species, environmental conditions, and ecosystem dynamics often defies simple computational modelling. Existing machine learning algorithms struggle to capture the nuanced, often unpredictable nature of ecological relationships, with non-linear interactions and context-dependent behaviors.

Benefits of AI – remote sensing and analysis

AI can substantially reduce the time and costs of biodiversity surveys: human-walked transects through ecosystems can now be supplemented with data collected from sensors such as camera traps, passive acoustic sensors, drones and satellite imagery.[10] These are particularly valuable in remote or rugged environments where human access is limited. Unlike human observers, these sensors can operate continuously and across a broader area of ecosystems providing a finer-grained picture.

Using camera trap images, AI analysis can identify common species of wildlife as accurately as human experts.[11] AI can also classify audio recordings of animal calls which are particularly valuable for monitoring nocturnal species, or for 'cryptic' species that are otherwise difficult for human observers to distinguish.[12]

AI can also be used to prioritize policy enforce regulation, and provide early warning to mitigate human-wildlife conflict. AI can help identify areas where deforestation is likely to occur next,[13] and forecast species migration under climate and anthropogenic change. With sufficient bandwidth to send data to a central hub, or sufficient computational capacity on the sensors themselves, AI-enhanced acoustic monitoring systems can detect chainsaw noise in forests and alert rangers before illegal logging escalates, [14] or highlight the potential for human-wildlife conflict. In India, AI-enhanced camera traps detect the presence of tigers and alert nearby villagers of potential danger.[15] This real-time response capability can transform enforcement and adaptive management.[16]

Finally, AI-enabled technology can combine diverse data sources into unified platforms to enable more integrated analysis. This improves the understanding of complex ecological interactions, supports predictive modelling, and provides a basis for more strategic and proactive conservation planning.

Threats from AI – disruption and exclusion

Alongside these benefits, AI can also be disruptive and even misleading. One of the most pressing concerns is the potential for AI to introduce significant bias into monitoring systems. AI systems are only as good as the data they are trained on, and many existing biodiversity datasets are geographically skewed toward the Global North or certain charismatic species.[17] As a result, AI models may perform poorly in underrepresented areas, many of which are in Asia and the Pacific, leading them to misclassify species or fail to detect important ecological changes.[18]This imbalance in AI performance can reinforce or expand existing global power and resource imbalances.[19]

There are also risks of AI deployment related to surveillance and privacy. AI systems that monitor environmental sounds or track wildlife movement may inadvertently capture sensitive information about human activity – which could be used to monitor communities without their consent or criminalize traditional land uses.[20]

In addition, there are issues of sustainability. Advanced AI applications have high infrastructure and maintenance costs – for expensive sensors, high-throughput communication networks, and software and hardware upkeep. Deploying technical infrastructure and expertise often requires significant human oversight – for validating models, maintaining systems, and interpreting data. In these circumstances, countries without these resources remain dependent on foreign institutions to support their access to these technologies and may struggle to build AI systems specialized to work well within their own changing ecological contexts. In regions where technical capacity is low and capacity building is not prioritized, this over-dependence on external support makes sustaining such projects difficult. And when donor funding ends, such projects may be abandoned.[21]

Finally, technological innovation can sometimes overshadow, or divert funding from, fundamental non-technical conservation needs – community organizing, legal reform, or ecological restoration. This form of 'techno-solutionism' risks addressing symptoms without tackling root causes, such as land tenure insecurity, extractive industries, or weak governance.[22] And with AI only sporadically deployed the outputs of such systems, despite their local value, are less likely to be integrated into conservation policy.

Balancing the benefits and disruptions of AI requires a holistic approach. Tools must be evaluated not only for their technical performance but also for their social, ethical, and ecological impacts. Ensuring that AI contributes to, rather than detracts from, inclusive and sustainable conservation requires participatory design, transparent evaluation frameworks, and adaptive governance mechanisms.

The need for AI systems specific to Asia and the Pacific

Machine learning systems require "training" to perform well, via large, expert-curated, well-labelled datasets. Such data is lacking for many species and ecosystems in Asia and the Pacific, and models trained in one region or on certain species often underperform when transferred to new settings, a phenomenon known as 'domain shift'.[23] For example, models trained on North American camera trap images or European satellite imagery often fail in Asian landscapes which can have different lighting conditions, vegetation cover, or miss endemic species.[24] These problems are particularly acute in tropical forest and island ecosystems rich in species but from which there is little systematic data collection.[25]

We have seen examples where concentrated effort to build training data has led to significant benefits: in Canada, for example, the careful curation of a dataset including audio recordings for 317 Canadian bird species led to the development of the powerful, accurate HawkEars species recognition model, which is now deployed across Canadian national parks.[26] To see such benefits in Asia and the Pacific, a strategic, multi-country effort to curate AI-ready biodiversity datasets would significantly reduce current imbalances in AI performance relative to other parts of the world.

The value of local knowledge

Another significant challenge for AI systems is the integration of local ecological knowledge. Traditional ecological understanding has developed through generations of intimate environmental interaction and often contains subtle insights that elude quantitative technological approaches. Predictive modelling in these situations demands extraordinary complexity and will push current AI technologies to their conceptual and computational limits.

Developing models that can meaningfully represent ecological complexity requires a fundamental reimagining, where interactive, data-driven biodiversity monitoring and understanding systems can be a tool for local experts, where their knowledge can be introduced to expand and benefit ecosystem understanding.[27] At the same time, AI systems must continuously adapt to shifting baseline conditions, a task that requires sophisticated, flexible learning mechanisms that go beyond traditional computational approaches. Crucially, AI systems should respect ethical and legal frameworks that prioritize data sovereignty over local knowledge, ensuring that the communities and nations from which the biodiversity data originates retain control and authority over its use and distribution.

The dangers of deepening inequality

While AI can benefit biodiversity monitoring, its deployment risks deepening existing inequalities relating to who can access, influence, and benefit from AI technologies, and whose knowledge, data, and priorities are represented.

Within-country inequalities

Disparities are often most visible in the division between urban and rural areas, or between state institutions and Indigenous Peoples and local communities. In many parts of Asia and the Pacific, Indigenous Peoples are the primary stewards of biodiversity-rich landscapes but often marginalized in conservation technology development and policy, particularly at the regional or global levels. Conservationists from global NGOs or well-endowed research institutions often deploy drones, camera traps, or acoustic sensors in developing countries but bypass IP and LCs, failing to secure free, prior, and informed consent.[28] The prevalent data governance model remains extractive and non-transparent, with minimal benefit-sharing mechanisms that perpetuate historical patterns of technological and ecological marginalization.

This has multiple implications. First, it undermines trust in conservation institutions and technologies, especially when monitoring is perceived as surveillance. Second, it can disrupt customary land management by introducing tools that are misaligned with local governance systems. Third, it misses opportunities: indigenous ecological knowledge, when integrated respectfully with scientific methods, can enhance the performance and relevance of AI systems.[29]

Between-country inequalities

There are also stark divides between countries. Richer countries with stronger scientific infrastructure, and deeper integration into global technology networks are much more likely to lead and benefit from AI innovation. In Asia and the Pacific, Australia, China, Japan and Singapore, for example, have active AI research communities, strong digital infrastructure, and greater access to competitive grant funding.[30] These are also the countries with the greatest capacity for AI model development and interpretation.[31] They benefit from centralized biodiversity databases, robust digital infrastructure, and well-funded research institutions. In Singapore, the National Biodiversity center has advanced camera trap systems and acoustic monitoring integrated into urban ecological networks.[32] Similarly, the Australian Acoustic Observatory uses cutting-edge approaches and is partnering with Google to search decades of passive acoustic monitoring data for observations of specific bird species.[33]

By contrast, remote Pacific island nations or poorer developing countries have far fewer resources and tend to rely on external NGOs and universities whose AI models may not be tailored to their ecological or institutional contexts.[34] Often these countries are also the ones lacking the technological capacity, data and computational infrastructure to develop targeted conservation strategies.[35] This systematically impedes conservation efforts. Technology transfer is further complicated by linguistic diversity combined with low digital literacy.[36] Their environmental protection agencies are often critically underfunded and lack the technical expertise to develop, deploy, and maintain sophisticated AI-driven conservation technologies.[37]

Unequal access to technology could also be exacerbated through a different channel. Countries, regions, or protected areas in the region with pre-existing relationships or partnerships with newly emerging leaders in AI (countries, companies, or academic institutions) often have readier access to their technology partnerships and platforms. While often beneficial in terms of rapid adoption, this can affect the type of technologies prioritized through these partnerships and the strategic interests they serve. For example, if the relationship is with a partner that has an interest in carbon offsets, the AI that is prioritized for deployment may focus on estimating carbon for global carbon markets but may not consider or prioritize local-held biodiversity or community land-use goals. These externally designed and built AI-enabled systems may lead to a shift in priorities in local or global conservation decisions downstream, driven by what environmental information is made readily available via AI. In contrast, countries and communities that have the capability to build their own AI systems can directly encode their local conservation priorities, cultural values, and land-use goals into the systems.

Historical data collection

These disparities are compounded by legacy issues in biodiversity data, which is a key component of successful AI development. Colonial-era specimen collection and unequal research funding historically prioritized accessible or economically significant species.[38] As a result, many global biodiversity databases – such as the Global Biodiversity Information Facility – are still heavily skewed toward species and ecosystems in the Global North. AI models trained on these datasets underperform when applied to data-poor regions, reinforcing cycles of invisibility and underinvestment.

There are also problems of data ownership.[39] In the developing world, many research repositories and comprehensive biodiversity datasets are collected, owned and managed by European or North American institutions. This may be the only practical way to fund data collection and analysis, nevertheless, organizations from the Global North are capturing data from the Global South but the benefits of that collected information are not always realized in the communities and regions where the data was collected.[40]

Inequalities in access to existing systems

Some countries and communities are excluded by language barriers or lack of expertise. Much of the documentation, software, and training resources for AI are available only in English, creating additional hurdles for practitioners in non-Anglophone countries. Moreover, environmental science curricula may not include computer science or data ethics, making it harder for conservation professionals to engage meaningfully with AI systems.[41] Finally, existing databases, tools, and platforms may not be accessible to those without institutional connections, academic or otherwise, effectively marginalizing local communities acting to conserve species.

Regional variations in biodiversity value and support

In the Asia-Pacific region, some countries are richer in biodiversity but economically poorer. In Indonesia and the Philippines, for example, funding for conservation has to compete with priorities like economic growth and poverty alleviation.[42] Further disparities emerge between areas that receive priority because of their ecotourism potential and those that provide essential but less visible ecosystem services such as insect pollination or protecting watersheds.[43] Priority may also be given to areas where biodiversity objectives chime with livelihoods and disaster risk reduction, such as mangrove conservation for coastal protection and flood mitigation.[44]

External financing may also be attracted to areas with famous or charismatic species, such as tigers, while other regions with less charismatic but equally threatened forms of biodiversity struggle to secure comparable resources. Additionally, external funding for AI technology adoption often prioritizes high-visibility conservation projects with flagship species or ecotourism potential.[45]

Conservation efforts can thus be weakened by a misalignment between global interests, external funding mechanisms, and local priorities.[46] Addressing these intersecting inequalities effectively, requires multi-faceted and targeted interventions. These include:

- In-country data collection and processing infrastructure
- Training programs tailored to diverse user groups – such as policymakers, forest rangers, and indigenous monitors
- Platforms for cross-country collaboration.
- Open-source models and data-sharing agreements
- Participatory governance mechanisms
- Local data ownership, where national frameworks function primarily to support rather than supersede community-level decision-making.

To conclude, regional disparities are compounded by technological dependency on imported pre-trained models and contracts for foreign technical teams, creating systemic barriers to local technological sovereignty. This dependency compromises long-term sustainability, as ongoing system maintenance, updates, and troubleshooting remain contingent on continued external engagement and funding.

Inequality in the deployment and efficacy of AI tools for biodiversity conservation in Asia and the Pacific is deeply rooted in complex, multifaceted disparities that extend far beyond data limitations and technological capabilities.[47] These inequalities are fundamentally shaped by historical power dynamics, colonial legacies, and uneven development priorities that persist in contemporary conservation efforts,[48] inhibiting the development of local conservation capabilities – perpetuates a colonial approach to ecological research.[49]

Overcoming technical and institutional barriers

Addressing these profound inequalities demands a comprehensive, multi-faceted approach that transcends technological solutions. Key interventions include sustained investment in national and regional biodiversity data collection infrastructure, development of robust AI and technological education programs, and promotion of open-source technology. Critically, technological design must include local and indigenous communities to ensure solutions are contextually appropriate and culturally sensitive.

Local and regional computing infrastructure

Many AI applications require high-performance computing infrastructure, including GPUs, large-scale data storage, and stable internet connectivity – requirements which are difficult to meet in remote or resource-constrained areas – from highland forests in Nepal or outer island chains in the Pacific. One emerging solution is to process data locally on low-power 'edge'-devices that have embedded artificial intelligence.[50] For example, in India AI-enabled camera traps can identify endangered Sumatran tigers directly on the device, enabling alerts to be sent rapidly over limited networks without needing to send entire images.[51] However, widespread adoption remains constrained by high initial hardware costs, limited local technical expertise, the need for new machine learning models that often require sophisticated model compression and can accurately perform within the limitations of edge devices and in diverse and complex ecological environments.[52] Despite these challenges, edge AI shows promise for wildlife monitoring and conservation in the Asia-Pacific region – empowering local researchers and practitioners with advanced technological capabilities.[53]

Interdisciplinary collaboration and capacity building

Current educational systems are often poorly equipped to produce professionals with the interdisciplinary skills required for AI-driven or AI-enabled work.[54] AI for biodiversity will require breaking down institutional silos so as to foster meaningful and informed dialogue between conservation scientists, computer scientists, local practitioners, and policymakers.[55]

Curriculum redesign must occur from primary education through to advanced professional training, creating integrated learning pathways that break down traditional disciplinary boundaries. Universities, research institutions, and government agencies can develop sustained strategies that view interdisciplinary expertise as a core institutional value. This requires creating supportive ecosystems that reward complex, boundary-crossing research and professional practice.

Targeted capacity-building programs can enhance technical skills within government agencies and local research institutions, while simultaneously developing AI tools that are contextually relevant and that align with specific regional conservation needs.[56] Examples are educational programs such as CV4Ecology,[57] and the AI for Science Masters program at the African Institute of Mathematical Sciences,[58] which are developing curricula that increase AI development capacity in the conservation and biodiversity communities. Around the world, a growing number of conservation technology programs are making practical use of technology and supporting decision-making,[59] but there are fewer such programs in Asia and the Pacific where open-source education tools can be hampered by language barriers. Successful adoption of these technologies will require significant investment in local and accessible AI and technology capacity building.

Impact assessments

AI deployment must be evidence-based and supported by informed and rigorous impact assessments. Information from pilot projects can show if projects are technically feasible, but few systematically assess whether they improve conservation outcomes, increase efficiency, or reduce costs. Without robust impact metrics, it is difficult to justify ongoing investments or to learn from past successes and failures. Weak evaluation also makes it harder to identify unintended consequences, such as reinforcing data biases or displacing local knowledge systems.

Evaluation of technology should capture the regional and local value.[60] This will enable a fundamental reimagining of conservation technology governance and prioritization – shifting from top-down, globally-driven models to more inclusive, locally-empowered approaches that center on the knowledge, priorities, and capabilities of regional researchers and communities.

By prioritizing local agency, developing adaptive institutional capacities, and creating flexible technological infrastructures, the conservation sector can begin to develop AI solutions that are not just technologically sophisticated, but also broadly accessible and responsive to local ecological and social contexts.

People-centered AI for biodiversity

The UNDP 2024 Regional Human Development Report presents a transformative vision for development in Asia and the Pacific – one that is centered on people, prioritizes inclusion, and advances sustainability.[61] This requires re-evaluating current paradigms for design and deployment of AI for biodiversity monitoring – moving the conversation from purely technical performance to questions of equity, empowerment, and social outcomes.

People-centered development prioritizes human dignity, agency, and well-being. For biodiversity, this means recognizing the roles of local communities, indigenous peoples, and under-resourced governments not just as beneficiaries but as key actors whose participation, knowledge, and governance must shape AI tools.[62]

AI systems should be responsive to local values, and interpretable and usable without extensive technical expertise. A local ranger should be able to understand and act on the model's outputs, so the main priority should be useability rather than absolute prediction accuracy.

People-centered development must address the dangers of 'data deserts'. AI is notoriously data hungry, and struggles to learn concepts robustly if it has few examples to learn from.[63] Filling these voids requires investment in locally led data collection and human infrastructure. Community-based monitoring programs, when equipped with appropriate technology and training, can fill data gaps while building local ownership and capacity.[64]

In parallel, AI systems should be designed to operate in low-resource environments. Research is still needed to develop AI models that can robustly recognize species with limited training data. AI algorithms should optimize for energy and computational efficiency and be able to operate with limited bandwidth and less access to cloud computing or local access to GPUs. This also reduces the environmental footprint of AI itself – given the extensive carbon, energy, and water costs of training large models.[65]

Another critical aspect is skills. People-centered AI requires more than just awareness workshops; it demands sustained investments in education, mentorship, and institutional development. Local ecologists need to be trained in AI tools, while AI developers need to be sensitized to ecological principles and local contexts. Tool developers and end users should collaboratively define goals and metrics, bridge disciplinary divides, and build mutual understanding.[66]

It is also important to establish policy frameworks. National strategies should mandate inclusive stakeholder engagement in technology initiatives and create mechanisms for feedback, redress, and shared governance. Regional bodies like ASEAN and the Pacific Islands Forum can support alignment by promoting best practices, facilitating knowledge exchange, and providing member states with technical support. International donors, meanwhile, must reorient to long-term community-embedded approaches.

Finally, AI needs to be embedded in broader visions of sustainable development. Technological tools should not just be monitoring biodiversity but supporting human well-being, land rights and customary governance systems. Biodiversity data should therefore be linked with health, agriculture, and climate resilience indicators. AI-generated insights can also be used to guide conservation finance mechanisms such as payments for ecosystem services and more generally as a catalyst for inclusive environmental stewardship.

Policy implications and recommendations

The Asia-Pacific region is a critical nexus of biodiversity hotspots scattered across diverse ecological, social, and technological landscapes.[67] It also has complex socioeconomic challenges and widely differing technological capabilities. This demands a nuanced and people-centric approach that sees AI technology not as a solution, but as an opportunity for collaborative knowledge creation and environmental stewardship – moving beyond technological determinism to embrace a holistic vision centered on human and ecological well-being.[68]

Policymakers will need to collaborate with ecologists, computer scientists, and local communities, who together can develop AI technologies that are not only scientifically robust but also socially and contextually appropriate.[69] Country strategies should also be linked to regional collaborative mechanisms that foster knowledge sharing and collective technological development.

By prioritizing local agency, cultural sensitivity, and adaptive strategies, the Asia-Pacific region can emerge as a global leader in reimagining the relationship between technology, human communities, and the natural world.

Inclusive and sustainable digital infrastructure development

Governments can tailor digital infrastructure to the region's diverse geographical and socioeconomic conditions, building distributed computing networks and low-power and climate-resilient infrastructure. They can also work through regional bodies including ASEAN, the Pacific Islands Forum, and the South Asian Association for Regional Cooperation (SAARC) to create regional data-sharing platforms that uphold local data sovereignty.

It is particularly important to employ open-source tools, datasets, and commons-based digital public infrastructure.[70] Open access to AI tools can accelerate innovation across data-reliant sectors such as public health and ecosystems.[71] Policymakers can also help democratize the development and use of AI-enabled technologies by mandating open access to publicly funded research where ethical to do so.[72] This is especially critical for small island states, and other countries likely to be excluded from commercial AI ecosystems.[73]

Adaptive and contextual technology

AI technologies should be localized to specific ecologies and cultures. This requires bottom-up innovation that empowers local communities to develop and adapt solutions to their unique environmental challenges with support for small-scale, community-driven AI projects that demonstrate innovative approaches to biodiversity conservation. These initiatives should be viewed not as isolated technological interventions, but as part of a broader strategy of active ecological and social resilience.[74]

Capacity building and human capital development

Capacity building must be reimagined as a holistic, culturally embedded process that goes far beyond traditional training to create an ecosystem of knowledge and innovation that bridges technological expertise with deep ecological understanding.

Collaborative research networks across national boundaries will enable knowledge exchange and joint innovation. Regional centers of excellence in AI and biodiversity conservation can create interdisciplinary training programs that integrate indigenous ecological knowledge with advanced computational techniques that can capture nuanced ecological insights with multilingual capabilities and local language processing technologies.[75] And to reflect the diversity of the region's ecological and cultural landscapes, fellowship and mentorship programs should support researchers from underrepresented communities.[76]

Diverse sources of funds

The costs of AI infrastructure for biodiversity monitoring can far exceed the budgetary capacities of many national environmental agencies in the region.[77] Support can come from a variety of sources. Multilateral development banks, for example, can provide targeted financial support for technological infrastructure. Governments can also leverage private sector expertise and capital. Public-private partnerships offer another promising avenue, along with regional collaborative funding pools. Companies and organizations can also establish nature-positive supply-chain certification that safeguards equity and ecological integrity.[78] Further funds can come from such mechanisms as green bonds, and carbon and biodiversity offset credits that directly support nature stewardship.

Participatory governance and ethical frameworks

Governance mechanisms must move on from top-down to participatory models of technological development deeply rooted in the region's diverse cultures and ecologies. Region-specific ethical AI guidelines should establish indigenous rights principles, local community consent mechanisms, and culturally sensitive data collection practices.

Legal frameworks must be developed to protect community data rights, ensure transparency in AI systems, and provide robust mechanisms for addressing potential technological harms. Policymakers should require that AI systems disclose their training data sources, model limitations, and decision criteria.[79] Countries can reduce the risks of misuse or bias and build public trust through independent audits, public reporting, and multi-stakeholder oversight bodies that include representatives from indigenous communities, ecological scientists, AI ethics experts, and local policymakers.[80] National AI strategies can include local adaptations of ethical AI standards – such as those developed by the EU, OECD, and UNESCO.[81]

Regional collaboration and knowledge sharing

An essential mechanism for building technological and ecological capacity is international collaboration based on equitable sharing of knowledge, ensuring that technological and ecological insights flow in multiple directions, not just from leading AI countries to less advanced ones.

Regional institutions such as ASEAN, the Pacific Islands Forum, and the UN Economic and Social Commission for Asia and the Pacific (ESCAP) should invest in collaborative platforms, harmonized policy frameworks, and regional AI observatories. Cross-border ecosystems – such as coral reefs, river basins, and migratory routes – require coordinated monitoring and management. The region can create shared AI biodiversity monitoring infrastructures based on common data standards and joint analysis.[82]

Promising initiatives are emerging. Regional collaboration mechanisms like the ASEAN center for Biodiversity and the Pacific Islands Roundtable for Nature Conservation offer potential frameworks for joint capacity building and shared data repositories. However, realizing their transformative potential requires sustained political commitment, financial support, and a genuine commitment to technological equity.[83]

Flexible and iterative innovation

Translating policy recommendations into effective, sustainable practices requires careful, nuanced navigation through multiple interconnected barriers. This involves a flexible, iterative approach with continuous evaluation, allowing for responsive adjustment based on real-world outcomes. Leadership will need to prioritize flexibility, interdisciplinary collaboration, and be willing to continuously reassess and reimagine technological interventions. Institutions will need to embrace uncertainty, value experimentation, and view failure as an opportunity for refinement.

These recommendations converge on a central principle: AI for biodiversity must be designed and governed as a public good. Only by embedding values of equity, inclusivity, and sustainability can we ensure that the application of AI contributes to people-centered development and ecological resilience.

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Case Study 1 – Community- and institutionally driven coral reef monitoring

This case study compares two distinct approaches to coral reef monitoring: community maintenance of coral gardens in the Pacific Islands, and institutional projects by the King Abdullah University of Science and Technology and the Swiss Federal Institute of Technology Lausanne along the Red Sea coastlines.

GEOGRAPHIC AND DATA CONSTRAINTS

- The Pacific Islands reef systems are dispersed across vast oceanic expanses. As a result, monitoring has had to be distributed across countries and communities – and coverage has been determined by accessibility and local priorities.As a result, coverage has been patchy with significant temporal and spatial gaps. These could be partially filled by indigenous ecological knowledge though it can be difficult to combine these insights with AI integration.[85]
- Red Sea reefs form a more continuous system along linear coastlines, enabling systematic surveys supported by research vessels and permanent stations, with extensive temporal datasets for AI training.[86]

RESOURCE AND TECHNOLOGY

- Pacific Islands monitoring operates with limited resources, relying on community volunteers and basic machine learning with consumer-grade equipment.[87] Funding depends on short-term grants and volunteerism.[88]
- Red Sea initiatives benefit from specialized research teams, advanced equipment including remotely operated vehicles and hyperspectral imaging, substantial institutional funding, and high-performance computing capabilities.[89]

GOVERNANCE AND STAKEHOLDER COMPLEXITY

- Pacific Island conservation operates across multiple national jurisdictions complicated by customary marine tenure systems, requiring engagement with village councils, traditional leaders, national governments, and international NGOs.[90]
- Red Sea initiatives feature fewer jurisdictions but have greater geopolitical tensions, with stakeholders dominated by research institutions and regulatory agencies, though recent efforts have expanded community engagement.[91]

ECONOMIC STAKES AND PRIORITIES

- Pacific Island reefs contribute 30-80 percent of household protein and support 50-90 percent of rural livelihoods, with coral loss potentially creating annual economic losses of 3-8 percent of GDP in countries like Kiribati.[92]
- Red Sea reef value predominantly derives from tourism – $7 billion annually along the coast of Egypt. These nations have greater financial resources and more diversified economies where coral degradation impacts a lower proportion of GDPs – 0.3-1.2 percent.[93]

IMPLICATIONS FOR PEOPLE- CENTERED AI DEVELOPMENT

- The Pacific Islands model demonstrates AI adaptation to resource-constrained environments through simplified interfaces, offline functionality, and community integration, while maintaining local control over data and knowledge systems.[94]

- The Red Sea approach showcases advanced technological capabilities generating high-resolution insights but risking dependencies on external expertise.

AI implementation is thus shaped by resource contexts, geography, governance, and economic realities. Neither model offers a complete solution but it is possible to combine elements of both, with AI systems incorporating both quantitative data and qualitative observations, and having tiered approaches with local and accessible tools but also advanced analysis at regional hubs.

Case study 2 – Urban biodiversity monitoring in Singapore and Jakarta

Singapore and Jakarta are South-East Asian cities with different governance structures and levels of resources – with contrasting experiences in urban biodiversity monitoring.[96]

RESOURCES AND INFRASTRUCTURE

- Singapore benefits from robust resources including well-trained environmental scientists through academic institutions and the National Parks Board (NParks).[97] Around 80 percent of monitoring sites have automated systems. With significant governmental funding, the city-state has invested in remote sensing, AI-enabled camera traps and environmental DNA sampling.[98]
- Jakarta enjoys less funding divided among competing environmental priorities; its staff-to-monitoring-area ratio is one-eighth that of Singapore.[99] Infrastructure remains concentrated in a few urban parks, and sensor deployment is limited, relying primarily on conventional methods like manual species counts and basic camera trap networks.[100]

DATA LANDSCAPES AND HISTORICAL CONTEXT

- Singapore has comprehensive urban biodiversity datasets with systematic records dating back to the 1800s and continuous monitoring data spanning 60 years.[101] The Singapore Biodiversity center maintains records for an estimated 95 percent of known species, enhanced by citizen science initiatives through iNaturalist with nearly 800,000 species observations. [102]
- Jakarta's data sets involve more gaps. Systematic record-keeping was only standardized in the late 1990s, and rather than documenting ecosystems comprehensively it concentrates on economically significant species.[103] The Jakarta Green Open Space program has improved data collection since 2015, but integration with community programs remains somewhat incomplete.[104]

INTERNATIONAL PARTNERSHIPS AND STANDARDS

- Singapore leads regional biodiversity monitoring through the ASEAN center for Biodiversity initiatives and hosts the GBIF Southeast Asia node.[105] NParks collaborates with over 20 international institutions, and the Singapore Index on Cities' Biodiversity has been adopted as a standardized framework by over 70 cities worldwide.[106]
- Jakarta's international involvement is growing but more limited, participating in the Urban Biodiversity Hub network and partnerships with international NGOs. Jakarta joined Cities4Forests in 2018 and participated actively at COP16 in 2024, signaling increased commitment to international biodiversity monitoring practices.[107]

ECOSYSTEM SERVICES AND URBAN BENEFITS

- Singapore's monitoring system quantifies significant ecosystem services: urban forests reduce local temperatures by 3-5°C;[108] native pollinators contribute to 30 percent of urban food production;[109] and monitored waterway biodiversity supports natural filtration and reduced treatment costs.[110]
- Jakarta's assessments indicate the importance of ecosystems which provide flood protection and carbon sequestration.[111] Monitored green spaces show

particulate matter reductions of up to 24 percent.[112] Visitor surveys demonstrate the mental health benefits of urban parks.[113]

IMPLICATIONS FOR PEOPLE- CENTERED AI DEVELOPMENT

Singapore's resource advantages enable sophisticated technological implementation while, despite the constraints, Jakarta demonstrates progress through strategic partnerships and community engagement. Rather than applying a one-size-fits-all approach, AI tools must acknowledge differing contexts.[114] Overall, Singapore and Jakarta demonstrate four priorities for people- centered AI development for biodiversity in cities:

- Democratize access through lightweight mobile applications enabling broader community participation.[115]
- Integrate indigenous and local knowledge systems, ensuring that algorithms recognize locally significant species and ecosystem relationships.[116]
- Establish regional data-sharing protocols, allowing resource-constrained communities to benefit from innovations while contributing local insights.[117]
- Prioritize transparent AI systems that build community trust through collaborative approaches where participants can meaningfully engage with technological outputs.[118]

By centering on human needs, knowledge, and participation, cities throughout Asia and the Pacific can develop more resilient, inclusive, and effective conservation approaches benefiting both Nature and people.

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Case Study 3 – Biodiversity monitoring programs in India and Papua New Guinea

India and Papua New Guinea (PNG), are megadiverse but very different nations with distinct approaches to biodiversity monitoring.

NATIONAL PRIORITIZATION AND APPROACHES

- India has demonstrated strong institutional commitment through flagship initiatives like Project Tiger, which expanded from 9 to 53 reserves covering 75,000 km^2.[119] The Wildlife Institute of India is a premier research institution, and the country combines species-centric programs with ecosystem-level planning, incorporating satellite imagery, camera traps, and AI-based tools for species identification.[120]
- PNG has 7 percent of global biodiversity in less than 1 percent of global land area. Over 97 percent of land is under customary ownership.[121] PNG's approach to indigenous stewardship integrates traditional ecological knowledge with scientific monitoring through initiatives like the Tenkile Conservation Alliance. The Conservation and Environment Protection Authority (CEPA) coordinates monitoring but has limited resources.

DATA SOVEREIGNTY FRAMEWORKS

- India has developed robust national governance through the Biological Diversity Act (2002) and the National Biodiversity Authority, asserting sovereign rights over biological resources and associated knowledge. The Indian Biodiversity Information System provides centralized data management with clear protocols, maintaining stringent controls on bioprospecting and requiring benefit-sharing arrangements.[122]
- PNG approaches data sovereignty through community-level ownership reflecting customary land tenure. The 2014 National Strategy for Responsible Sustainable Development recognizes traditional knowledge as integral to conservation and asserts community rights to control information about their biological resources. This decentralized approach creates national monitoring challenges but aligns with local data sovereignty.[123]

TECHNOLOGICAL CAPACITY AND AI DEVELOPMENT

- India possesses substantial technological infrastructure through its robust IT sector, extensive scientific institutions, and Digital India initiatives. The National Mission on Biodiversity includes provisions for emerging technologies, through the Indian Biodiversity Portal and the Wildlife Institute of India's automated species identification systems. Challenges remain, however, in bridging digital divides and incorporating diverse knowledge systems.[124]

- PNG faces funding constraints, sparse technological expertise and limited digital infrastructure – internet penetration is only 15 percent. CEPA relies on international partnerships and donor funding, collaborating for technological solutions with organizations like the Wildlife Conservation Society. [125] Externally developed systems may not, however, reflect local contexts and can be difficult to sustain.[126]

DATA INFRASTRUCTURE AND COLLECTION

- India operates multi-scale infrastructure. The National Biodiversity Authority coordinates with the Zoological and Botanical Surveys and research institutions. Long-Term Ecological Observatories have established systematic data collection across ecosystems, though it can be difficult to harmonize different methodologies and timeframes.[127]

- PNG's infrastructure is more fragmented, according to some. Data collection occurs primarily through time-bound projects, and coverage by the PNG Biological Records Database is less complete. Community-based monitoring provides valuable local data but can employ inconsistent methodologies, while limited rural digital infrastructure might necessitate hybrid approaches to data collection.[128]

POLICY FRAMEWORKS

- India's comprehensive framework centers on the Biological Diversity Act and National Biodiversity Action Plan (revised 2019), with strong centralized planning and state-level implementation. The 2020 National Mission on Biodiversity explicitly recognizes the role of emerging technologies, though there are difficulties in balancing conservation with development pressures.[129]

- PNG's framework emphasizes the Protected Areas Policy (2017) and community-based conservation areas as primary protection mechanisms. The policy acknowledges that biodiversity conservation is inseparable from indigenous practices and land rights, though there are capacity and funding constraints and limited provisions for digital tools.[130]

RECOMMENDATIONS FOR PEOPLE- CENTERED AI DEVELOPMENT.

Five key recommendations emerge:

1. Develop tiered technological solutions functioning across different infrastructure levels, enabling resource-constrained regions to benefit from appropriate AI applications.

2. Institutionalize collaborative design processes, meaningfully engaging local communities and indigenous knowledge holders throughout development.

3. Establish regional technology transfer mechanisms enabling poorer developing countries to benefit from innovations developed in technologically advanced countries like India.

4. Create flexible data sovereignty frameworks protecting indigenous knowledge while enabling scientific collaboration.

5. Invest in local capacity building, ensuring AI tools can be locally maintained, adapted, and governed. People-centered AI development must build upon existing capacities while respecting local interests.

Integrating elements of India's centralized, technology-intensive approach with PNG's decentralized, community-centered model can help Asia-Pacific countries develop AI technologies that enhance biodiversity monitoring while respecting diverse knowledge systems, governance structures, and technological capacities. Such hybrid approaches ensure technological advances empower rather than marginalize communities at conservation's frontlines.

END NOTES

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2. (Mora et al., 2011)
3. (Ha Van, Lichang and Dang Thanh Quoc, 2024; Campaign for Nature, no date)
4. (Pimm et al., 2015; Schmeller et al., 2018; Stephenson, 2020)
5. (Brubacher et al., 2024)
6. (IPBES, 2019)
7. (Ngcamu, 2023)
8. (Christin, Hervet, and Lecomte, 2019; Tuia et al., 2022)
9. (David Obura, Mishal Gudka, and Suraj Bacha Gian, 2017)
10. (Norouzzadeh et al., 2018; Christin, Hervet, and Lecomte, 2019)
11. (Norouzzadeh et al., 2018; Gadot et al., 2024)
12. (Wrege et al., 2017; Sethi et al., 2023)
13. (Jetz, McPherson and Guralnick, 2012)
14. (Prasetyo, Mutiara and Handayani, 2018)
15. (Dertien et al., 2023a)
16. (Cash and Moser, 2000)
17. (Sullivan et al., 2009; Farley et al., 2018; Gibb et al., 2019)
18. (Bevan et al., 2025)
19. (Stevens, 2024)
20. (Sandbrook, Luque-Lora and Adams, 2018)
21. (Danielsen, Burgess, Jensen and Pirhofer-Walzl, 2010)
22. (Morozov, 2013)
23. (Jetz, McPherson and Guralnick, 2012; Horn and Perona, 2017)
24. (Beery, Van Horn and Perona, 2018; Sethi et al., 2018)
25. (La Salle, Williams and Moritz, 2016)
26. (Huus et al., 2025)
27. (Reynolds et al., 2025)
28. (Whakatane, 2019)
29. (Danielsen, Burgess, Jensen and Pirhofer-Walzl, 2010)
30. (Jenkins, 2022)
31. (Kidangoor, 2024; Kyodo News, 2024; Sharon, 2024)

32. (Corlett, 2022; Sharon, 2024)
33. (A20Search, 2025)
34. (Speaker et al., 2022)
35. (Speaker et al., 2022)
36. (UNEP-WCMC, 2025)
37. (Díaz et al., 2019a)
38. (Amano, González-Varo and Sutherland, 2016; Meyer, Weigelt and Kreft, 2016)
39. (Seth, 2009; Ricaurte, 2019; Pritchard et al., 2022)
40. (Sterling et al., 2017a; Baker, Eichhorn and Griffiths, 2019; San Martín, 2021)
41. (Cole et al., 2023)
42. (UNESCAP, 2022)
43. (Raymond et al., 2017)
44. (Seddon et al., 2021)
45. (Chaplin-Kramer et al., 2023)
46. (Díaz et al., 2019b)
47. (Rintelen, Arida and Häuser, 2017)
48. (Navarro et al., 2017; Fletcher, 2019)
49. (San Martín, 2021; Baker, Eichhorn, and Griffiths, 2019)
50. (Biegajewski, 2023; Berenguer-Agullo et al., 2024)
51. (Dertien et al., 2023b)
52. (Beery, Van Horn and Perona, 2018; Wang et al., 2020)
53. (Elias et al., 2017; Arshad et al., 2020; Zualkernan et al., 2022)
54. (UNESCO, 2024)
55. (Amano, González-Varo and Sutherland, 2016)
56. (Speaker et al., 2022)
57. (Cole et al., 2023)
58. (AISM, 2025)
59. (De Klerk and Buchanan, 2017; WILDLABS, 2024)
60. (Rolf et al., 2024)
61. (UNDP, 2024b)
62. (UNDP, 2025c)
63. (Horn and Perona, 2017)
64. (Danielsen, Burgess, Jensen and Pirhofer-Walzl, 2010)
65. (Strubell, Ganesh and McCallum, 2019)
66. (Reed et al., 2009)
67. (Morand, Lajaunie and Satrawaha, 2018)
68. (Debnath, Tkachenko and Bhattacharyya, 2025)
69. (Christin, Hervet, and Lecomte, 2019; Tuia et al., 2022)
70. (Santos, Zaytseva and Serrano, 2025; UNDP, 2025c)
71. (Pollock et al., 2025)

72. (Chan, 2018; Reynolds et al., 2025)
73. (OECD, 2025b)
74. (Cash and Moser, 2000)
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76. (Powles and Nissenbaum, 2018)
77. (GPAI, 2025)
78. (Nobre and Nobre, 2019; Dasgupta, 2021; Nepa, Phoumin and Khatri, 2021; Klusak, 2023; Grabbe and Moffat, 2024)
79. (Mitchell et al., 2019)
80. (Armitage et al., 2020; Vignieri, 2023)
81. (Madiega, 2019; Carter, 2020; UNESCO, 2021)
82. (DeSantis et al., 2025; Freitas and Gouveia, 2025)
83. (Sajise, 2015)
84. (Burns et al., 2024)
85. (Alexander et al., 2019)
86. (Berumen et al., 2019)
87. (Roelfsema et al., 2018)
88. (Bennett et al., 2021)
89. (Berumen et al., 2019; Mills et al., 2023)
90. (Jupiter et al., 2017; Burns et al., 2024)
91. (Burt, 2024)
92. (Laurans et al., 2013)
93. (Hilmi et al., 2019)
94. (Sterling et al., 2017b)
95. (Villon et al., 2018; Alexander et al., 2019)
96. (IPBES, 2018)
97. (Davison et al., 1018)
98. (WWF, 2024)
99. (Lechner et al., 2024)
100. (Sumarga et al., 2023)
101. (Centre for Liveable Cities, Singapore, 2015)
102. (iNaturalist, 2025)
103. (Darajati, 2016)
104. (Lechner et al., 2024)
105. (Webb, Slik and Triono, 2010)
106. (CBD Secretariat, 2021)
107. (Tanahair, 2024)
108. (Tan, Lau and Ng, 2016)
109. (Diehl et al., 2020)
110. (Khoo and Chew, 2017)

111. (Sumarga et al., 2023)
112. (Lechner et al., 2024)
113. (MD Alwi, 2020)
114. (Rajappan et al., 1 AD)
115. (Turner et al., 1994)
116. (IPBES, 2018)
117. (Lechner et al., 2024)
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119. (NTCA, 2025)
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121. (van Helden, 2005)
122. (Morgera, Tsioumani and Buck, 2015)
123. (van Helden, 2005)
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126. (Choquez-Millan et al., 2024)
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PART 2

ECONOMY: IN SEARCH OF DIVIDENDS FOR GROWTH, JOBS, AND LIVELIHOODS

CHAPTER 5 — AI FOR PRODUCTIVITY AND EMPOWERMENT IN AGRICULTURE, HEALTH, EDUCATION, AND TRANSPORT

Iyad Rahwan, Max Planck Institute for Human Development, and Michael Muthukrishna, London School of Economics and Political Science

Artificial intelligence represents a new frontier for innovation and competitiveness. As with previous technological waves, however, it can either expand human potential or entrench existing hierarchies. Its impact will depend not on the algorithms themselves, but on how we deploy them, who they are designed to serve, and whether they advance the freedoms that underpin true human development. AI-driven solutions – from smart farming to virtual tutors – can empower individuals and communities. With the right policies and institutions, AI can expand people's capabilities: not only enabling them to be more productive, but also to learn and express themselves, and to be healthier and participate fully in their economies and societies.

History is punctuated by transformative technologies that changed our lives and rearranged global power. The steam engine sparked the Industrial Revolution, unleashing unprecedented productivity and altering global geopolitical dynamics. It led to what economic historians call the "Great Divergence", marked by the widening economic gap between industrializing nations and other regions in the 19th century, driven in large part by access to energy and the ability to convert that energy to productive work[1]. Later waves of innovation – electricity, oil, mechanization – added power to that productivity, remaking cities, societies, and economies, leading to an overall rise in human development.[2]

Among these shifts, the standardization of the shipping container in the 20th century deserves special mention for its unique impact on Asia and the Pacific. Before containerization, global trade was slow and expensive, with goods loaded and unloaded manually at each port. Once containers became the norm, the cost of shipping fell dramatically. Countries like China, Japan, Republic of Korea, and Malaysia with their lower manufacturing costs were poised to benefit from the removal of the friction in trade with the global markets. Efficient trade logistics underpinned export-led growth across East and South-East Asia, reshaping global value chains and lifting millions out of poverty. This illustrates how technological innovations, when coupled with the right policies and capacities, enabled parts of Asia and the Pacific to rapidly integrate into the world economy.[3]

The late 20th century brought the computing revolution and later the internet - transformations of information rather than industry. These digital technologies further shrank distances and lowered the cost of knowledge, creating new pathways for development. We now find ourselves at the cusp of another epochal shift: the era of Artificial Intelligence, and in particular Generative AI. Observers compare this moment to the arrival of the internet or even the steam engine in its potential scale of impact. But AI – especially Generative AI – is a qualitatively different kind of technology, one that offers new capabilities and affordances.

What is generative AI?

Generative artificial intelligence (GenAI)[4] refers to AI systems capable of creating new content - text, images, video, code, and more - that mimics the data on which they were trained. In essence, GenAI models learn the patterns of language, images, and more in the world from vast datasets, and can then produce novel outputs following those patterns. This goes beyond previous software tools that could only follow explicit instructions. GenAI can compose an essay or a poem, create a realistic image from a prompt, or carry on a conversation, exhibiting what experts call "emergent" capabilities.[5] This is for two reasons:

- First, in order to generate data that is similar to the training data, GenAI algorithms effectively need to learn the underlying (e.g. physical, cognitive, or social) processes that generated the original data. That is, the AI must learn a good model of the world,[6] approximating how the world (e.g. described in words, images or videos) evolves over time.

- Second, once the AI has learned a world model, the AI can be engineered to use this knowledge in new ways through a variety of techniques (such as fine-tuning on specific data, reinforcement learning from specific human preferences, or prompt engineering). That is, the AI can be further taught to generate more helpful, more factual or more original answers. It can be taught to generate suggestions that reflect contextual ethical values. It can be taught to generate more aesthetically appealing images or prompted to generate images in a particular artistic style, and so on.

In sum, so-called GenAI 'foundation models' contain extremely rich representations of all kinds of knowledge, and this knowledge can subsequently be adapted to all kinds of specific purposes.[7]

What sets GenAI apart, and makes it transformative, is its profound impact on cognitive work and creativity. Unlike earlier digital tools that helped us calculate or retrieve information, GenAI tools can reason, summarize, translate, simulate scenarios, draft content, and even invent new designs or solutions. In short, they do not just store and process information, they can autonomously generate new ideas and content. If traditional computers are like libraries – holding and indexing information – then GenAI is like having a creative assistant who can instantly read all the books and produce a tailored output for a given task. This represents a fundamental shift: many tasks once requiring human judgment or creativity can now be partly or fully automated. Such a shift carries immense promise and uncertainty – especially for the diverse countries of Asia and the Pacific.

GenAI has taken the world by storm. ChatGPT, a conversational AI (bot) offered by OpenAI, has been the fastest-growing computer application in history.[8] GenAI systems helped generate an artwork sold for $432,500 at the prestigious auction house Christies,[9] defeated world-class players in strategic games,[10] helped guide human intuition to discover new mathematical theorems,[11] and vastly improved the prediction of protein folding,[12] earning its creators the 2024 Nobel Prize in Chemistry.[13]

How could AI increase human development in Asia and the Pacific?

GenAI offers new capabilities and affordances, but just because AI can do something, doesn't mean that it is the best or cheaper option than current or alternative practices. The Asia-Pacific region is marked by enormous diversity in economic context, institutional capacity, and human development levels. Cutting-edge applications that make sense in Seoul or Singapore might not be viable or what is needed in Vientiane or Kalimantan. Wages, infrastructure reliability, and state capacity differ vastly: an AI solution that is cost-effective in a high-income city may not be the best option in a lower-income community with unreliable internet connectivity or electricity. Some parts of the region, like Republic of Korea and Singapore, are AI power houses, investing heavily in talent, research, and industry adoption. Other parts, like Kiribati, Afghanistan, or rural Nepal, struggle with basic connectivity and human capital gaps. Within countries, too, inequalities persist. Urban-rural divides are stark: a teenager in Bangkok or Kuala Lumpur may already be using AI-powered learning tools, while their rural peer in the same country lacks even stable internet. Women often have less access to digital tools and STEM opportunities than men, and many people with disabilities or linguistic minorities are overlooked by tech design. In short, if left purely to market forces, AI could easily mirror and magnify existing inequalities – concentrating benefits in well-connected hubs and among more privileged groups.

Yet, AI also represents a potential leapfrogging opportunity for developing countries. Just as cell phones allowed many nations to bypass the need for universal landlines, and solar panels now offer off-grid energy where power grids do not reach, AI could let countries skip certain developmental bottlenecks. For example, an acute shortage of doctors or teachers might be partly alleviated by AI-driven diagnostic tools or tutoring systems reaching remote areas. Weak administrative capacity could be strengthened by AI decision-support that improves targeting of social programs. These prospects are not automatic, however. Realizing them requires addressing affordability, skills, and infrastructure so that AI is usefully deployed in low-resource settings – and doing so in a way that doesn't simply entrench the advantages of a few. The central question is not just what AI can do, but what it should do in the Asia-Pacific context to maximize human development gains. In what sectors and tasks can AI deliver the biggest boost to productivity, inclusion, or service quality? Who stands to gain the most, and who might be left behind? And critically, what policies and investments are needed to ensure AI narrows gaps rather than widens them?

This chapter examines how AI is already affecting – and could radically reshape – innovation and competitiveness in Asia-Pacific economies, while also probing its impact on inequality. Our aim is to imagine what's possible, backed by emerging evidence, and to offer concrete policy guidance for steering AI toward a better trajectory for human development in the region. In doing so, we pay close attention to who benefits from AI-driven innovation, and how deliberate strategies can ensure that AI adoption enhances inclusive growth, builds local capacity, and expands human capabilities and freedoms – instead of entrenching existing disparities or creating risks of dependency.

Research questions and scope

Artificial Intelligence is a general-purpose technology and force multiplier across virtually all sectors.[14] Like electricity or the internet, it can embed itself into daily operations from agriculture to manufacturing, from education and healthcare to governance. This ubiquity means AI's impact will be pervasive. In this study, we focus on several central questions for the Asia-Pacific region:

1. *How can AI drive sector-specific innovation and economic development in the Asia-Pacific region?* Where are the opportunities to boost productivity or quality via AI, and in which sectors or industries are these opportunities most significant?

2. *Which domains offer the greatest potential for competitiveness gains through AI adoption — and for whom?* Are certain countries, communities, or groups positioned to gain more (or less) from AI-driven improvements in, say, farming, manufacturing, finance, or service delivery?

3. *How can governments, industries, and institutions shape AI deployment to reduce, rather than reinforce, inequalities?* What approaches can ensure that AI benefits marginalized groups (rural populations, women, small enterprises), instead of only well-resourced firms or urban elites?

4. *What policies can help developing countries leapfrog developmental bottlenecks through AI, and what safeguards are needed to prevent unintended harms?* Essentially, how can Asia-Pacific nations harness AI to overcome challenges like lack of doctors or teachers, while avoiding pitfalls such as data misuse, or misuse of technology for surveillance or control?

To address these questions, our analysis is organized around three thematic pillars that structure the discussion:

1. Sector-specific innovation and frontier technology adoption

First, we examine how AI is being applied in key sectors that are central to competitiveness and human development: agriculture, manufacturing, services (including finance), education, and healthcare. Each sector faces unique challenges and is beginning to experiment with frontier AI solutions. For instance, AI-enhanced crop monitoring in Bangladesh is helping smallholder farmers detect pests early, boosting yields and incomes. In Bhutan, AI-equipped mobile vans are bringing tuberculosis screening to remote villages, bridging healthcare access gaps. Fintech innovations are expanding credit access for unbanked communities, as seen with Bangladesh's mobile money platforms. These are not just theoretical promises – they are already happening in parts of the region, albeit unevenly. The same technology that improves outcomes in one context might less effective – or even exacerbate inequalities – in another, due to differences in infrastructure, literacy, or affordability. Thus, a core task is to identify where AI is working, under what conditions, and how to replicate successes more broadly.

2. Inequality and inclusion: AI across divides

Second, we analyze how AI intersects with existing divides – between countries, within countries, and between different demographic groups. AI does not emerge in a vacuum; it enters ecosystems already shaped by inequality, and it can easily widen those gaps. We consider multiple dimensions:

- *Geographical divides* – Urban centers in Asia and the Pacific (from Bangkok to Jakarta to Suva) often enjoy better connectivity, tech talent, and pilot projects, while rural areas lag behind in digital access. AI initiatives must confront this urban-rural gap – otherwise, they risk mainly benefiting city dwellers. For example, while a major city might use AI for smart traffic control, many villages still lack basic internet for an AI application in agriculture to even function.
- *Gender disparities* – Women in many Asia-Pacific countries are under-represented in STEM fields and have less access to digital tools. They also predominate in sectors vulnerable to AI-driven job disruption (e.g. routine clerical work, textiles, call centers). Without intentional design, AI could worsen gender inequality – whether by entrenching biases in algorithms or by automating jobs predominantly held by women. Yet AI could also be a lifeline in crisis-affected or restrictive environments, where online platforms (some using AI translation/tutoring) are one of the only avenues for women and girls to continue learning despite severe barriers to access.
- *Income and digital literacy* – Many AI applications assume a minimum threshold of access – a smartphone, an internet connection, basic literacy. In lower-income settings, these prerequisites are not a given. We explore how AI initiatives can be designed to include those at the margins (for example, delivering AI-driven advisories via simple feature phones or through community intermediaries), so that the benefits reach people without high-tech devices.
- *Inter-country gaps* - Regionally, there is a widening gulf between nations investing heavily in AI and those barely online. A handful of Asia-Pacific countries – notably China, Republic of Korea, Singapore, and Japan – are pouring resources into AI research, talent development, and infrastructure. Many others – e.g. Nepal, Cambodia, Papua New Guinea – are still working on basic digitalization. Without intervention, AI could drive a new kind of divergence: not between industrial and non-industrial economies, but between AI-empowered and AI-dependent countries. The former will shape the technology and reap most of the gains; the latter risk becoming mere consumers of foreign AI products, with little capacity to innovate or govern these tools. We consider strategies to prevent this, emphasizing regional cooperation and capacity-building to democratize AI benefits.

3. Leapfrogging or locking-in: strategic AI deployment in development contexts

Third, we look at AI from a development strategy perspective: can AI enable countries to leapfrog traditional development paths, or might it "lock in" new forms of dependency or exclusion? There is optimism that AI will allow countries to overcome long-standing hurdles – for example, AI tutors to compensate for teacher shortages, or diagnostic algorithms to reach patients in remote clinics. Indeed, we document cases where this is already starting. However, leapfrogging with AI is not automatic. It requires strategic investment in locally relevant AI solutions (not just importing tech from abroad), institutional capacity to deploy and regulate AI responsibly, inclusive data so that AI systems work for local populations (and do not ignore underrepresented groups), and regulatory foresight to avoid unintended consequences (like monopolies or IP barriers). Without these, there is a risk of "locking-in" patterns where local users rely heavily on external AI ecosystems, value from local data is not fully retained, or labor markets are disrupted before safety nets can adapt. Our research highlights not just where AI is being used in development, but where it could be used more effectively – and how proactive policy can ensure that AI becomes a tool for inclusive development and national technological learning, rather than a source of new vulnerabilities.

The research presented in this chapter highlights not just where AI is being used, but where it could be used more effectively — and how countries can avoid the "lock-in" of extractive models where local users become passive consumers of foreign AI systems.

By examining these pillars, this study aims to build an evidence-driven picture of AI's current and potential impacts on innovation and inequality in Asia and the Pacific. The next section (Thematic Analysis) groups findings by sector, diving deeper into concrete examples – from farms and factories to classrooms and clinics – to illustrate how AI-driven innovation is unfolding on the ground. Cross-cutting insights are then derived regarding the risks and downsides that must be managed. Finally, the report turns to policy implications and recommendations, proposing how stakeholders can maximize AI's benefits for competitiveness and human development while mitigating its pitfalls.

Thematic analysis

In this section, we present a sector-by-sector analysis of AI-driven innovation in Asia and the Pacific, highlighting both measurable gains in competitiveness and contributions to human development, as well as the risks and inequality concerns arising in each domain. The sectors covered are agriculture, manufacturing, services/finance, education, healthcare, and urban infrastructure, followed by a discussion of cross-cutting risks. Each sector analysis first outlines recent precursor projects (pilots or early deployments that signal the potential of AI in that field), then discusses emerging opportunities on the horizon, and notes any evidence of inequality impacts or inclusion efforts.

Agriculture

PRECURSORS

Agriculture remains a livelihood backbone for much of Asia and the Pacific, and there is growing recognition of AI's potential to transform this sector – from boosting yields and reducing input waste, to making farming more climate-resilient. Many current efforts are still pilots or small-scale, but they point to what is possible.

- *Bhutan* – a team of young innovators developed an AI-powered mobile app for crop disease monitoring that won a regional innovation award in 2024.[16] Farmers can snap photos of their plant leaves with a smartphone; the app's AI model instantly identifies pests or diseases and suggests treatments, putting expert knowledge directly into farmers' hands. Such a tool can be transformative in rural communities where agricultural support services are not readily available.
- *Bangladesh* – A consortium is piloting the "Groundnut Integrated Pest Management (IPM)" app. Using image recognition, this app diagnoses peanut crop pests from a farmer's photo and recommends specific management steps, even linking farmers to nearby suppliers of appropriate pesticide or fertilizer. Early results are promising: by integrating GPS and weather data, the system gives context-specific advice and has the potential to help thousands of smallholders avert crop losses. A pilot would target 1,000 farmers across two districts.[17] These kinds of AI-driven advisory apps – also being tested for rice, wheat, and other crops – effectively bring precision agriculture to small farms.

- *Thailand* – Several countries are leveraging AI beyond crop pest management. Thailand, for instance, is actively promoting "AgriTech" solutions; its AI-in-agriculture market was valued at around $80 million in 2023 and is projected to reach $114 million by 2029.[18] The National Electronics and Computer Technology center (NECTEC) has developed HandySense B-Farm, an AI+IoT platform that provides farmers with real-time data on weather, soil moisture, and seedling health to optimize farming decisions. This platform exemplifies how partnerships can bring advanced tools to farmers.[19]

- *China* – Meanwhile, China has gone even further in integrating AI with farming. The Chinese government has set up dozens of unmanned pilot agriculture zones – testing autonomous tractors, drone crop dusters, and AI systems that can monitor and manage large farms with minimal human labor. Chinese agri-tech startups have rolled out platforms like Nongpinhui, which uses AI to balance supply and demand in produce markets, reportedly facilitating over 200,000 transactions and generating more than ¥5.9 billion (≈$800 million) in farmer income by intelligently connecting growers with buyers. Even in livestock, AI is making inroads: "smart" pig farms in China equipped with automated feeding, climate control, and AI health monitoring have dramatically scaled up productivity – one case saw pig-rearing capacity jump tenfold (from roughly 500 to 5,000 animals) with feeding costs cut by 20 percent after AI systems were introduced.[20]

- *Viet Nam and Bangladesh* – AI is also being applied to aquaculture and fisheries, crucial industries for many Asia-Pacific economies. World Bank-backed projects use AI and sensors to monitor fish health (for example, detecting early signs of disease in ponds) and to optimize feeding schedules, which has improved yields and resource efficiency.[21]

- *Kiribati* – In the Pacific Islands, where vast ocean territories make monitoring challenging, AI is aiding enforcement against illegal fishing. Kiribati has piloted the analysis of satellite data to detect suspicious vessel movements in its exclusive economic zone.[22] This contributed to a successful enforcement action with a $1-million fine for illegal fishing[23] – supporting enforcement efforts in a small island nation with limited patrol capacity. Similarly, initiatives like FishGuard deploy affordable AI-guided drones and machine-vision systems to help governments of Small Island Developing States survey their waters.[24] These examples illustrate AI's potential to strengthen resource management and governance in agriculture and fisheries, even for countries with constrained human resources.

- *Nepal* – a 2024 initiative showcases how AI can empower marginalized groups in agriculture. Heifer International and a local AI group launched the AI for Women Farmers Challenge, focusing on rural women-led cooperatives.[25] One project uses AI-based optical character recognition to digitize handwritten farm ledgers and financial records. By turning paper records into analyzable data, these women farmers can access insights on their operations, improve their financial planning, and even build credit histories to approach formal lenders. This kind of innovation addresses a common issue in developing contexts – fragmented, manual data – and shows how AI can support financial inclusion and better decision-making at the grassroots level.

Across these cases, from Bhutan's disease-detection app to Nepal's smart farms – we see local experiments turning into real results. They remain modest in scale today, but they paint a picture of what could soon be commonplace. Notably, they also highlight inequities. Most AI-agriculture projects are still in pilot stages or in relatively wealthier locales; the poorest and most remote farmers often lack smartphones, reliable connectivity, or even awareness of these tools. In some areas, digital literacy is a barrier – an app is only useful if farmers can navigate it and trust its advice. These challenges temper the successes and underscore that without deliberate inclusion efforts (such as training programs or providing analogue interfaces like radio/SMS outputs), AI could bypass those who arguably need it most.

OPPORTUNITIES

Despite the hurdles, the trajectory for AI in agriculture over the next decade is very promising – and potentially transformative for rural areas in Asia and the Pacific. Generative AI and foundation models are lowering the cost and skill barrier for developing new, localized applications. It is becoming feasible for a small team to build an AI that understands a niche crop or a minority language, which means local agricultural knowledge can be scaled out faster and cheaper than before. We anticipate that the first breakthrough applications in this domain will be AI-driven decision- support systems for farmers. Imagine a single application that a farmer can speak to in their own dialect: the farmer could ask why her rice leaves are turning brown, snap a photo of the field, and the AI – now capable of processing images and text multilingually – would diagnose the likely problem (say, a fungal disease) and suggest remedies, all in simple terms. Thanks to advances in multimodal AI, such a tool can combine capabilities (vision, speech, language) and does not require massive local data to be effective, because it builds on global foundation models. This drastically lowers the development time for niche solutions, meaning even less-popular crops or small language groups could get customized AI support.

Within 5–10 years, AI could help unlock a shift toward climate-smart, highly productive agriculture in Asia and the Pacific. One opportunity is AI-augmented crop breeding – analyzing genomic and environmental data to develop crop varieties that are more nutritious and climate-resilient. This could strengthen food security in the face of climate change. Another is the convergence of AI with robotics: affordable, autonomous farm machinery (for planting, weeding, harvesting) guided by AI could address labor shortages in aging rural communities and improve precision. For this to work, it has to be affordable relative to local labor and easily maintained given local skills and material availability. Nevertheless, we are already seeing policy support in this direction. For example, India is advancing public digital infrastructure for agriculture[26] and public-private "AI for Agriculture" partnerships to encourage data-driven farming.[27] Similarly, agricultural sectors in China are using cloud-based AI systems to remotely monitor crop trials and speed up breeding cycles.[28] As governments invest in these enabling systems, the economics of farming could change – AI can help farmers do more with less land, less water, and fewer chemicals, which is crucial for sustainable growth.

AI can also enhance government planning and resource allocation in the agricultural sector.

- *Viet Nam* – The coffee sector is experimenting with satellite imagery and AI (the "Coffee Vision" project[29]) to map deforestation and climate risks in coffee-growing regions. The system generates geospatial data to inform where interventions are needed, and such an approach could be extended to other crops and countries.

In the Pacific, where climate change threatens fisheries and agriculture, AI-based models for climate forecasting and land-use planning could help leaders make proactive decisions (e.g. identifying which areas will remain arable, where to invest in irrigation or flood defenses).

A particularly exciting medium-term development is the use of digital twins in agriculture. Some Asia-Pacific researchers are creating digital replicas of farms or even entire agricultural zones to simulate different scenarios.

As computing power becomes cheaper, more countries could deploy such virtual modelling to support their farmers – testing, for instance, how altering planting dates or fertilizer application might affect yields under various weather patterns, all in a simulated environment.

In the fisheries domain, the next few years may bring AI-enhanced local fishing advisories. By combining satellite data, oceanographic models, and historical fish catch data, AI can forecast where fish shoals are likely to be on a given day. This information delivered via mobile phone can help small-scale fishers in countries like Indonesia, the Philippines, or Fiji to reduce fuel wasted searching for fish, improve their catch efficiency, and avoid overfished areas.

These innovations – from high-level monitoring systems to on-the-ground advisory apps – could significantly boost resilience and productivity for both subsistence and commercial farmers/fishers, if they can be scaled and made accessible.

In sum, if these advances materialize, the impact on human development could be substantial. Higher and steadier crop outputs mean better farmer incomes and improved nutrition; AI-optimized use of water and fertilizer supports environmental sustainability; and critically, the knowledge gap between large agribusinesses and smallholders could narrow, promoting greater equity in rural areas. The major challenge will be ensuring inclusivity – that even small farmers with limited means can access and trust these AI tools. Solutions like Bhutan's approach (having local agriculture extension centers use the AI app on behalf of farmers without smartphones) will be important. So will investments in rural connectivity and digital literacy. With enabling policies, AI-driven agricultural innovation could herald a new green revolution across Asia and the Pacific – one focused not just on yield, but on sustainable, inclusive growth in the countryside.

Manufacturing and Industry

PRECURSORS

Manufacturing has long been the engine of economic growth in the Asia-Pacific region, from the textile factories of South Asia to the high-tech electronics plants of East Asia. Today, AI is beginning to transform manufacturing processes through automation, intelligent quality control, and supply-chain optimization. However, there is a marked disparity: advanced economies and larger emerging economies are rapidly adopting cutting-edge practices, while lower-income manufacturing hubs risk falling behind.

- *The Republic of Korea* – The country is a global leader in industrial automation – it has the world's highest density of industrial robots, over 1,000 robots per 10,000 workers.[30] Korean conglomerates across automotive, electronics, and chemicals are investing in AI-driven predictive maintenance systems and autonomous production lines. The Government is actively supporting this through initiatives like the AI Autonomous Manufacturing Pilot Project. In late 2024, the Ministry of Trade, industry and Energy (MOTIE) announced 26 AI Autonomous Manufacturing pilot projects with private companies, expected to increase to 200 by 2027.[31] This reflects a national strategy to maintain competitiveness by pushing the productivity frontier. These investments are yielding results in efficiency and consistency of output, and they are helping some firms move up the value chain from low-cost labor-based production to more sophisticated, higher-value manufacturing.
- *Thailand* – In middle-income countries, certain industries are also moving toward AI-enhanced manufacturing. Examples include Thai electronics firms using AI for predictive maintenance – sensors on machinery feeding data to machine-learning models that predict failures before they happen, thus reducing downtime.[32]
- *Malaysia* – In Malaysia's automotive parts plants, AI-powered computer vision is used for quality control, with cameras that automatically detect defects faster and more consistently than manual inspection.[33]
- *India* – Aan Industry 4.0 strategy through the National Association of Software and Service Companies (NASSCOM), has projected that AI and related digital tech could account for 40 percent of all manufacturing spending by 2025 (up from 20 percent in 2021). This signals that even labor-abundant countries see value in AI automation not just as labor saving, but for accuracy and quality assurance. Some Indian textile factories, for instance, are piloting AI-driven fabric inspection systems that use high-speed cameras and neural networks to find weaving flaws in real time, preventing defective rolls from progressing downstream.[34 35]

- *Indonesia* – In Indonesia, large manufacturers — especially in oil and petrochemicals — are partnering with multinational tech providers to introduce AI for process optimization.[36]
- *Bangladesh* – In Bangladesh's garment factories – which employ millions, predominantly women – trials are underway on a limited scale: e.g. using AI for production planning (to optimize line balancing and reduce idle time).[37]

The implications for inequality are large. Within countries, as factories automate, there is a concern for the workers – often less-skilled – whose jobs may be eliminated. Without robust retraining and social protection, this could worsen unemployment or push workers into informal jobs. Between countries, there is a risk of a new divide: an "automation gap" where countries that can afford and deploy AI in industry surge ahead in productivity, while late adopters lose out on investments and orders. For example, if Viet Nam's factories embrace AI and IoT quickly (and Viet Nam is investing in smart manufacturing in its electronics sector),[38] they might attract more foreign direct investment compared to a slower-adapting economies. A new Great Divergence and competition for effective use of AI is underway and will reshuffle the Asia-Pacific region.

OPPORTUNITIES

In the short term, AI offers "low-hanging fruit" to many manufacturers in Asia and the Pacific: predictive maintenance, energy management, and supply chain optimization. These are applications that usually pay for themselves by reducing costs. AI-driven maintenance systems can extend the life of expensive machinery by predicting failures – something particularly valuable in places where capital is costly and equipment downtime is disruptive. Even mid-sized factories can install IoT sensors and use cloud-based AI services to start seeing benefits without huge upfront investment. Governments and industry bodies could accelerate this by setting up shared AI demonstration centers or subsidized programs for factories (some countries are doing this – e.g. Singapore's model factories, or India's AI hubs for SMEs). Such moves would help small and medium manufacturers adopt AI, not just the big multinationals.

Another immediate opportunity is in quality control and process optimization. AI computer vision systems can drastically improve defect detection rates in industries like electronics, apparel, or food processing. By deploying AI, the company cut rework costs and improved customer satisfaction. Multiply such gains across thousands of factories in Asia, and the aggregate competitiveness gains are substantial. Additionally, AI can potentially optimize supply chain logistics – predicting demand surges, managing inventory, and routing shipments efficiently.

Over a 5–10 year horizon, we may see a more profound AI-driven transformation of manufacturing in the region. One prospect is the rise of fully smart factories: highly automated facilities that leverage AI at every step, from design to delivery. In such factories, AI could autonomously adjust production in real time in response to market data (for example, ramping up certain products if online trends show a spike in demand). Generative design AI might create optimized product designs or factory layouts that humans then implement – already companies are using AI to design lighter car parts and more efficient circuit boards that a human engineer might not conceive of. Asia-Pacific's advanced economies are likely to pioneer these approaches, but importantly, they could spread to emerging economies via multinational networks. For example, if a global apparel brand implements an AI-driven design-to-manufacture system, its supplier factories in Bangladesh or Cambodia might be integrated into that system, thus indirectly adopting AI even if they aren't leading it. This could help with global value chain participation, ensuring developing Asian manufacturers remain part of high-tech supply chains rather than being bypassed by automation in rich countries.

Another medium-term development is AI-driven mass customization. Asia has long been the workshop of the world for mass production. AI can enable a shift to mass customization – producing smaller batches of highly customized products efficiently. This could open new markets and business models for manufacturers in the region. Imagine local factories using AI to produce custom-fit clothing or personalized electronics on demand for individual consumers worldwide. Already, some Chinese manufacturers use AI to rapidly switch production lines to new designs based on real-time e-commerce data. By 2030, this trend could allow even smaller countries' industries to tap into global niches, provided they invest in flexible manufacturing systems guided by AI.

From a development perspective, it will be crucial that the productivity gains from AI in manufacturing translate into broader societal benefits (higher wages, more jobs in complementary roles, cheaper goods for consumers) rather than just higher profits or a concentration of wealth. This will require policies to retrain workers for new roles (such as robot maintenance, AI system supervision, or more creative tasks in the production process). Countries like Republic of Korea are already proactive on this: the country's national AI strategy includes worker training and even re-thinking education to prepare the next generation for AI-augmented workplaces. Middle-income countries will need to adapt quickly to avoid a skills gap.

Finally, AI adoption in manufacturing should be seen not only as an economic necessity but as an opportunity for greener industry. AI can significantly improve energy efficiency in factories – for instance, by intelligently controlling heating, ventilation, and air conditioning systems or optimizing the operation of energy-intensive equipment during off-peak hours. It can also reduce material waste by catching defects early or optimizing cutting patterns in textiles. For Asia-Pacific countries balancing industrial growth with climate commitments, these AI applications will be valuable for sustainable industrialization (contributing to SDG 9 and SDG 13). We might see governments incentivize AI for green manufacturing through subsidies or carbon credit schemes.

In summary, AI is set to redefine manufacturing competitiveness in Asia and the Pacific. Those who move quickly to integrate AI will likely gain productivity and quality advantages, attract investment, and climb up the value chain. Delayed adoption may lead to reduced industrial competitiveness and labor market challenges. The upside scenario is one where AI-augmented manufacturing leads to better jobs (more high-skilled positions managing automated systems), safer workplaces (robots taking over dangerous tasks), and more innovation (AI-designed products). The downside is significant job displacement and a widening tech gap between firms and countries. Managing this transition with foresight – through training, phased adoption, and social dialogue – will determine whether AI in industry becomes a story of shared prosperity or one of deeper inequality.

Services and Finance

PRECURSORS

The services sector, including finance, has been a major driver of growth in many Asia-Pacific economies. Here, AI is making inroads through fintech innovations, e-government services, retail and customer service enhancements, and more. A standout area is financial services – where AI can help expand inclusion and efficiency. For example, in Mongolia and Bangladesh, banks and fintech startups are deploying AI-based alternative credit scoring to reach people with little or no formal credit history.

- *Mongolia* – In Mongolia, fintech innovators have developed an AI-driven credit scoring system that analyzes alternative data to instantly assess loan applicants. Since launch, LendMN has disbursed over $70 million in micro-loans to nearly 4,000 businesses, many of which previously lacked access to credit.[39]
- *Bangladesh* – Several banks have rolled out similar AI credit analytics. One program notably allocated over 30 percent of its new micro-loans to women

borrowers – actively countering gender bias in lending by using non-traditional data points that do not penalize women's lack of collateral or formal employment. These efforts illustrate AI's role in empowering marginalized groups (women, rural entrepreneurs) by looking beyond conventional metrics and expanding financial inclusion.

- *China* – Payments and e-commerce are also being transformed. China's digital finance giants, like Ant Group's Alipay and Tencent's WeChat Pay, use AI algorithms to analyze users' purchase behavior and bill payment history, thereby offering small loans or "buy now, pay later" services to customers who never had formal credit cards. These platforms also rely on AI-powered fraud detection to monitor millions of daily transactions and have sharply reduced fraud losses, boosting public confidence in digital finance.
- *Brunei Darussalam* – Meanwhile, smaller economies are innovating in their own niches. In Brunei Darussalam, an app called BloodKad applies AI and mobile tech not to finance per se, but to social services – it matches blood donors to hospitals in need, using AI to optimize the donor–recipient matching and timing.[40] This example shows how local startups are leveraging digital platforms (with AI algorithms) to solve community problems, supported by an emerging fintech ecosystem.
- *Bhutan* – The Bank of Bhutan has launched BoB Loan, a digital lending portal where AI algorithms approve small loans without requiring a branch visit.[41] This dramatically improves access for people in remote areas of Bhutan's mountainous terrain, who previously might have had to travel hours to a bank.

Across these examples, the common theme is streamlining processes and reducing barriers: AI In Viet Nam's Mekong Delta, is cutting paperwork, removing the need for collateral by using new data, and speeding up decisions – thereby widening participation in the formal economy. The human development benefits are clear: more people can save, borrow, invest, or insure themselves, which supports poverty reduction and entrepreneurship, and small businesses find it easier to get capital, spurring inclusive growth. A notable application in finance is fraud detection and security.

- *Thailand* – Take Thailand's Krungthai Card (KTC), a major credit card issuer which has integrated AI to detect fraudulent transactions in real-time. The result has been exceeding their fraud detection targets by 85 percent, and improving detection of certain scams by 1.5× (detection rate jumped from 33 to 50 percent). The AI models analyze transactional patterns and customer behavior, flagging anomalies (like an unusual location or spending spree).[42] By catching fraud faster, banks reduce losses and increase trust in digital banking – which is crucial for convincing users to adopt cashless services. Many banks in the region are following suit, using machine learning to monitor everything from credit card usage to online banking logins for suspicious activity. Policymakers are beginning to catch up with these innovations.

Beyond fintech, AI is also permeating other service areas. In health insurance, for instance, companies use AI to detect fraudulent claims and to personalize premiums. In customer service, AI chatbots are handling routine inquiries for telecom providers, utilities, and retail companies across Asia, improving response times and freeing human agents for complex cases.

- *Malaysia* – For example, Malaysia's national electricity company has introduced an AI chatbot that handles billing inquiries 24/7, resulting in higher customer satisfaction and lower call-center loads.[43]

Crucially, many of these innovations in services carry an inclusion dimension. For instance, conversational AI that supports multiple languages is helping extend services to linguistic minorities.

- *Indonesia* – An example is Indonesia's online marketplaces using AI chatbots that understand Javanese or Sundanese, not just Bahasa Indonesia, thereby enabling rural users to comfortably engage in e-commerce in their mother tongue. This reduces language barriers in accessing services.[44]

OPPORTUNITIES

In the near term (next two to three years), AI could further democratize finance and commerce across Asia and the Pacific. A key opportunity is mainstreaming AI-driven credit for the unbanked. Many countries are on the cusp of adopting regulations to allow alternative-data credit scoring at scale; considerations around risks and biases will be critical to ensure application is truly inclusive (see chapter 4 for a more detailed discussion). For example, Bangladesh Bank's new guidelines for credit bureaus include the use of using AI and non-traditional data to assess creditworthiness.[45] This could inform related approaches in other contexts, enabling partnerships with tech firms on AI models that consider utility payments, mobile top-up patterns, and even social media data to score "credit-invisible" customers. The impact could be millions of new borrowers – farmers able to get small loans for better seeds, women entrepreneurs financing home businesses, etc. These models can be more inclusive than traditional ones. As noted, Bangladesh's AI-based system significantly increased loans to women. We expect similar outcomes in less gender-equal societies where women lack formal credit histories – AI can help bypass biased legacy metrics.

Another imminent development is the rise of AI virtual assistants in banking and financial literacy. We already see chatbots in banking apps, but the next generation will be more advanced "financial coaches." Imagine an AI assistant on a smartphone that speaks Nepali or Vietnamese, which can guide a user through budgeting, alert them if their spending on, say, mobile data is unusually high this month, or advise them on choosing a micro-insurance product. In countries where bank branch networks are sparse, such AI assistants can essentially provide personalized financial advice to people who've never had access to a human financial advisor. This improves financial literacy and planning, contributing to household empowerment. There is also potential for AI to streamline government-to-person payments (like social welfare transfers) by automating identity verification and reducing leakage – something a few Indian states are testing with AI facial recognition for pension disbursements (though this raises privacy issues to monitor).

E-commerce will also get a boost. In the short term, small merchants can use AI tools for tasks like demand forecasting and inventory management, which were once the domain of big companies. For example, a family shop on India's Flipkart platform could use an AI plugin to predict next month's popular products and plan stock accordingly. This can increase their sales and reduce waste from unsold inventory. On the consumer side, AI-powered translation and localization will make cross-border online shopping easier. A shopper in rural Lao PDR might browse a Malaysian or Korean e-commerce site and see product descriptions automatically translated into Lao, with prices converted to Kip in real-time. By removing language and currency barriers, AI can open up regional markets to consumers and sellers who previously stuck to local channels. This contributes to regional integration and gives consumers more choice (often at better prices). It is also a way for small businesses to reach international customers without needing specialized expertise.

Security will remain a parallel focus – as digital transactions grow, so do cyber risks. We expect a surge in AI-based cybersecurity for financial services. AI systems can detect anomalies in network traffic or login patterns far faster than human IT teams, helping to block phishing or hacking attempts proactively. This is crucial for maintaining trust in digital finance, especially among first-time users who may be wary of fraud. If people trust that their mobile wallet or online bank is safe (because, say, the app warns them "this transaction looks suspicious – are you sure?" thanks to AI), they are more likely to embrace cashless finance. Countries like Singapore are already investing in AI cybersecurity at the national level, and those tools can be shared or adapted region-wide.

Over a five-to-ten year span, AI could truly revolutionize financial services and commerce, driving inclusion in ways that directly advance development goals. One medium-term prospect is the emergence of AI-driven "financial health" platforms. Instead of siloed services (separate apps for budgeting, loans, insurance), we might see integrated super-apps that use AI to holistically manage an individual's financial life. By 2030, for example, an app could automatically allocate a user's income each month: it pays their utility bills on time, sets aside some savings based on their goals (e.g. education fund for a child), invests a portion into micro-investments or bonds, and offers affordable micro-insurance, all customized by AI to that person's needs and risk profile. This kind of "autopilot" for personal finance could improve household financial stability and resilience – especially for lower-income users who struggle to plan for emergencies or navigate complex financial options. It essentially gives them a virtual financial advisor and money manager in their pocket.

For small and medium enterprises (SMEs), which form the backbone of many Asia-Pacific economies, AI could help close the persistent financing gap. Banks often hesitate to lend to SMEs due to perceived risks and lack of data. But AI can analyze granular business data (point-of-sale records, supplier transactions, even social media reviews) to better assess SME creditworthiness. China's MYBank (an Ant Group offshoot) has already used AI to extend credit to over 20 million SMEs – often approving loans in minutes using algorithms.[47] By 2030, we expect such models to be adapted across Asia and the Pacific, enabling tens of millions more SMEs – from a handicraft cooperative in Fiji to a parts manufacturer in Viet Nam – to access the credit they need for growth. This would fuel job creation and innovation at the grassroots, contributing to dynamic and inclusive economies.

Cross-border payments and remittances (hugely important in Asia and the Pacific, which has many migrant workers sending money home) could become much cheaper and faster with AI. AI can optimize currency exchange timing and routing of payments. Already, Ant Group's Alipay+ connects hundreds of millions of users across Asian digital wallet platforms; by using AI to predict forex rates and net settlements across these networks, opportunities exist to reduce remittance transaction costs. Cheaper remittances mean more money reaches families for spending on health and education. By five-to-ten years, we might see near-real-time AI-optimized remittance corridors across Asia, benefiting countries like the Philippines, Nepal, and Pakistan that rely on remittance income.

Looking further, the medium-term vision is that digital finance becomes so ubiquitous and user-friendly that even a street vendor in a remote village can use a suite of financial tools on her phone for all her needs – payments, savings, credit, insurance. Achieving this will directly support multiple SDGs: reducing poverty, enabling business growth, promoting gender equality (since women often benefit greatly from financial inclusion), and fostering innovation. The caveat is that regulators will need to keep up. Issues of data privacy, algorithmic bias (e.g. if an AI unintentionally redlines a neighborhood), and competition (ensuring big-tech platforms do not monopolize markets) will need active oversight. Encouragingly, some Asia-Pacific regulators are exploring RegTech and SupTech – using AI themselves to monitor financial markets and detect risky behaviors or biases in algorithms.[48] For instance, future regulators might use AI to simulate and catch a lending algorithm that consistently offers worse terms to women or minorities and mandate fixes.

In summary, AI's infusion into services and finance holds tremendous promise for inclusive development. It can extend the reach of financial systems to those historically excluded, provide personalized services that improve quality of life, and make markets more efficient. The region is already seeing glimmers of this, and with sensible policies (around interoperability, consumer protection, and innovation sandboxes), Asia and the Pacific could leapfrog to a scenario where a farmer's daughter in a remote village can access a loan for university, get insurance via her phone, start an online business, and even invest small savings – all enabled by AI-driven platforms. That vision, if realized, means more equitable growth and empowerment across society.

Education

PRECURSORS

Education is a sector with arguably the most direct long-term impact on human development and competitiveness. AI in education (often dubbed "EdTech") is quickly spreading around the world and Asia and the Pacific is no exception.

- *Bhutan* – Aan EdTech pilot integrating a Finnish AI-driven, math-learning platform (called Eduten) into primary schools showed impressive results. Over a 10-week trial with nearly 1,000 fifth-grade students, those using the AI-assisted system improved their numeracy scores by 11 percentage points more than control groups. Teachers reported that the platform's gamified exercises kept students engaged and that its AI analytics provided real-time feedback and helped tailor difficulty to each student's level. Off the success of this pilot – supported by Bhutan's Ministry of Education and UNICEF – Bhutan is now scaling the AI-enhanced math program nationwide for Grade 5. This shows that even a lower-middle-income country with limited connectivity can adopt cutting-edge AI tools in classrooms with the right partnerships and training.[49]
- *Afghanistan* – In a very different context, in Afghanistan, we see how technology can provide lifelines where traditional systems face disruptions. For instance, where access to formal education is suspended, digital platforms can serve as critical avenues for continued learning. In response, thousands of Afghan women turned to online learning platforms.[50] While these platforms aren't government-run (they include international MOOCs and NGO initiatives), they demonstrate AI's potential role: e.g. automatic translation tools can enable an Afghan student to take an online course in a foreign language, or AI tutors can be available on messaging apps to answer questions. Despite infrastructure challenges (patchy internet, electricity issues, and more recent additional restrictions to internet access), this phenomenon exemplifies resilience through technology – and underscores how crucial inclusive digital access is for education equality.
- *Republic of Korea* – On the higher-income end, Republic of Korea is pioneering a national rollout of AI-powered digital textbooks. Korean schools have introduced AI-enhanced textbooks in subjects like English and math for certain grades.[51] These e-textbooks use AI to adjust content difficulty to each learner's pace, and they provide teachers with data-driven insights (dashboards) on student progress. The goal is to personalize learning at scale – something that traditional one-size textbooks cannot do. The Government's plan was to expand these AI textbooks to all grades by 2028, potentially benefiting millions of students. Early trials indicated improved engagement and learning outcomes, and importantly, the initiative is accompanied by guidelines on safe and age-appropriate AI use in schools (including drafting rules to address privacy and bias issues in EdTech). While this program was discontinued following stakeholder feedback, the potential for interactive textbooks remains.[52]
- *Malaysia* – Malaysia has launched an initiative called AI untuk Rakyat ("AI for the People")[53], which offers free AI literacy courses in multiple local languages to both civil servants and the public. This program, part of Malaysia's digital inclusion strategy, explicitly targets underserved and rural populations to ensure they are not left behind in the AI era. By improving basic AI awareness and skills across society, Malaysia aims to foster a more equitable digital economy. This is an example of a government proactively trying to narrow the coming knowledge gap by treating AI literacy as a public good.

- *Pakistan* – Initiatives to reach marginalized groups are also emerging. Pakistan, for example, in partnership with UNESCO, set up "Smart Classrooms" in 40 girls' schools in remote areas.[54] These classrooms are equipped with AI-powered interactive learning tools (like adaptive quizzes and educational games) aimed at boosting engagement and retention for girls who face barriers to schooling. Early reports suggest improved attendance and a sense of empowerment among students. Such initiatives align AI deployments with human development goals – here, gender parity in education (SDG 4 and SDG 5).

Across these diverse examples – Bhutan's primary schools, Korean smart textbooks, Pakistan's girls' classrooms – there is a common pattern: AI has potential to personalize learning, reach marginalized learners, and support teachers in ways previously not possible. At the same time, these initial efforts are quite modest relative to need. They also face common challenges such as patchy infrastructure (devices, electricity, internet), teacher shortages, workload and buy-in, and content localization. In many places, introducing fancy AI tools without strengthening basic systems can even backfire as the failed One Laptop per Child program illustrated,[55] where without tech and maintenance support, localization, teacher training, and curriculum support, laptops were used for games, broke down, or gathered dust.

OPPORTUNITIES

In the immediate future, there are some "low-hanging fruit" uses of AI that could substantially improve education delivery and equity in Asia and the Pacific. One is language translation at scale. AI can now translate text and even speech between dozens of languages with reasonable accuracy. This could enable students to access a much larger corpus of educational materials in their mother tongue, including minority and indigenous languages. For example, an AI could translate math or science content from English into Bislama or Tagalog instantly, and even read it out via speech synthesis for the blind. Students from linguistic minority communities – whether indigenous peoples in South Asia or remote Pacific islanders – could receive quality learning resources in their first language as the list of machine translatable languages grows. Commercial publishers and governments could collaborate to use AI translation to produce textbooks and videos in multiple local languages quickly, at low cost. This would be a step toward inclusive education, preserving linguistic diversity while expanding access (and also represents a market opportunity for content providers).

Another short-term opportunity is the rise of AI tutors. With multilingual generative AI models becoming available, we can expect more AI-powered tutoring platforms accessible via smartphone. Imagine a student in a remote village who has no access to after-school tuition: an AI tutor app could help answer their questions, explain concepts in different ways until the student understands, and provide practice problems tailored to their level. Importantly, such AI tutors can operate 24/7 and do not get tired or frustrated. Early versions exist (like Khanmigo, an AI tutor developed by Khan Academy in partnership with OpenAI), which can create lesson plans in minutes and give learners step-by-step hints instead of outright answers. AI has the potential to undermine learning or create dependence, but as we learn what works, it could have an overall positive effect.[56] A human-centered approach to AI in education, where AI augments teachers rather than replacing them is likely to be a more effective approach. For Asia and the Pacific, this could mean that community volunteers or less-qualified teachers in remote areas could deliver better education outcomes with AI support.

In the next few years, we'll also likely see AI helping with teacher workloads – automating administrative tasks like grading multiple-choice tests or summarizing student performance. For example, an AI may instantly grade quizzes and even provide analysis like "Topic X needs reinforcement, 40 percent of the class missed question 5." This frees teachers' time to focus on lesson planning or individual student support. Some schools in Japan and Singapore are already testing AI-assisted grading and analytics. If scaled, this could be particularly helpful in countries where teachers are few and stretched thin – AI may act as a force multiplier for the teaching force.

Another area is inclusive education for learners with disabilities. AI can generate real-time captions or sign language interpretations for deaf students (through computer vision that outputs sign language from speech, for example) or convert text to audio in local languages for visually impaired students. These technologies exist and could be implemented in classrooms with proper equipment, facilitating better access to regular curricula – an often overlooked aspect of inequality.

Overall, in the next two-to-three years, AI is poised to make learning more engaging and tailored, potentially contributing significantly to SDG 4 (Quality Education for All). By enabling personalized support at scale, AI tools can help students from various backgrounds catch up or excel at their own pace, which in turn can reduce learning gaps between rich and poor, urban and rural. As AI spreads into classrooms, governance will be key to ensure it is used ethically and equitably.

- *Japan* – We can draw lessons from early movers: Japan's MEXT has issued national guidelines (Ver. 2.0, Apr. 2025) for using generative AI in primary and secondary education, emphasizing human centered use and strengthened information literacy.[57] Japan's draft guidelines stress transparency in AI use (students should know when they're interacting with AI), age-appropriate content filtering, and teacher training to use AI properly. Similar frameworks may emerge in other economies, possibly informed by UNESCO or other international organizations, so that AI in education enhances learning without causing harm or deepening divides (such as a divide between well-resourced schools that can afford AI and those that cannot).

Looking at the 5–10 year horizon, AI could catalyze more profound, systemic changes in education across the Asia-Pacific region. The integration of AI tools into classrooms may become increasingly prevalent. By 2030, a typical classroom might have a teacher with an army of AI teaching assistants, supplementing lessons, monitoring each student's understanding in real time, and offering highly personalized learning pathways. If AI can reduce teachers' workloads, it would also allow them to spend more time on the human side of teaching, such as mentorship, encouragement, and one-on-one instruction for those who most need it.

Another medium-term shift will be in lifelong learning and workforce upskilling. As technology evolves, workers will need continuous training. AI can provide on-demand, personalized training modules to adults. Envision upskilling programs where an AI tutor helps a factory worker learn to operate a new machine, or teaches a rural entrepreneur how to use e-commerce tools in her local language. This could vastly expand access to adult education and make economies more adaptable, thereby improving workers' income prospects and supporting economic transitions (important for aging societies and those facing automation of certain jobs).

We might also see AI-integrated assessments and credentials. Looking ahead, education systems may explore the feasibility of integrating AI tools into national assessments—potentially to support proctoring integrity or assist in evaluating practical components (like coding challenges or virtual science labs). Done well, this can make exams more holistic and fairer (testing real skills, not just rote memorization) and help universities or employers identify talent that might be missed by conventional tests. However, it will require careful implementation to avoid bias.

In summary, by the early 2030s, AI could help achieve inclusive, quality education by personalizing learning, supporting teachers, and reaching those who were hard to reach before. Each learner could, in theory, have access to one-on-one style guidance – something only the elite had in the past – if AI tutors become widely available. The big "ifs" will be infrastructure (devices, connectivity), political will to invest in equal access, and training for educators to harness AI effectively. If implemented well, Asia and the Pacific could see significant improvements in learning outcomes, narrowing rural-urban and rich-poor education gaps, and a better-prepared workforce for the knowledge economy.

Healthcare

PRECURSORS

Healthcare is emerging as a prime frontier for AI-driven innovation across Asia and the Pacific, with early projects – many still small in scale – foreshadowing broader transformations to come.

- *Bhutan* – Bhutan recently deployed a "clinic on wheels" to fight tuberculosis in remote areas. In 2024, a mobile medical van was outfitted with a digital X-ray and Qure.ai software to scan for TB on the spot. The AI can analyze chest X-rays within minutes to flag likely TB cases, enabling immediate confirmatory tests and treatment in villages far from any hospital.[58] This approach is bringing advanced diagnostics directly to high-risk communities and helping bridge the rural healthcare gap.
- *Brunei Darussalam* – In a different context, Brunei Darussalam has introduced its first medical AI to combat diabetic blindness. With diabetes affecting roughly 13 percent of Bruneians and one in three diabetic patients developing retinopathy (a leading cause of blindness), the Government launched SELENA+ in 2024 – an AI system at the national eye center that analyzes retinal images for early signs of disease. By catching problems early, this tool aims to enable preventive treatment before patients lose vision.[59] These examples illustrate how even smaller nations are beginning to adopt AI for critical public health needs.
- *Bangladesh* – Local social enterprises have developed digital health platforms using AI chatbots and analytics to facilitate confidential access to essential health services and mental well-being support via mobile phones.[60] With over 3.5 million subscribers, it provides education, symptom screening, and referral advice remotely, which is particularly valuable for youth and women in areas where clinics or specialists are scarce.
- *Mongolia* – As part of Mongolia's commitment to fight cervical cancer,[61] innovations are supporting a vast country where specialist resources are concentrated in the capital – a startup called AI Medi Mongolia teamed with a Korean tech firm to introduce CerviCare AI in 2023, an AI system for early cervical cancer detection intended to screen women in remote provinces who rarely get traditional screenings.[62]

At the other end of the spectrum, the Asia-Pacific region's more advanced economies have been pioneering AI integration in mainstream healthcare.

- *China* – Tech giants like Ping An, Alibaba, and JD.com have rolled out AI-powered health platforms that serve millions. Ping An's "One-Minute Clinics" – essentially unmanned telemedicine kiosks – use AI to triage patients, provide instant medical consultations, dispense basic medications, and even process insurance claims on the spot.[63] In parallel, online services, such as AliHealth and Ping An Good Doctor, deploy AI chatbots for initial consultations and health Q&A, a boon for elderly or rural Chinese patients who struggle to travel long distances for care.

These cutting-edge deployments remain limited in number, but they demonstrate what is technologically possible. Across these diverse cases – from Bhutan's mountain villages to China's megacities – AI is already proving its value in healthcare. The projects are modest in scale today, yet they paint a vivid picture of how AI could become a routine part of medical practice, saving lives and improving efficiency in the near future. Notably, they also reveal challenges that temper the excitement, especially around equitable access and inclusion, which we explore further below.

OPPORTUNITIES

Over the next decade, AI's role in healthcare is projected to expand, opening new frontiers in patient care, public health, and medical research. In the short term, there are several "low-hanging fruit" applications that many Asia-Pacific health systems can adopt relatively quickly to boost efficiency.

One is automating routine administration and documentation in clinics and hospitals. Generative AI tools are increasingly capable of transcribing doctor-patient conversations and summarizing clinical notes. By acting as tireless medical scribes, they can free up doctors and nurses from paperwork to spend more time with patients. For example, an AI assistant could automatically draft a patient's discharge summary or flag abnormal lab results for follow-up, reducing the cognitive load on overburdened staff. Some hospitals in technologically advanced cities (like Singapore's Tan Tock Seng or Seoul's Asan Medical Center) are already testing such systems that listen during consultations and produce first-draft notes. Even in middle-income countries, simpler AI chatbots can handle patient triage and scheduling – answering common health questions, booking appointments via messaging apps, and sending medication reminders in local languages. These applications usually pay for themselves by streamlining operations: a triage bot can direct non-urgent cases to a nurse or telemedicine call instead of clogging emergency rooms, for instance. Implementing these widely could markedly improve service delivery in both urban and rural settings without requiring massive new infrastructure.

Another immediate opportunity lies in AI-assisted diagnostics, building on the pattern- recognition prowess of modern AI models. In the coming years, we can expect AI "second opinions" to become commonplace for interpreting medical images and tests. AI algorithms are demonstrating high levels of precision in analyzing X-rays, CT scans, and ultrasounds – tasks such as spotting tuberculosis lesions on a chest X-ray or identifying tumors in an MRI. Scaling this up could effectively put a virtual radiologist or pathologist in every district hospital. A clinic in a remote province of Indonesia or Papua New Guinea, for example, might use a cloud-based AI to analyze chest X-rays for TB or pneumonia, getting results in minutes instead of waiting weeks for a specialist. Likewise, an AI could analyze a digital scan of a blood smear or a biopsy slide, flagging potential indicators of diseases like malaria or cancer to support early diagnosis.

Beyond imaging, generative AI models hold promise as on-demand medical consultants. Imagine a rural health worker who can describe a patient's symptoms to a smartphone-based AI (potentially in the local language) and receive clinical decision support or potential management options informed by comprehensive medical protocols. This kind of AI-powered decision support could augment human capacity – not replacing doctors and nurses, but equipping them with instant expert guidance. It could also enhance medical training: junior doctors might practice on AI-driven simulators or consult an AI for complex cases to double-check their reasoning. In fact, simulators are becoming more sophisticated. China's experimental AI hospital, for instance, uses AI "doctor" agents to create realistic training scenarios for medical students, hinting at future AI-assisted education for healthcare workers across the region.

AI can also enable predictive analytics for public health and personalized care. Health authorities in Asia and the Pacific are increasingly interested in using AI to forecast disease outbreaks and track health trends in real time. By analyzing a combination of epidemiological data, climate patterns, human mobility, and even social media signals, AI systems strengthen public health surveillance capabilities to forecast, say, a dengue fever outbreak weeks in advance or identify the early spread of a new influenza strain. Given the region's vulnerability to epidemics (from SARS to COVID-19), such predictive modelling could save lives by enabling proactive measures (vector control, vaccination campaigns, travel advisories) before a crisis peaks.

Some pilot projects are already underway: for example, Sri Lanka and Thailand have experimented with AI to map mosquito breeding sites and optimize dengue prevention, while research groups in India have modelled COVID-19 spread using machine learning to inform lockdown policies. Over a longer horizon, AI could be integral to a global disease early warning system, and Asia-Pacific countries – with their experience and data – stand to contribute significantly to that effort.

On the personalized medicine front, the convergence of AI with genomics and wearable technology supports the potential for more personalized therapeutic strategies. In the next five-to-ten years, it is plausible that AI will help doctors choose the best therapy based on a patient's genetic makeup, predict who is at higher risk for conditions like diabetes or stroke, and recommend highly individualized prevention plans. For instance, AI could analyze data from a patient's fitness tracker, diet app, and genome sequence together to alert them and their physician about subtle health changes or risk factors, prompting early interventions. This would represent a shift from one-size-fits-all healthcare to precision health, which could particularly benefit populations in Asia with diverse genetic backgrounds and disease profiles (e.g. South Asian populations' predisposition to diabetes or Pacific Islanders' risk of cardiovascular disease could be managed with more nuance).

Crucially, emerging AI solutions are becoming more accessible and user-friendly, which could help bring quality healthcare to underserved groups. Enabled by multimodal AI (which processes images, speech, and text together), a new wave of health interfaces will not require full literacy or English fluency to use. We might soon see AI health assistants that a person can simply speak to in their native language and describe their ailment or show a picture of a rash or injury – and the AI will understand and respond with advice or a diagnosis in simple terms. Consider a villager in the highlands of Papua New Guinea or a mother in a remote Bangladeshi char (river island): instead of traveling hours to the nearest doctor, she could interact with a voice-based AI agent on a basic smartphone to access initial health information, potentially facilitating critical referrals (for example, flagging symptoms associated with a dangerous pregnancy complication and urging her to seek help).

With the Asia-Pacific region's linguistic diversity, the trend of training large language models on local languages is pivotal – and it is underway. We are seeing the beginnings of AI systems conversant in everything from Bahasa Indonesia to Hindi to Khmer. As this progresses, it will greatly expand the reach of health information and services. In short, AI offers a chance to leapfrog some of the traditional barriers in healthcare: rather than requiring a full clinic with specialists in every village, a health worker with a tablet and an AI app could deliver a significant fraction of primary care services on-site. Additionally, AI-enabled devices and robotics may further extend reach – for instance, drones guided by AI are being tested to deliver medicines and vaccines to isolated Pacific islands, and simple robotic assistants (like automated pill dispensers or elder-care robots) could help aging societies like Japan, the Republic of Korea, or Thailand care for their seniors with fewer human caregivers.

All these opportunities, from smart diagnostics to predictive public health, align with a vision of more innovative and competitive health systems: ones that are efficient, adaptive, and inclusive. Countries that harness these AI tools effectively could see healthier populations (boosting productivity and human capital) and also foster domestic industries around health tech. The potential is substantial – but realizing it will depend on how the region navigates the inequality dynamics associated with AI, ensuring the benefits reach everyone.

Without deliberate efforts, the digital divides within and between countries would almost certainly translate into health divides, where some groups enjoy AI-augmented care and others are left further behind. Within countries, a key concern is the gap between urban, well-resourced settings and rural or marginalized communities. Urban hospitals and private clinics are often the first to adopt new technologies, from AI diagnostic tools to telehealth platforms, while rural clinics may still lack basic internet or even reliable electricity. For example, Bhutan's experience with AI-driven TB screening showed immense potential, but also highlighted that many rural health posts lacked connectivity or trained staff to use such tools initially. Similarly, in Bangladesh and India the rollout of mobile health apps and AI chatbots has been fastest in cities, whereas rural villagers – especially those without smartphones – have had limited access.

There is a risk that AI could bypass those who need it most: the poor, the elderly, and the less educated. Digital literacy is a significant barrier – an AI app is only useful if people can navigate it and trust its advice. Older patients and those with varying levels of digital literacy may face usability challenges. Indeed, Brunei Darussalam found that many older citizens and rural residents were initially hesitant to use the new AI features in its national health app, prompting the Government to pair the app rollout with on-the-ground outreach and training to avoid widening gaps.

Gender disparities are another facet: in specific contexts within South Asia and the Pacific, women may face disproportionate barriers to accessing technology and information, influenced by factors such as localized social norms. If AI health solutions (like a maternal health SMS service or an online consultation platform) are not designed with these constraints in mind, women could benefit less. On the other hand, inclusive design can empower under-served groups – for instance, Bangladesh's SuSastho.AI platform provides confidential health guidance on sensitive issues, which can be especially empowering for young women who might feel uncomfortable seeking help in person. The lesson is that inclusion must be baked in: governments and NGOs may need to subsidize devices or data plans for low-income users, offer voice-based interfaces for the illiterate, and deploy community health workers as intermediaries who use AI tools on behalf of those who cannot. Without such measures, the AI revolution in healthcare might end up mostly helping the urban middle class and affluent, potentially widening internal health inequities.

The inequality challenge is even more pronounced between countries. Asia and the Pacific spans some of the richest and poorest places on earth, and their starting points in healthcare are vastly different. At one end, you have high-income economies like Singapore, the Republic of Korea, or Australia that boast advanced hospitals, high doctor-to-patient ratios, and robust digital infrastructure. At the other, there are countries like Afghanistan or Pacific states (e.g. Solomon Islands, Papua New Guinea) where healthcare facilities are sparse and skilled health workers are in critically short supply. Singapore, for instance, has around 28 doctors per 10,000 people, while Solomon Islands has only about 2-3 per 10,000.

On the one hand, AI has the potential to act as a great equalizer by alleviating some of these resource gaps (for example, AI tools could help a single doctor in a Pacific Island manage a workload that would normally require several specialists). On the other hand, there is also the very real risk of an AI-driven health divide: wealthier nations will quickly implement life-saving AI technologies (and even develop homegrown AI industries, exporting their solutions), whereas poorer nations might lack the bandwidth – financially, technically, and politically – to do the same. If a country cannot afford the latest AI diagnostic algorithms or fails to build the digital infrastructure needed for telemedicine, it could see its health outcomes stagnate while neighbors improve, affecting everything from life expectancy to economic productivity. In an extreme scenario, diseases that become easily managed by AI in rich countries (say, an AI that detects and controls hypertension early) might continue to cause high mortality in poorer countries that do not have access to that innovation. Such divergence would not only be unjust but could also undermine regional development goals – a population in poor health struggles to participate in the economy, reducing the competitiveness of that country in the long run.

To prevent these gaps from widening, collaborative and inclusive strategies are required. One approach is knowledge and technology transfer: high-capacity countries (or companies within them) can help open-source certain AI health tools or adapt them for low-resource environments. Multilateral organizations and regional forums can play a convening role, ensuring that standards and best practices for ethical, inclusive AI are disseminated widely. Investment in infrastructure remains pivotal: without broader internet access and electricity, even the most advanced AI application is moot.

Capacity building is equally important – training more healthcare workers in digital skills and AI literacy, so they can effectively use these tools and also contribute local data and insights to improve them. UNDP and other development partners are increasingly viewing digital public goods (like AI algorithms for common health issues) as something to support and scale in less-developed countries, analogous to providing essential medicines. Policymakers will also need to address regulatory and ethical questions to maintain trust: ensuring AI systems are transparent, respect patient privacy, and are tested for biases (for example, an AI diagnostic should be validated on local populations to make sure it works equally well for all ethnic groups and genders).

In sum, the trajectory of AI in healthcare carries both tremendous promise and critical risks for inequality. If guided with foresight, AI could help Asia-Pacific countries leapfrog toward universal health coverage – bringing quality care to remote villages, strengthening disease prevention, and easing the workload on overstretched clinics. This would translate to tangible human development gains: longer, healthier lives, lower medical costs, and a more productive workforce powering economic growth. It could also spur home-grown innovation, with Asia-Pacific firms designing affordable AI solutions for the world.

However, without conscious inclusion, the opposite outcome is possible – a scenario where advanced hospitals in big cities or rich countries reap most of the AI benefits (better outcomes, higher efficiency) while rural communities and least-developed nations see little improvement, or even relative decline as the gap widens. Managing this transition will determine whether AI in healthcare becomes a story of converging outcomes (narrowing health gaps between and within societies) or one of divergence. The challenge for leaders is to ensure that the AI revolution in healthcare is not just technologically transformative, but also socially equitable – that it truly serves all of the Asia-Pacific region's 4.3 billion people, not just the connected and fortunate few.

Urban planning and transportation

PRECURSORS

Asia and the Pacific is home to some of the world's largest and fastest-growing cities, and these urban centers face challenges like traffic congestion, pollution, and strained public services. AI is emerging as a tool to help manage and plan cities more efficiently. A prominent application is intelligent traffic management. In Dhaka, Bangladesh, a mega-city facing significant urban congestion, authorities have piloted an AI-based traffic signal control system. Cameras and road sensors feed real-time data on vehicle flows into an AI that dynamically adjusts the timing of traffic lights.[64]

Early trials on a few intersections showed the AI could respond to changing traffic conditions faster and more efficiently than manual control – reducing average wait times, though Dhaka's chaotic traffic (with frequent rule-bending by drivers) poses unique challenges. Still, despite the mixed results, this pilot signals openness to data-driven traffic solutions. Ulaanbaatar, Mongolia, for example, has partnered with Google on a "Green Light" project to network 170 traffic signals citywide. By late 2024, the city will centrally manage these lights using Google's AI algorithms, joining a roster of cities globally that saw reduced commute times and emissions from similar systems.[65] Even Auckland, New Zealand – a developed city – has implemented adaptive traffic lights.[66] These examples illustrate that there are common use cases for AI, such as traffic management, but also that each city has unique challenges. Traffic management in Auckland is very different to that in Dhaka, but a platform developed in Dhaka may hold greater relevance for cities with similar urban dynamics, such as New Delhi.

Beyond traffic, cities are using AI for various public services. In China, the cities of Shanghai and Hangzhou have implemented "City Brain" platforms (developed by Alibaba) that integrate data from thousands of cameras and IoT sensors to optimize multiple urban systems. In Hangzhou's case, City Brain started with traffic management and reportedly reduced congestion by 15 percent and cut ambulance emergency response times by nearly half in pilot districts. It does so by, for example, clearing routes for ambulances or adjusting traffic signals across a whole corridor when it detects heavy buildup. City Brain has since expanded to other functions like detecting accidents or crimes on CCTV and dispatching responders. While those are high-end systems requiring extensive infrastructure (and raise privacy concerns with so many cameras), they illustrate what's possible when AI is applied at a city-wide scale.[67]

Smaller scale but impactful uses include public transit optimization. In Wellington, New Zealand, transit planners are testing AI analytics to better design bus routes and schedules, aiming to match services. Wellington is modernizing real-time transit information (RTI 2.0) with improved tracking and onboard capacity measurement; planners use operational data/analytics to refine routes and timetables.[68]

Cities are also exploring AI for environmental monitoring. Researchers in Seoul use AI to predict air quality a day in advance, based on weather and emissions data, which helps authorities issue alerts and adjust policies (like factory operations or traffic restrictions) proactively.[69]

Auckland piloted sensor-equipped bins and data-driven route-optimization software: fullness data from public litter bins was used to dispatch trucks only where service was needed and to optimize routes. In a 135-bin pilot, route time fell from ~7.5 hours to ~4 hours, with projected city-wide CO_2 reductions if scaled.[70]

In Thailand, large retail/logistics firms (like Central Retail Logistics) are using AI in transport management to optimize delivery routes and inventory movement, reducing costs and improving on-time performance. While this is a private sector use, it contributes to overall urban efficiency (less congestion from delivery trucks taking smarter routes) and shows that AI logistics is catching on in emerging markets too.

Malaysia provides a strong example of public-private collaboration for smart transport: PLUS, the country's biggest highway operator, partnered with a startup (Tapway) and NVIDIA to deploy an AI-powered, barrier-free toll system. Highways often cause jams at toll booths; this system uses computer vision (cameras with AI) to recognize vehicles at speed (up to 40 km/h) and automatically charge tolls without requiring cars to stop. The AI achieves 97 percent accuracy in identifying vehicle license plates and types within 50 milliseconds. With this, over 1.5 million daily commuters on PLUS highways experience smoother travel and reduced congestion around toll plazas. This demonstrates how AI can modernize infrastructure to deliver tangible benefits for daily mobility.

Japan is pushing the envelope with projects like a priority lane for self-driving trucks on a roughly 100-kilometer section of the Shin-Tomei Expressway. AI systems could coordinate self-driving trucks/platoons to address driver shortages and reduce fuel use on this route. This not only helps logistics efficiency but can cut emissions and improve road safety.[71]

All these cases share a theme: AI helping city authorities make data-driven decisions in real time, leading to tangible benefits like shorter commutes, lower emissions, or more reliable services. However, they also highlight prerequisites – reliable electricity, widespread connectivity, and good data governance – which vary widely across Asia and the Pacific. A well-off city like Singapore can deploy a comprehensive smart-city platform easily, whereas a city in a least developed country might struggle to even maintain traffic lights. So while the positive impacts of AI in urban management are evident, scaling these solutions equitably is a challenge.

OPPORTUNITIES

In the short term, many Asia-Pacific cities could implement proven AI solutions relatively quickly. One immediate opportunity is expanding intelligent transport systems (ITS) from pilots to broader coverage. As noted, it is not just megacities – mid-size cities like Colombo, Jakarta, Cebu, or Kathmandu could benefit immensely from AI-coordinated traffic signals and better bus scheduling. The technology and know-how exist; often it is a matter of political will and modest investment. Given how much economic loss happens due to congestion, even a 10–15 percent improvement via AI would have big economic and quality-of-life payoffs. Additionally, smoother traffic means lower idle emissions and fuel waste – a public health and climate benefit. So we foresee more cities adopting AI traffic control and bus rapid transit optimizations.

Another short-term trend is using AI for urban safety and infrastructure maintenance. Many cities can deploy AI vision systems to monitor infrastructure – for instance, identifying potholes, or cracks in bridges, from camera feeds, or detecting when garbage dumpsters are full. In India, Bengaluru's civic body BBMP is piloting AI-enabled cameras mounted on vehicles to detect and map potholes across arterial and sub-arterial roads.[72]

AI can also help cities respond better to climate and disaster risks in the short term. A case in point is flood management. Cities in the Philippines, Viet Nam, Thailand and others face frequent floods. AI models that take in rainfall forecasts, drainage data, and soil saturation levels can give early warnings of which neighborhoods are likely to flood and how severely. Some pilot systems in Ho Chi Minh City are doing exactly this – researchers have used machine-learning surrogate models to forecast urban flood depths, supporting faster scenario testing.[73]

City authorities can also amplify AI's impact through open data initiatives. By opening transit data, traffic data, etc., to developers, they enable local startups or civic tech groups to build AI-powered apps – like real-time bus trackers, carpool matching services, or mapping tools for disabled-friendly routes. We see hints of this: in Malaysia, a community-developed app uses AI to suggest carpool matches for commuters, reducing traffic volume. Such participatory approaches can generate early benefits and solutions adapted to a city's context.

In summary, the next couple of years present a chance for Asia-Pacific cities to deploy proven AI solutions for cleaner, safer, more efficient urban living. Many of these technologies are not prohibitively expensive, especially compared to hard infrastructure. The key is capacity: city officials need the know-how to procure and manage these systems, and the public needs assurance (through policy) that AI use will respect privacy and equity.

In the longer term (five to ten years), AI could fundamentally reshape how cities are planned and managed, leading to smarter and more sustainable urbanization. One major medium-term opportunity is the adoption of AI-driven digital twins for cities. A digital twin is a virtual model of a city that updates with real-time data.

By 2030, it is projected that hundreds of cities globally will use digital twins, potentially saving billions in infrastructure costs by simulating and optimizing designs virtually before implementing them. In Asia and the Pacific, rapidly growing cities like Ho Chi Minh City (or Jakarta, which is even planning a new capital city – Nusantara) could use digital twins to test different urban development scenarios. For example, an AI-enhanced digital twin could simulate how building a new housing complex in one district would affect traffic, or how adding a park could improve air quality and temperatures, or how various flood defense designs would perform under extreme rain. This helps urban planners make better decisions that balance growth with quality of life and resilience. Singapore is already working on a city-wide digital twin, and Dubai too – their experiences will provide lessons on both the benefits and challenges. For developing cities, partnerships and donor support might make such sophisticated tools accessible.

Energy efficiency in cities will be another focus. By the early 2030s, many cities – from Canberra to Kuala Lumpur – could deploy AI to manage city-wide energy grids more smartly. This includes dynamically controlling street lighting (dimming when no one's around), optimizing HVAC (heating, ventilation, air conditioning) in public buildings by learning usage patterns, and managing charging of electric vehicles to avoid peak loads. These AI optimizations can substantially reduce urban energy consumption and carbon footprints, helping countries meet climate targets and saving municipal budgets which can be redirected to social services. Some cities in Australia and Japan are already testing such systems on small scales (like smart streetlights), and broader adoption will likely follow as the tech proves its return on investment.

Transportation in the medium term will venture into autonomy. Several Chinese and Japanese cities have ongoing pilots of self-driving buses and AI-guided metro trains. Within a decade, it is plausible that in controlled environments (campus towns, dedicated lanes, less complex urban areas), autonomous shuttles and buses could be operating at scale. This has inclusion benefits: it can provide mobility in areas or hours that aren't profitable for human-driven services, thus extending public transport access (for example, late-night autonomous minibuses in a suburb). It can also bring down costs in the long run, making public transit cheaper and more extensive – key for low-income users. And of course, AI drivers do not get tired or distracted, which could improve road safety if managed well. The caveat is that a mix of autonomous and human drivers is tricky; likely we'll see phased introduction (maybe autonomous public transport in segregated lanes first).

AI will also embed itself into urban governance. City officials could use AI to analyze vast datasets on population distribution, service usage, and socioeconomic indicators to identify optimal locations for new schools, clinics, or affordable housing. Instead of political guesswork, decisions on where to invest could be guided by algorithms highlighting areas of greatest need – e.g., an AI might identify gaps in service coverage within specific neighborhoods, providing data to support the placement of a clinic there to optimize impact. If coupled with participatory planning (getting community input), this could lead to cities that have more equitable in-service provision, ensuring resources go where they are most needed.

In summary, the medium-term future points to AI-integrated cities that are not just high-tech for the sake of it, but fundamentally more inclusive and sustainable. A child growing up in a medium-sized Asian-Pacific city in 2030 might breathe cleaner air because AI optimizes traffic and energy use, spend less time in traffic thanks to smart transport, and benefit from public services (school, clinic, library) optimally placed by AI analytics. However, to reach that point, investments in digital infrastructure are needed now, along with frameworks to safeguard privacy (smart cities generate a lot of personal data) and prevent a "techno-authoritarian" turn (e.g., using city AI systems for unwarranted surveillance or social control). The inclusive smart city is achievable – one where technology serves all citizens – but it must be pursued consciously, with communities involved in design and clear guardrails on how data and AI are used.

Risks and costs: disruption and exclusion

Up to this point, we have mostly highlighted the many potential benefits of AI-driven innovation across sectors with mentions of some specific risks. Here we summarize some of the cross-cutting risks, disruptions, and new inequalities that AI can introduce if not managed properly. These risks are not hypothetical – many are already materializing, and they tend to mirror existing structural inequalities, often magnifying them.

- *Market monopolization and concentration of power* – Advanced AI requires access to large datasets, significant computational power, and highly skilled talent – resources that are overwhelmingly concentrated in a few big tech firms and in wealthier nations. This gives a huge first-mover advantage to those actors. As AI scales, there is a danger that markets tip toward monopolies. Smaller domestic companies in developing countries could be edged out if they cannot compete with AI-powered multinationals. For instance, if one firm's AI credit scoring platform becomes the standard, it might be hard for alternatives to emerge – potentially locking in that firm's biases or priorities. Globally, we already see a handful of companies dominating AI research and cloud infrastructure. Without intervention, AI could entrench these power asymmetries, making it harder for new innovators (especially from developing countries) to catch up. Furthermore, countries with advanced AI ecosystems might capture disproportionate economic gains, while others become reliant on imported AI solutions, leasing AI as a service without building local capacity.

- *Workforce disruptions and potential deskilling* – AI's ability to automate tasks means many jobs will be transformed or even eliminated. While new jobs will also be created, the transition could be very disruptive. In manufacturing, routine assembly or quality inspection jobs are at risk; in services, clerical roles or support jobs could shrink. Even in education or healthcare, AI might take over certain tasks (grading, basic diagnoses) that professionals used to do. There is a risk of mass displacement of workers, particularly those in roles with repetitive tasks. For developing countries with large youthful populations, this is worrying – it could exacerbate unemployment if economies do not create new roles or retrain workers fast enough. Another subtle issue is deskilling: if workers come to overly rely on AI tools without understanding them, their own skills may atrophy over time. For example, junior doctors might lose diagnostic skills if they always defer to AI, or teachers might lose some creativity in lesson planning if they rely on AI-generated content. Over-reliance without understanding can reduce the long-term innovative capacity of the workforce.

- *Intellectual property (IP) and innovation bottlenecks* – AI blurs traditional IP frameworks. For instance, who owns an AI-generated design or artwork? If laws are unclear, it can create a chilling effect on innovation. In countries with weak legal systems, there is a risk that big players could exploit local data or content to train AI, then claim the outputs without benefiting the source communities. Startups might hesitate to invest in AI solutions if they fear their innovations can be easily replicated by a tech giant that scrapes their data (a form of IP capture). Moreover, global IP regimes could evolve in a way that favors those who already hold AI patents, potentially locking out newcomers. If, say, fundamental AI algorithms or pre-trained model weights get patented or dominated by a few, late-coming countries might have to pay steep licensing fees – a scenario of digital dependency.

- *Bias, discrimination, and exclusion in AI systems* – AI systems are only as good as the data and design behind them. If the training data is not representative, the AI's decisions will not serve everyone equally – in fact, they can actively discriminate. This is a well-documented risk: an AI health diagnostic trained on urban hospital data might misdiagnose rural patients because their profiles differ. A lending algorithm could inadvertently "redline" (deny credit to) entire neighborhoods if their data patterns differ from the mainstream that the AI considers "creditworthy." Facial recognition AIs have famously had higher error rates for darker-skinned individuals because of biased training sets – raising serious concerns if such tech is used in policing or public services. In Asia and the Pacific, where societies are often heterogeneous and stratified, the danger is that AI could reinforce social biases (gender, caste, ethnicity, urban/rural) under a veneer of objectivity. For example, if an AI hiring tool is fed past data that under-represents women in tech jobs, it may "learn" to favor male candidates, perpetuating gender gaps. Without local calibration and inclusive design, AI can end up serving only the majority or the elite, sidelining minority needs and even causing direct harm through false predictions or unjust decisions.

- *Techno-authoritarianism and erosion of privacy* – A specific risk in governance is that AI can be used as a tool of surveillance and control. Advanced facial recognition, sentiment analysis on social media, and predictive policing algorithms are already being used by some governments to monitor citizens. In the absence of strong legal protections, there is a risk of techno-authoritarian practices spreading – where regimes use AI to stifle dissent (e.g., by identifying protest participants via surveillance cameras) or to manipulate public opinion (through AI-generated propaganda, deepfakes, etc.). The export of such technologies is a concern: for instance, if one country perfects AI-driven censorship or citizen scoring systems and sells them to others, it could undermine democracy and human rights in multiple settings. This risk is particularly salient as some Asia-Pacific governments have shown interest in systems like "social credit" scoring or extensive CCTV networks. Policymakers must ensure that AI deployment is bound by privacy laws and democratic oversight. Human development is not just economic; it includes political freedoms and human rights – and AI, if misused, can threaten those.

It is important to note that these risks are not equally distributed. They tend to hit the already disadvantaged harder. Within countries, as mentioned, those with lower digital literacy, less education, or from marginalized communities are more likely to be adversely affected by biased AI or job automation without a safety net. Between countries, the less technologically developed ones risk falling into a dependency trap. While a tech-forward country can mitigate some risks through its own innovation and regulation, a tech-dependent country might simply have to accept whatever AI tools are imported, even if they are not aligned with local needs or values.

In essence, AI could usher in a new era of inequality – between those who develop and control AI versus those who merely use it. If unchecked, we may witness a scenario where a few countries and companies reap most of the AI dividends (greater productivity, wealth creation, strategic advantage), while others are left to deal with AI's downsides (job losses, privacy invasions, and a brain drain of their tech talent to AI hubs abroad). This would compound existing divides. For instance, countries like China, the United States, and the Republic of Korea – already investing massively in AI – attract more investment and talent, extending their lead. Conversely, countries still building digital foundations, like Lao PDR or Papua New Guinea, might fall further behind as AI advancements raise the bar for competition. They could end up as passive consumers of AI products from elsewhere, with little ability to adapt or resist those technologies.

Over time, these disparities can create feedback loops. Early AI adopters get more competitive, drawing more talent and capital, which helps them make even more advanced AI – a virtuous cycle for them, but a vicious cycle for laggards. The laggards might find that by the time they are ready to engage, the rules of the game (standards, platforms, patents) are already set by others, forcing them into subordinate roles in the digital economy.

In summary, AI's transformative potential is clear, but so is the risk of deepening exclusion. The challenge ahead for Asia and the Pacific is not simply to adopt AI or transplant solutions from the external markets, but to integrate it wisely and carefully adapt it to local context or even develop local solutions. This means actively shaping AI's rollout such that it reduces inequalities rather than exacerbating them. It means building local capacity – so countries are not just consumers but creators of AI solutions – and updating policies to safeguard fairness, competition, and rights in the AI era. In the next section, this report turns to exactly those policy implications and recommendations, aiming to ensure that the coming AI-driven age is one of equitable innovation and human-centric development rather than a scenario of concentrated benefits.

Policy implications and recommendations

The world now stands at the threshold of a new technological era. The policy decisions made today – about what to incentivize, what to regulate, where to invest – are expected to significantly influence whether AI becomes a force for inclusive prosperity or one that entrenches inequality. Given the region's vast diversity in development levels and capacities effective policies are context-sensitive, yet guided by a shared principle: AI adoption should enhance innovation and competitiveness without entrenching inequality or dependence. The following policy recommendations aim to provide concrete, evidence-based guidance for national governments, development partners, and regional bodies to harness AI for human development.

1. Build adaptive and inclusive national AI ecosystems

Countries that have advanced in AI did not achieve this by accident. They cultivated entire ecosystems: coherent national strategies, funding for research and innovation, strong education pipelines, and public-private partnerships to deploy AI solutions. AI offers an unprecedented ability to personalize and adapt to local context, which can only be realized with the right ecosystem. Developing countries in Asia and the Pacific will need support to build their own ecosystems, tailored to their context, offering a catalytic role for organizations like the UNDP.

- *Develop National AI Strategies aligned with development goals.* Every country should craft a national AI strategy or action plan that sets a vision for AI in society – not just for economic growth, but for broad human development priorities. This strategy should identify key sectors where AI can drive progress (e.g. agriculture for food security, healthcare for universal coverage, education for quality improvements) and lay out ethical principles and governance structures. For example, Bangladesh's National AI Policy 2024 explicitly links AI initiatives to its Sustainable Development Goals and is a promising model. The strategy should also delineate roles: which ministry leads, how academia and industry are involved, and how progress is monitored.
- *Invest in enabling digital infrastructure.* Without basic infrastructure, even well-designed AI tools will not scale. Governments, possibly with donor support, must invest in data centers and cloud services, widespread broadband/5G connectivity, and affordable compute resources (including exploring regional cloud hubs). For rural and remote inclusion, innovative solutions like community networks or satellite internet should be considered. Donors and development banks can help fund these foundational investments, treating digital infrastructure as critical development infrastructure, much like roads or electricity.
- *Nurture local innovation and skills.* An AI ecosystem thrives on local talent and experimentation. Policymakers should establish R&D grants and innovation challenge funds to spur problem-solving AI applications (for local language NLP, agri-tech, etc.). Setting up regulatory sandboxes allows startups to pilot AI solutions (in fintech, health, etc.) under relaxed regulations but with oversight, accelerating learning without putting consumers at risk. Incentives for AI startups (tax breaks, seed funding, incubation programs) can also be effective. Additionally, countries should build capacity to adopt global AI advances quickly into local apps – for instance, training local developers to fine-tune large language models for local use cases, even if they cannot build those models from scratch. This lowers the barrier to adoption and ensures locals are adapting AI to cultural and practical realities.
- *Leverage South–South and regional collaboration*. Many developing countries share similar challenges that AI could address – be it agriculture pests or disaster response. Peer learning and joint projects can save time and resources. Asia-Pacific nations should strengthen channels for South–South collaboration on AI. For example, middle-income countries like Viet Nam and Bangladesh could exchange lessons on

applying AI in the garment industry or rice farming. Regional bodies (ASEAN, the South Asian Association for Regional Cooperation, the Pacific Islands Forum, APEC, etc.) can facilitate knowledge exchange, set up regional centers of excellence, or even pool resources for big projects (like a shared regional dataset for disaster management AI). Such collaboration can be more relevant than trying to copy Silicon Valley models in every context. There is also scope for forming regional norms (akin to the EU's approach) so that smaller countries have a collective voice in setting standards around AI ethics and data governance.

2. Design for equity and representation from the start

Ensuring AI does not deepen inequality requires proactive measures upstream, at the design and data collection phase – not just downstream fixes. Equity must be a core design principle in AI projects, whether by government or private sector.

- *Mandate inclusive data practices* – Governments (especially funders of AI projects) should require that datasets used for AI training reflect the diversity of the population. This might mean including data from rural areas, from different ethnic groups, all genders, various income groups, etc. For instance, if a national AI health program is developing a diagnostic tool, the training data should include patients from different regions (not just the capital's main hospital) and groups. This could be enforced by funding conditions or review boards that check data bias. Open data initiatives can help provide diverse datasets. In cases where local data is scarce (like for rare languages), authorities should invest in data collection (e.g., via crowdsourcing or incentivizing data sharing) to avoid the easy path of using only foreign or non-representative data.

- *Ensure accessibility of AI tools* – In low-resource settings, high-tech solutions must meet people where they are. That means designing for low literacy and low connectivity. Governments can promote or provide multimodal interfaces – e.g., AI services accessible via voice (IVR systems) or SMS for those without smartphones. A good example comes from Bhutan: agricultural AI advisories are delivered through local extension centers to farmers without smartphones. Similar approaches (using community health workers to mediate an AI health app, or teachers to mediate EdTech) can bridge the last mile. Governments should also require usability testing of public-facing AI with target communities (women with low literacy, disabled users, etc.) before scale-up.

- *Avoid language lock-in* – The AI revolution shouldn't be confined to English, Chinese, or a few major languages. Public funding and regional cooperation should support AI development in local languages, including minority and indigenous languages. This can involve translating open-source model interfaces, creating language datasets, and sponsoring research on AI language models for languages like Khmer, Tagalog, Fijian, etc. Ensuring linguistic inclusion will both expand AI's market and preserve cultural diversity.

- Foster participatory AI development – A recurring lesson is that AI solutions work best and gain trust when the target community is involved in their design. Governments and NGOs should use co-creation models, involving teachers in designing an education AI tool, or farmers in defining features for an agri-advisory app. Such participatory approaches improve relevance, build community ownership, and can pre-empt misuse or cultural mismatches.

3. Regulate for fairness, competition, and autonomy

AI's rapid deployment in the market can outpace traditional regulations, potentially leading to unfair practices, anti-competitive behavior, or threats to individual autonomy. Policymakers must update and enforce regulations to get ahead of these dynamics, especially in contexts where existing safeguards (like antitrust enforcement or privacy laws) are weaker.

- *Prevent platform lock-in and monopolies* - To keep markets open and competitive in the AI era, regulations should encourage interoperability and data portability. For example, if a farmer uses a certain smart farming app, they should be able to export their data to another service if they switch – this prevents one company from "owning" all agricultural data. Governments might mandate common standards for data formats in sectors like finance and health to avoid vendor lock-in. Open Application Programming Interfaces (APIs) should be promoted for dominant platforms so that smaller players can build on them (with appropriate security). Competition authorities should be vigilant about big AI players acquiring local startups in ways that stifle competition.

- *Address labor transitions proactively* – Anticipating job displacement is crucial. Governments need to implement policies for reskilling and upskilling workers whose jobs are at risk from AI. This could mean expanding technical and vocational education to include digital and AI-related skills, or offering mid-career training programs (for example, training assembly line workers in maintaining and programming the robots that might replace some of their old tasks). Countries might establish worker transition funds (funded by a small levy on companies benefiting most from AI productivity gains) to support displaced workers through unemployment benefits and retraining. Importantly, the introduction of AI in workplaces should be guided by a principle of augmentation, not just automation. Where possible, encourage adoption of AI systems that assist human workers rather than replace them outright. For instance, the Republic of Korea's approach in education – deploying AI to enhance teachers' capabilities (like dashboards that help teachers focus on students' needs) rather than to replace teachers – is a model. Governments might offer tax incentives or grants for companies that choose AI solutions which augment human labor or that are implemented alongside a plan to retrain employees for higher-skill roles.

- *Clarify intellectual property and data ownership rights* - Legal uncertainties around AI-generated content and data rights must be resolved to promote local innovation. Countries should update IP laws to address questions like: if an AI-generated invention is created, can it be patented and by whom? If a local dataset is used to train an AI, do the data providers have any rights to the resulting model or its profits? A balanced framework can protect creators and innovators without overly favoring big tech. For instance, ensuring that local researchers or startups can use pre-trained models or global datasets under fair-use exceptions could spur innovation. Also, protecting traditional knowledge and community data from exploitation (e.g., by requiring benefit-sharing if such data informs AI products) might be considered. In short, clear rules of the game will reduce fear of IP theft or legal risks and thereby encourage more actors to develop AI solutions.

- *Safeguard individual rights and privacy* - From health records to facial images, AI raises serious privacy issues. Many Asia-Pacific nations currently lack robust data protection laws or face challenges in enforcement. It is imperative to enact comprehensive data protection legislation that covers AI use – including rules on consent for data usage, individuals' right to know when AI is being used, and redress mechanisms if AI decisions cause harm. Special attention should be given to sensitive use cases like facial recognition, where misuse can infringe on civil liberties. Some jurisdictions might decide to ban or strictly limit use of AI in surveillance without warrants or oversight. Additionally, AI ethics boards or review committees can be institutionalized for public-sector AI deployments (as done in Singapore and to some extent in Japan) to evaluate implications on rights. Crucially, regulators (like data protection authorities) need to be empowered and independent, with technical capacity to audit AI systems. This might require training or seconding tech experts to government, or pooling expertise at a regional level for smaller countries.

4. Focus on implementation and institutional capacity

Well-crafted policies mean little if countries lack the institutions and skills to implement them. A recurring development challenge is the "policy-practice" gap, especially with complex tech like AI. Hence, a major focus must be building the institutional capacity to execute, regulate, and scale AI initiatives. As one might say, policies without implementation are just wishes.

- *Strengthen regulatory and procurement capacity* – Governments need skilled personnel who understand AI sufficiently to evaluate vendors, audit algorithmic systems, and manage AI procurements. For example, if a city is buying an AI traffic system, do officials know what questions to ask about the algorithm's performance and biases? If a national health service adopts an AI diagnostic tool, is there capability to independently test its accuracy on local populations? To build this, countries may need to invest in training programs for civil servants and regulators on AI and data science. Regional cooperation can help: perhaps establish a regional AI training academy or facilitate secondments – e.g., sending officials to more tech-forward agencies (Republic of Korea's digital agency, Singapore's GovTech) for hands-on learning. Donors could support such exchange and capacity-building initiatives, as they are foundational for sustainable AI uptake.
- *Embed monitoring and evaluation (M&E) frameworks in AI projects* – Governments and development partners should treat AI interventions like any development project: measure their outcomes, not just outputs. This means up front, define what success looks like (e.g., did an AI education pilot actually reduce learning gaps? Did a fintech AI increase loans to small businesses without raising default rates?). Then, collect data to evaluate these questions. Because AI impacts can be complex, it is important to go beyond technical metrics (accuracy, etc.) to social impact metrics: are the benefits reaching the intended groups? Is anyone being unintentionally excluded or harmed? Such evaluations will inform scaling decisions and allow mid-course corrections. They also help build public trust if transparently reported. Thankfully, AI facilitates this by being self-documenting in many cases (using AI to monitor AI), but it is essential that what is measured isn't just deployment - not AI rolled out to 10,000 classrooms, but AI reduced freed teacher time by 20 percent which was used for mentorship and reduced learning gaps by 12 percent.
- *Pilot, then scale (with iteration)* – Pilot projects, rigorously evaluate them, and scale up what works – with adaptations as needed. This prevents costly failures and allows local customization. Many successful examples we cited (Mongolia's agriculture pilots, Bhutan's TB vans, etc.) began as small experiments. Governments should maintain sandbox environments for pilots and encourage a culture of experimentation in public services. However, they must also be ready to terminate or redesign pilots that do not show results, to avoid pilot-itis (lots of demos, no systemic change). Many current evaluation frameworks may not be fit for purpose if they assume time-consuming evaluation in a world where AI itself can provide evaluation data, analysis, and interpretation in real-time for immediate, even mid-study intervention.
- *Ensure fiscal and operational sustainability* – A known issue is that many AI (or ICT) projects in developing countries start with donor funding or as pilots and then flounder when that support ends. From the outset, plan for the long term: who will maintain the AI system? Where will funding come from for updates, for cloud compute costs, etc.? If an AI solution is donor-funded (say an agriculture app), a strategy should be in place to transition it to local ownership or integrate it into government services with budget allocated. Possibly involve the private sector in models where they can sustain the service (through reasonable fees or cross-subsidies) if appropriate. Also, consider appropriate cost-recovery models – e.g., maybe farmers pay a

small subscription for an AI advisory after a free trial, or a public healthcare AI is funded by savings it creates elsewhere. Public-private partnerships could help sustain certain AI infrastructures (like national clouds or broadband for AI connectivity) if well-regulated.

Finally, it is worth emphasizing a mindset: resist “techno-solutionism”. AI is not a magic wand to fix systemic issues overnight. Policymakers must invest in the “boring” but essential work of ecosystem-building, human capacity, and governance. The prize, if done right, is not just more innovation per se, but equitable innovation, innovation that broadens opportunities, builds sovereignty, and narrows gaps between and within nations.

To summarize our 12 key policy recommendations for harnessing AI for innovation and inclusive development in Asia and the Pacific:

1. Develop National AI Strategies grounded in human development priorities, with clear sectoral focuses and ethical guidelines.
2. Invest in digital infrastructure (connectivity, data, compute) as a foundation for AI.
3. Support local innovation ecosystems – through funding, sandboxes, and partnerships – so home-grown solutions emerge.
4. Mandate inclusive data and design practices to ensure AI systems work for all segments of society.
5. Promote language and cultural inclusion in AI tools (do not leave anyone behind due to language).
6. Deliver AI through trusted intermediaries or appropriate interfaces in low-connectivity or low-literacy areas (to ensure accessibility).
7. Enforce interoperability and open standards to prevent tech monopolies and platform lock-in.
8. Anticipate labor impacts with strong reskilling programs, social safety nets, and by choosing augmentation over pure automation.
9. Clarify IP and data rights to encourage innovation while protecting local interests.
10. Build regulatory and procurement capacity so governments can effectively evaluate and deploy AI.
11. Integrate monitoring and evaluation to measure AI’s social impact, not just its tech performance.
12. Plan for sustainability and scaling from the start, including securing budgets for maintenance and integrating successful pilots into broader systems.

CONCLUSIONS

Artificial Intelligence represents a new frontier for innovation and competitiveness in Asia and the Pacific. But as with previous technological waves, it presents a choice – it can either entrench existing hierarchies or expand human potential. Its impact will depend not on the algorithms themselves, but on how we deploy them, who they are designed to serve, and whether they advance the freedoms that underpin true development.

Used wisely, AI can help remove long-standing obstacles to human development in the region: lack of access to quality healthcare or education, financial exclusion, information gaps for farmers, inefficiencies that waste public resources. We have seen how AI-driven solutions – from smart farming to virtual tutors – can empower individuals and communities. With the right policies and institutions, AI can expand people’s capabilities: not only to be more productive, but to learn and express themselves, to be healthier, to participate more meaningfully in the economy and society. It can help a rural woman gain financial independence, or a child in a remote village to access world-class learning, or a small nation to better manage its limited resources.

As AI and digital infrastructure become so integral to opportunity, we believe that access to them will be seen as fundamental as access to electricity or education – a prerequisite for full participation in modern life. Without such access, people and countries risk being left behind from the emerging knowledge economy;

with it (and the preparation to use it effectively), even remote communities can find new pathways to growth and dignity.

This, ultimately, is the promise of AI for Asia and the Pacific: not just faster economic growth, but the expansion of human freedom. If we get it right – through inclusive innovation and thoughtful governance – AI can help countries leap over historical barriers: bridging gaps in infrastructure, overcoming isolation, democratizing information and services. It can lead not just to greater productivity, but to greater possibility for all citizens. The true measure of success will not be how intelligent our machines become, but how much more empowered our people become – how AI expands what individuals and communities are free and able to do. The choices we make now will determine whether the AI revolution in the Asia and the Pacific is one that uplifts and includes, ensuring this new era is one of increased but shared prosperity rather than a new era of inequality.

END NOTES

1. (Wrigley, 2010; Pomeranz, 2021)
2. (Martínez and Ebenhack, 2008; Muthukrishna, 2025)
3. (Levinson, 2016)
4. (Jebara, 2004)
5. (Wei et al., 2022)
6. (Vafa et al., 2024)
7. (Bommasani et al., 2021)
8. (Hu, 2023)
9. (Alleyne, 2018)
10. (Silver et al., 2016)
11. (Davies et al., 2021)
12. (Jumper et al., 2021)
13. (Royal Swedish Academy of Sciences, 2024)
14. (Eloundou et al., 2024)
16. (FAO, 2024)
17. (Shahzaib, 2024)
18. (Eurogroup, 2025)
19. (Nation, 2025)
20. (Cong and Minglai, 2025)
21. (Credence Research, 2025)
22. (Moody, 2016)
23. (Global Fishing Watch, n.d.)
24. (GRID Arendal, n.d.)
25. (Heifer International, 2024)
26. (Dobhal and Pathak, 2023)

27. (Business Market Insights, 2022)
28. (Xinhua, 2025)
29. (Google, n.d.)
30. (IFR International Federation of, 2025)
31. (Smart City Korea, 2024)
32. (Johnson, 2025)
33. (Vimatic, 2025)
34. (Textile Magazine, 2024)
35. (Kaur et al., 2024)
36. (FPT, 2025)
37. (Papri, 2025)
38. (Nat, 2025)
39. (Emanuel-Burns, 2025)
40. (Digital Brunei, 2020)
41. (Zangmor and Tshomo, 2024)
42. (Choo, 2025)
43. (Lei, 2025)
44. (Light Reading, 2025)
45. (Bangladesh Bank, Banking Regulation and Policy Department, n.d.)
46. (Kim, 2025)
47. (MyBank, n.d.)
48. (Asian Development Bank, 2022)
49. (UNICEF Global Learning and Innovation Hub, 2024)
50. (Greenfield and Yawar, 2023)
51. (Jung Da-hyun, 2024)
52. (Light Reading, 2025)
53. (MyDigital, n.d.)
54. (UNESCO, 2025)
55. (West, 2023)
56. (Wang and Fan, 2025)
57. (Japan Ministry of Education, Culture, Sports, Science and Technology, 2025)
58. (Chhophyel, 2025)
59. (Nova Group, 2024)
60. (Lima et al., 2025)
61. (World Health Organization, 2025)
62. (엔티엘헬스케어, 2023)
63. (Koh, 2019)
64. (Mahmud, 2024)
65. (Өнөболд, 2024)
66. (OurAuckland, 2024)

67. (Beall, 2018; Zhang et al., 2019)
68. (Greater Wellington Regional Council, 2023)
69. (Koo et al., 2024)
70. (DATACOM, no date)
71. (Japan Times, 2025)
72. (Times of India, 2024)
73. (Dang et al., 2024)

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CHAPTER 6 — THE MACROECONOMIC CONSEQUENCES OF AI

Shahid Yusuf, Growth Dialogue, George Washington University

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.

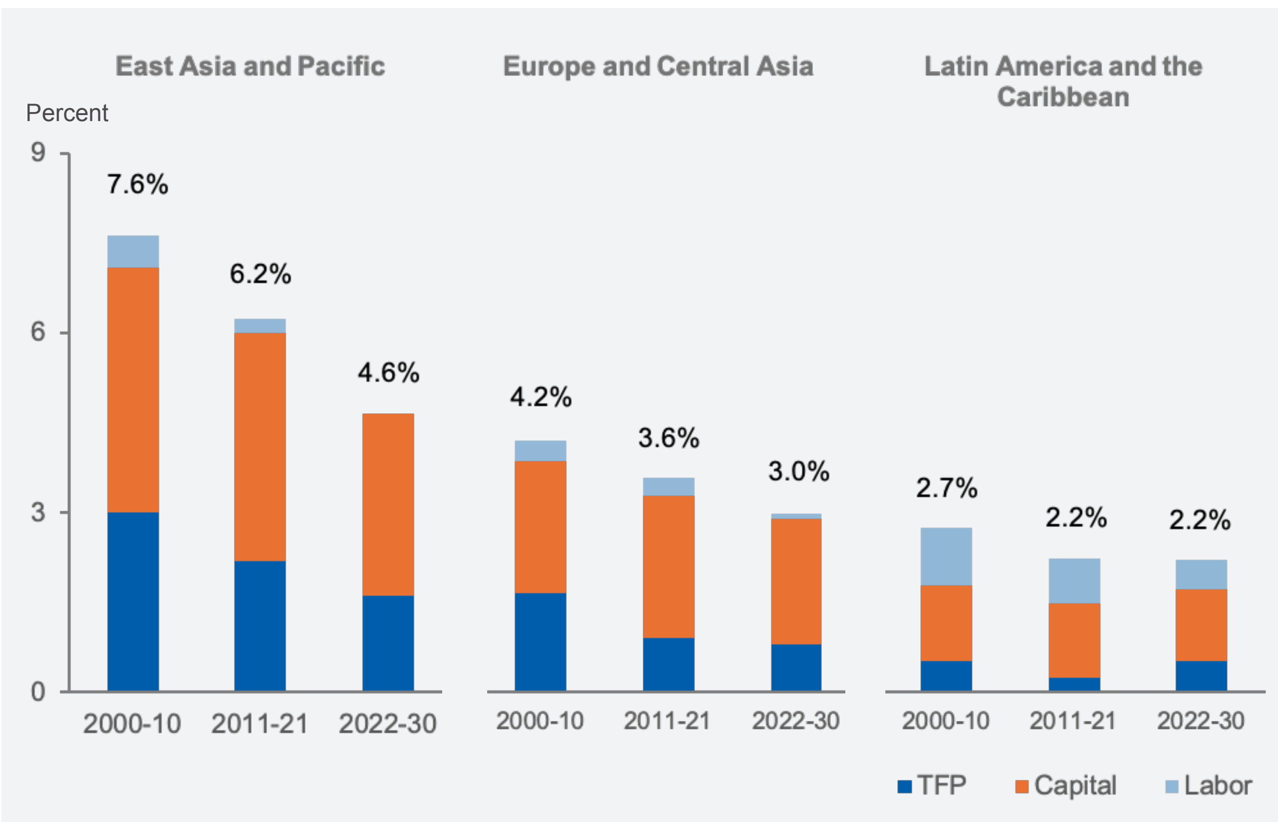
Table 1 – Total factor productivity growth by major region: 2000–2024

	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

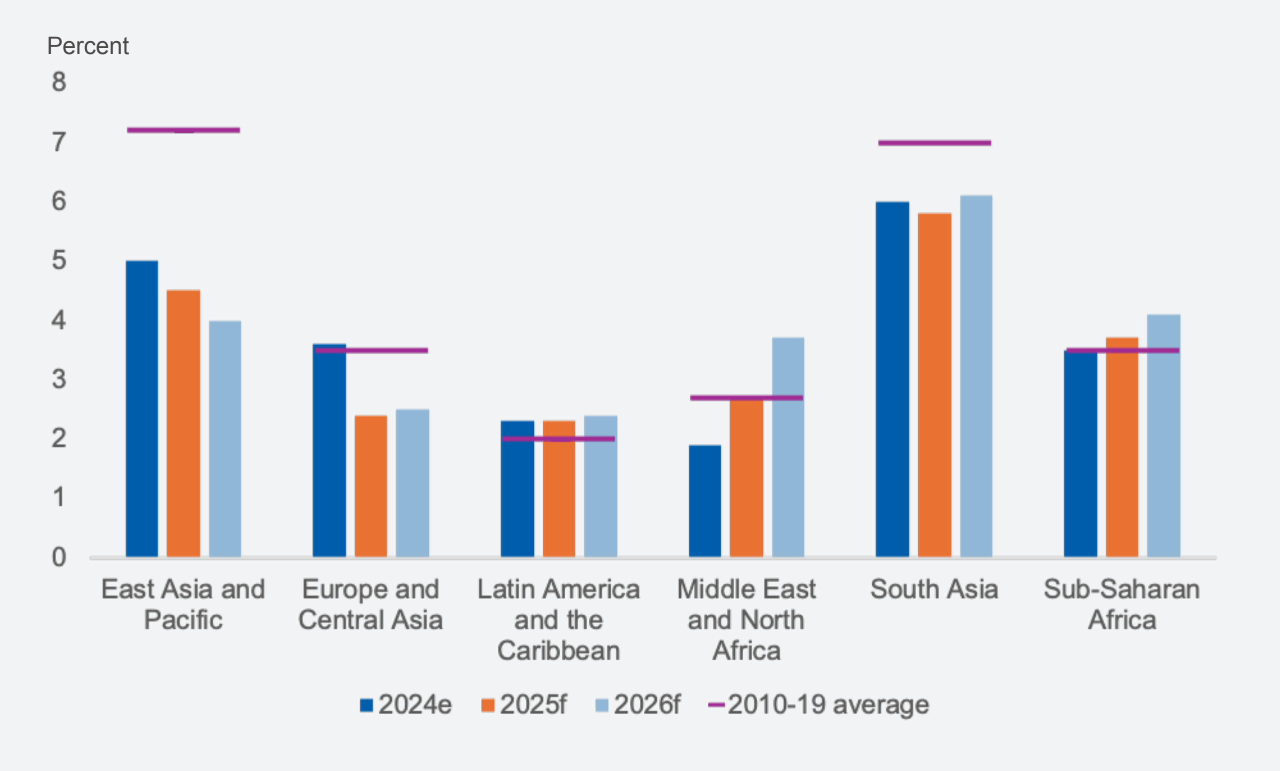
Source: (Conference Board, 2024)

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



Source: (Kose and Ohnsorge, 2024)

Figure 2 – GDP growth: past and projected



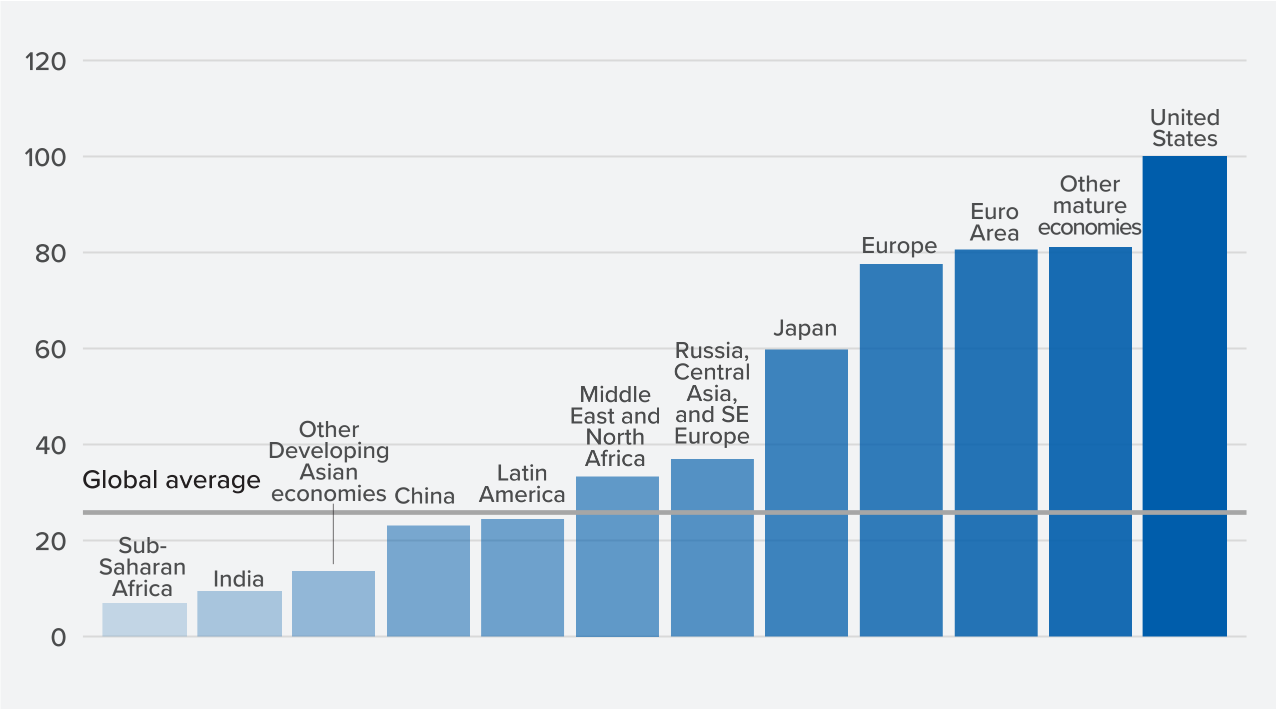
Source: (World Bank, 2025a)

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

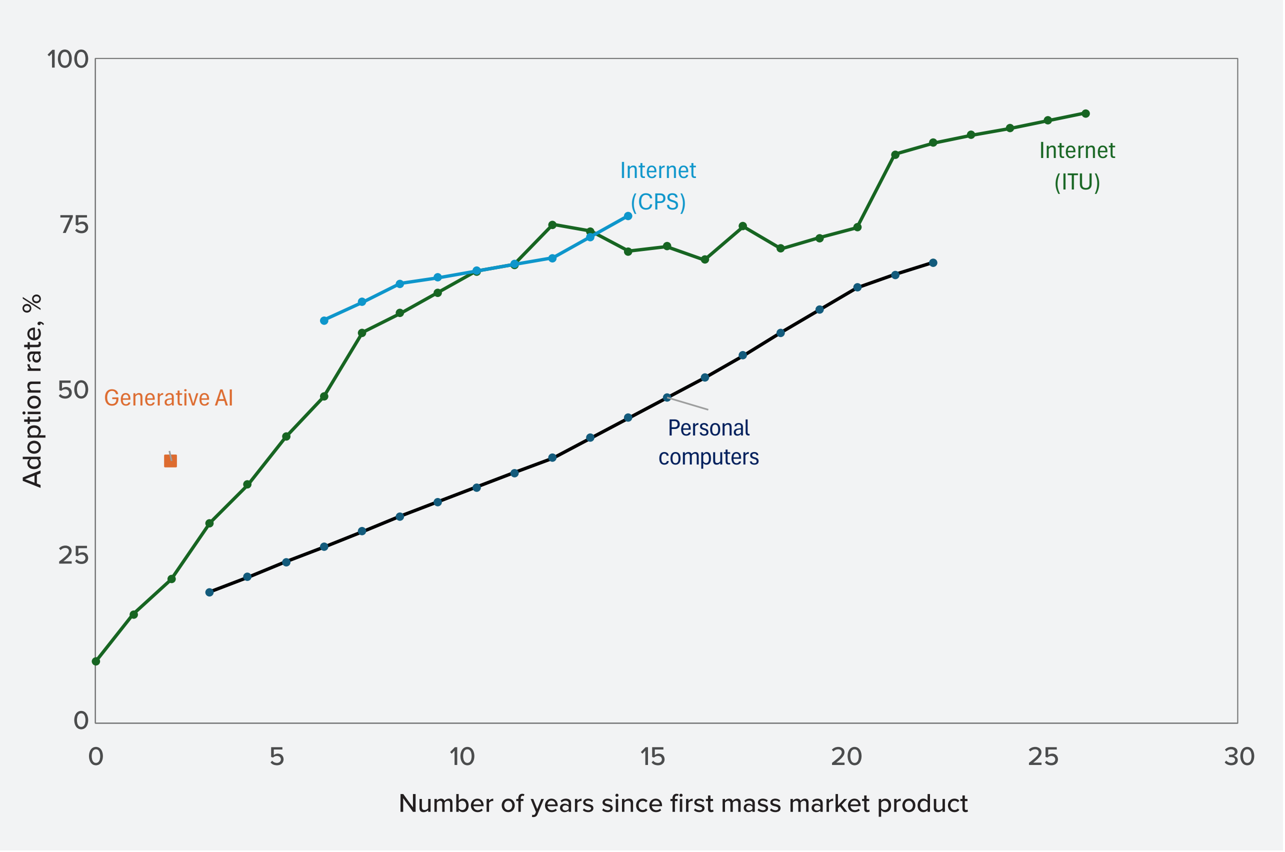


Source: The Conference Board. Data accessed Nov 2025.

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

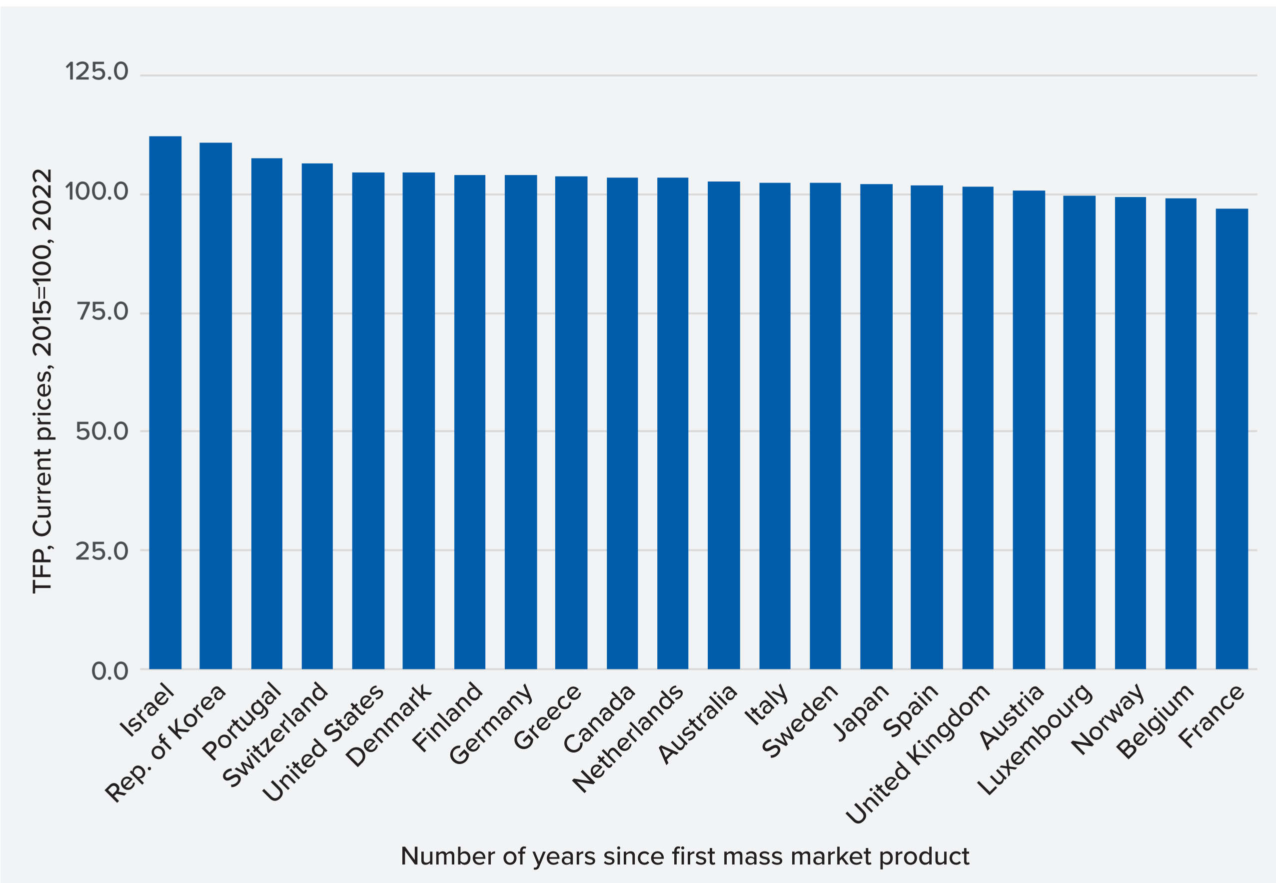
The economic benefits garnered from AI will depend on the degree to which AI ecosystems take root, the range of activities that are materially affected, and on how widely the benefits are shared. During the foreseeable future, most Asia-Pacific countries risks becoming largely reliant on AI innovations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

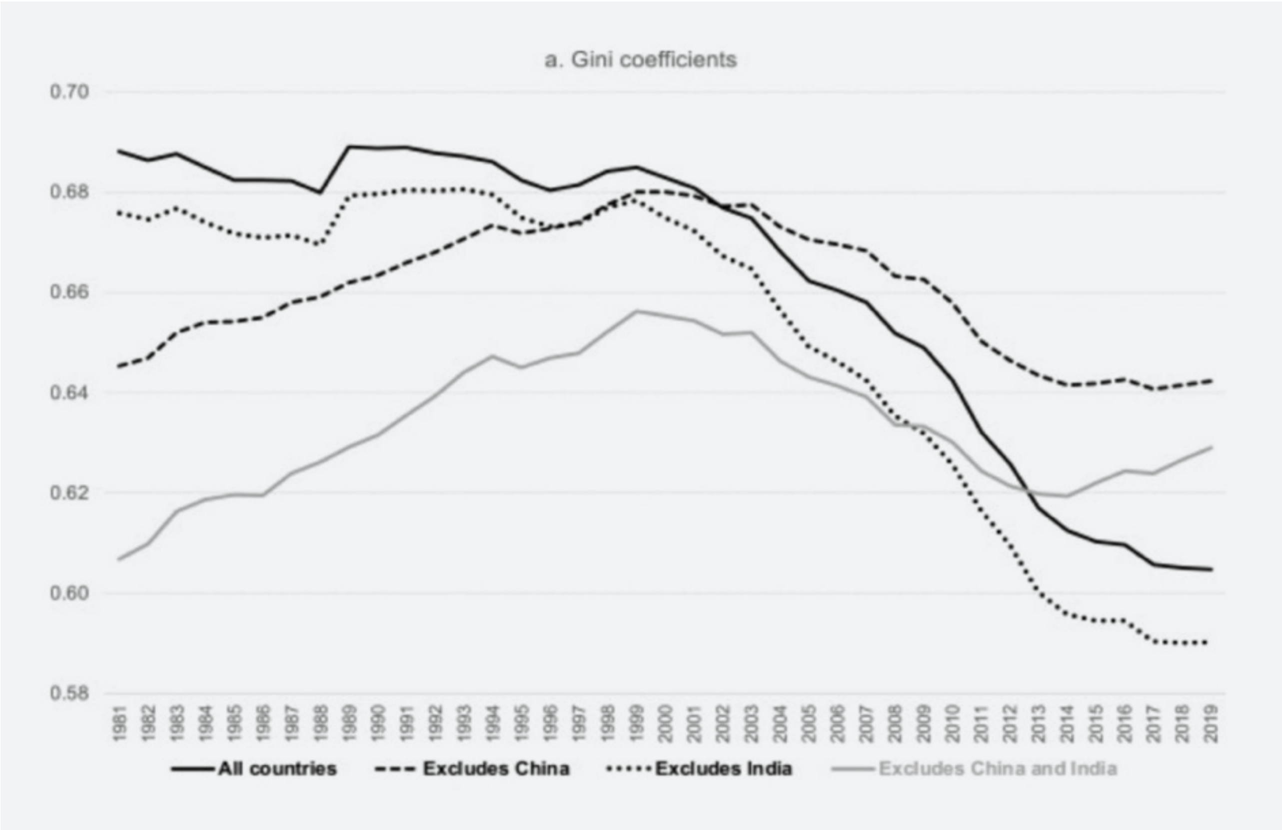
	2000-2007	2011-2019	2020	2021	2022	2023	2024 (Forecast)
Other Developing Asian Economies	**1.3**	**0.4**	**-2.7**	**-1.1**	**-0.7**	**-0.2**	**1.4**
Bangladesh	-0.1	0.6	0.7	-0.4	-0.3	0.2	0.4
Cambodia	0.5	-1.0	-8.1	-5.2	-1.8	-1.0	0.0
Indonesia	1.7	-0.1	-4.0	0.3	-0.8	-0.1	1.5
Malaysia	0.6	0.3	-4.1	-1.0	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

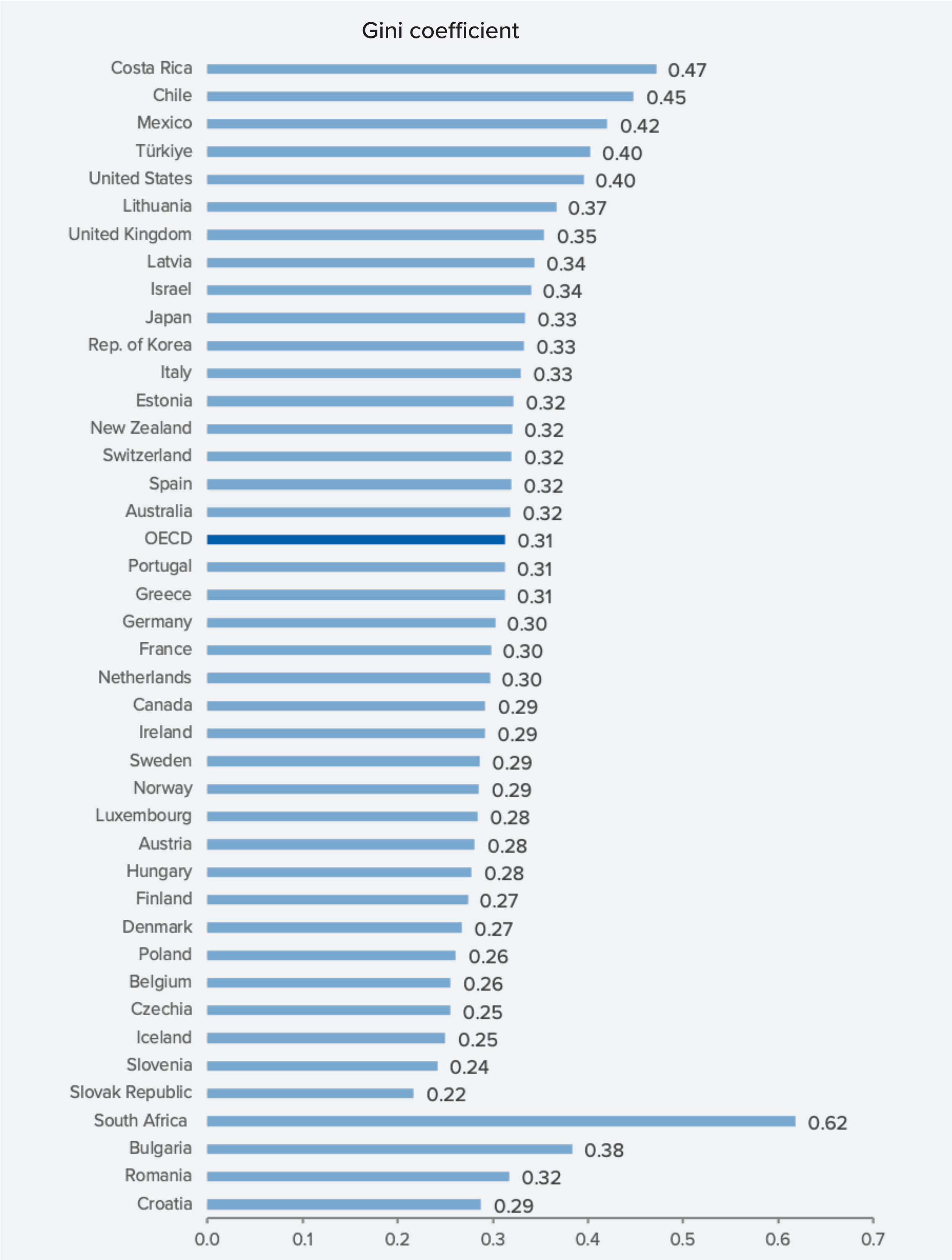
Equally challenging is gauging the distributional consequences. Measured by the Gini coefficient, global inequality declined from the late-1990s through 2015 – roughly the period during which EMDEs registered high rates of growth. Then it stagnated until 2020 (Figure 6).

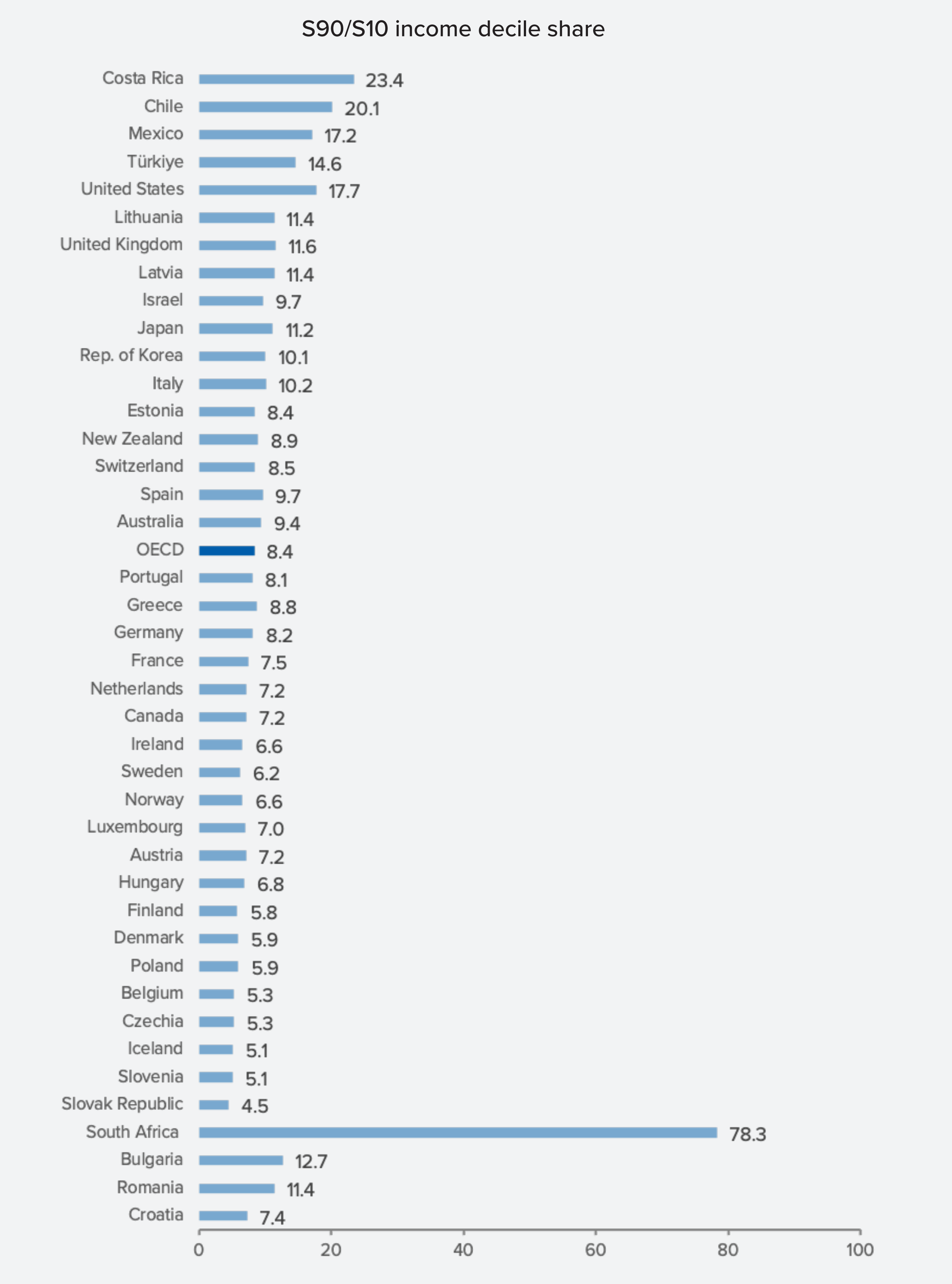
Figure 6 – Trends in global inequality



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

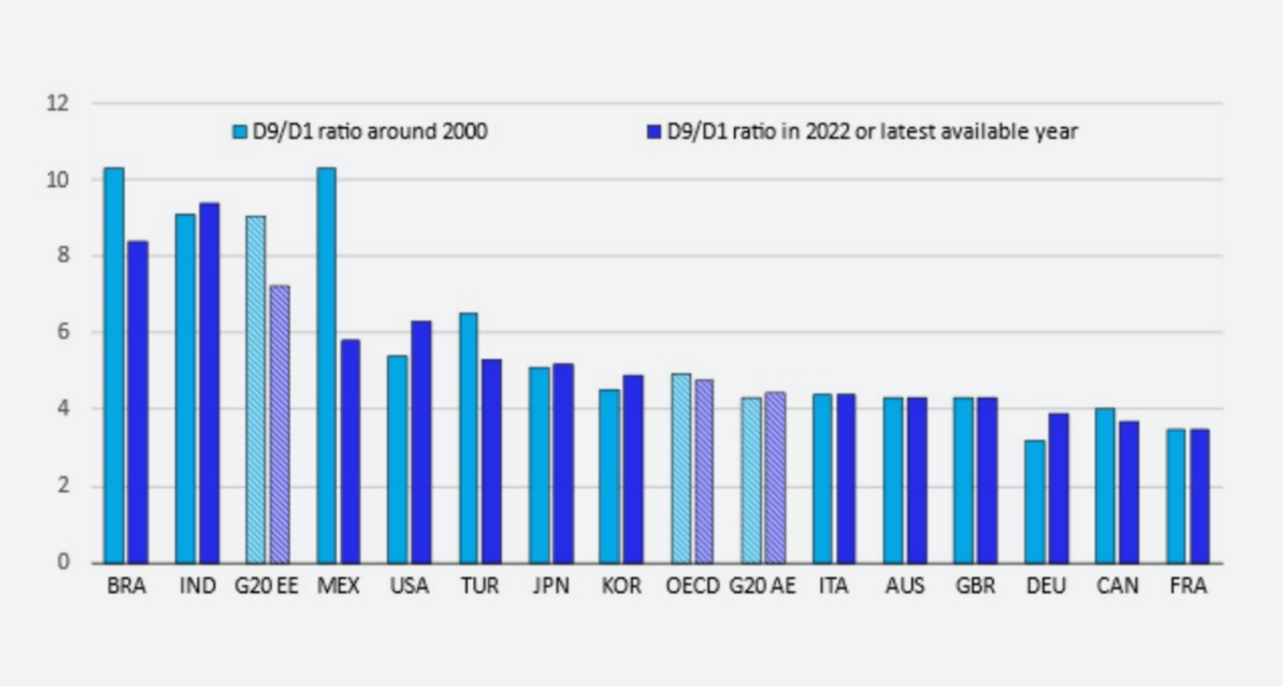
Between 2007 and 2019, within-country inequality rose in a few European countries. Income distribution also became more unequal in the United States, China and India, but in China it has diminished since 2010.[13] However, between-country inequality fell.[14]

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



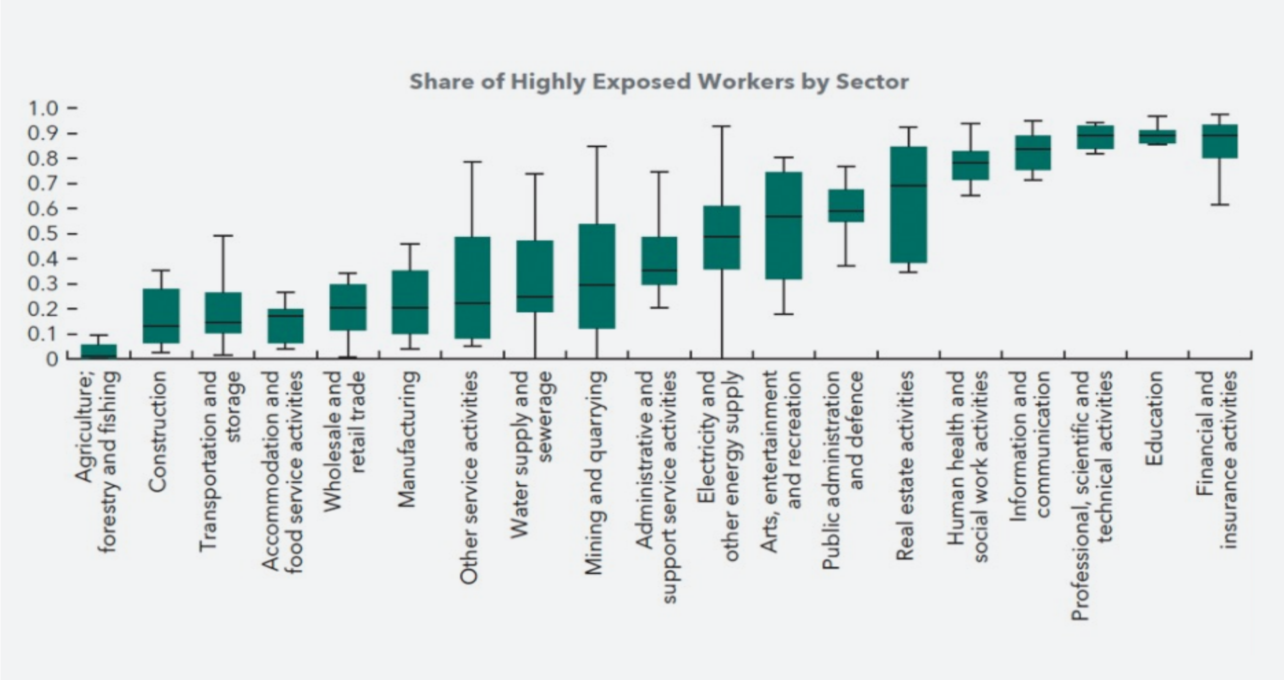
Source: (Soldani, 2024)

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.

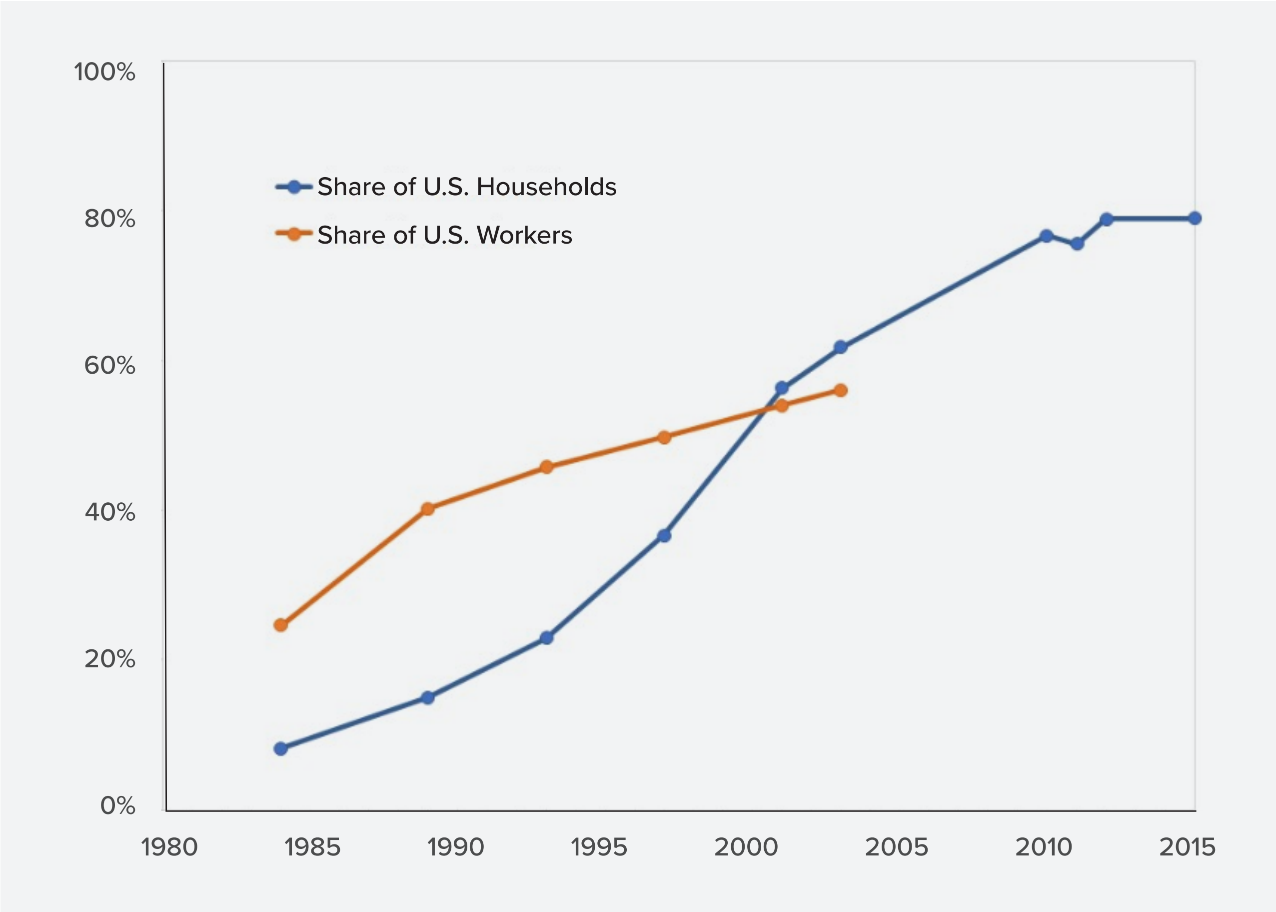
By the 1990s, however, computers had become ubiquitous and their impact was reinforced by broadband internet access and their contribution was becoming visible in the TFP data. As they were integrated into workplaces and the home environment, demand rose steeply, stimulating the manufacturing value chain. 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]

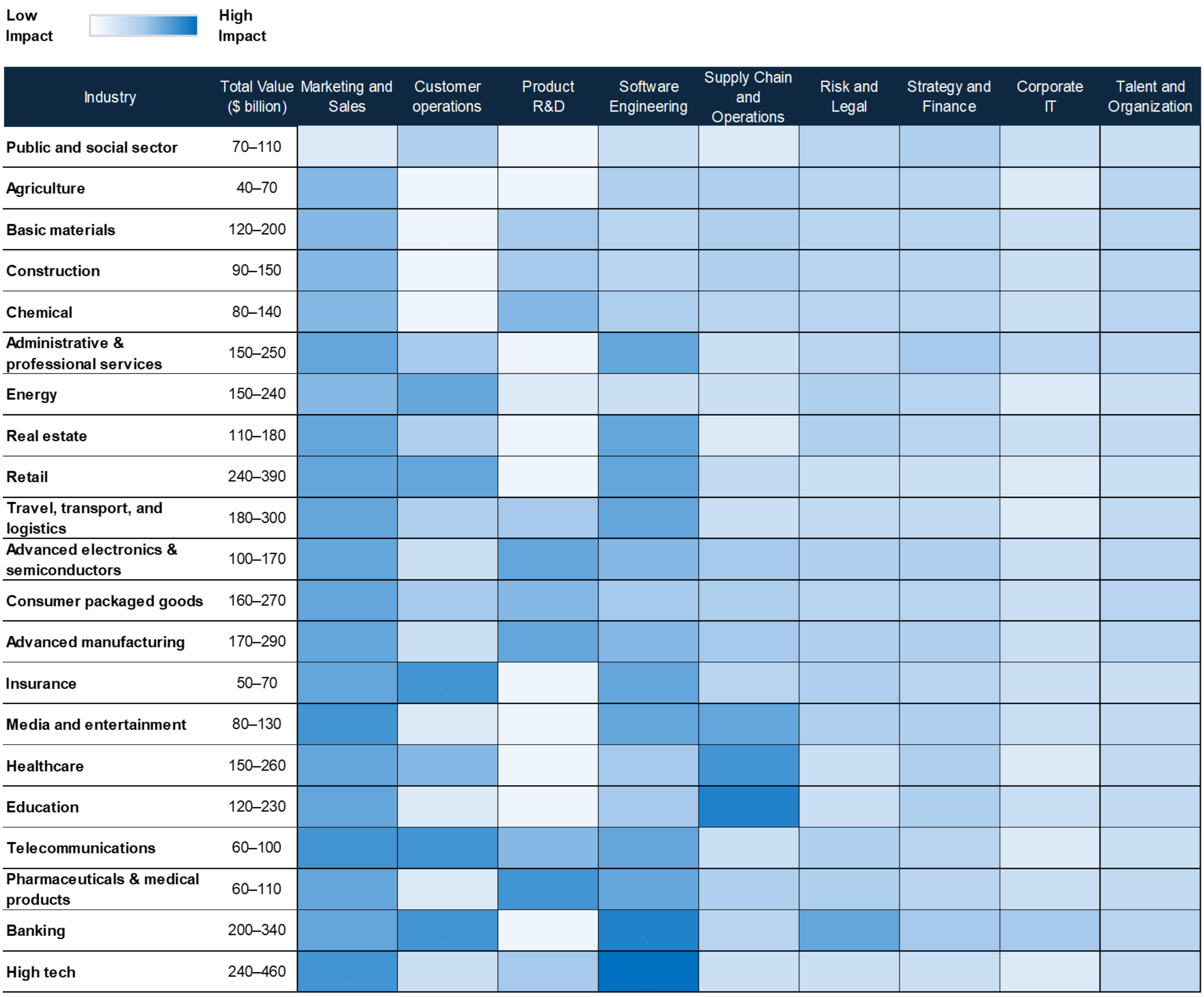
The effects of computerization and digitalization on productivity and income distribution were much less apparent in the EU and Japan, and played a limited role in several Asia-Pacific EMDEs. After the spurt in productivity had died down by the mid-2000s, in Germany, Japan and the US from 2004 through 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



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.

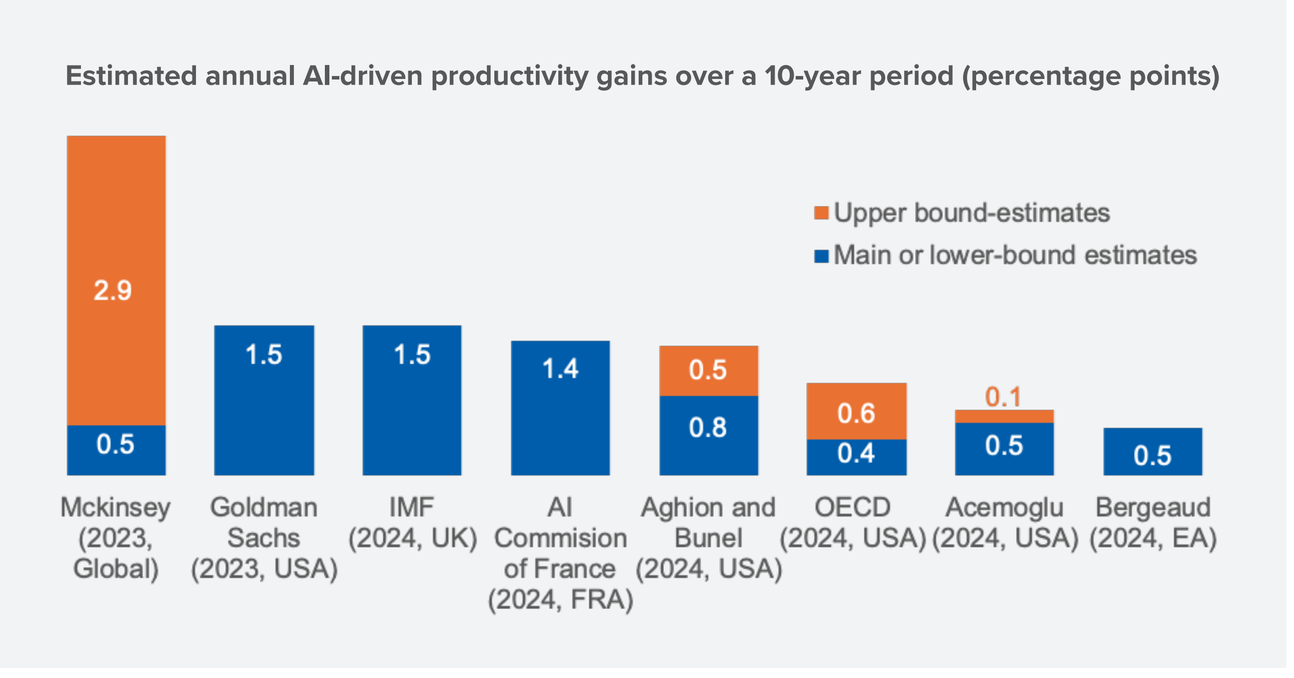
Forecasting AI gains

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

Services

Services around specialized knowledge on how to leverage generative AI (e.g., training, feedback, and reinforcement learning)

Applications

B2B or B2C products that use foundation models either largely as is or fine-tuned to a particular use case.

Model hubs and MLOps

Tools to curate, host, fine-tune, or manage the foundation models (e.g., storefronts between applicartions and foundation models)

Foundational models

Core models on which generative AI applications can be nuilt.

Cloud platforms

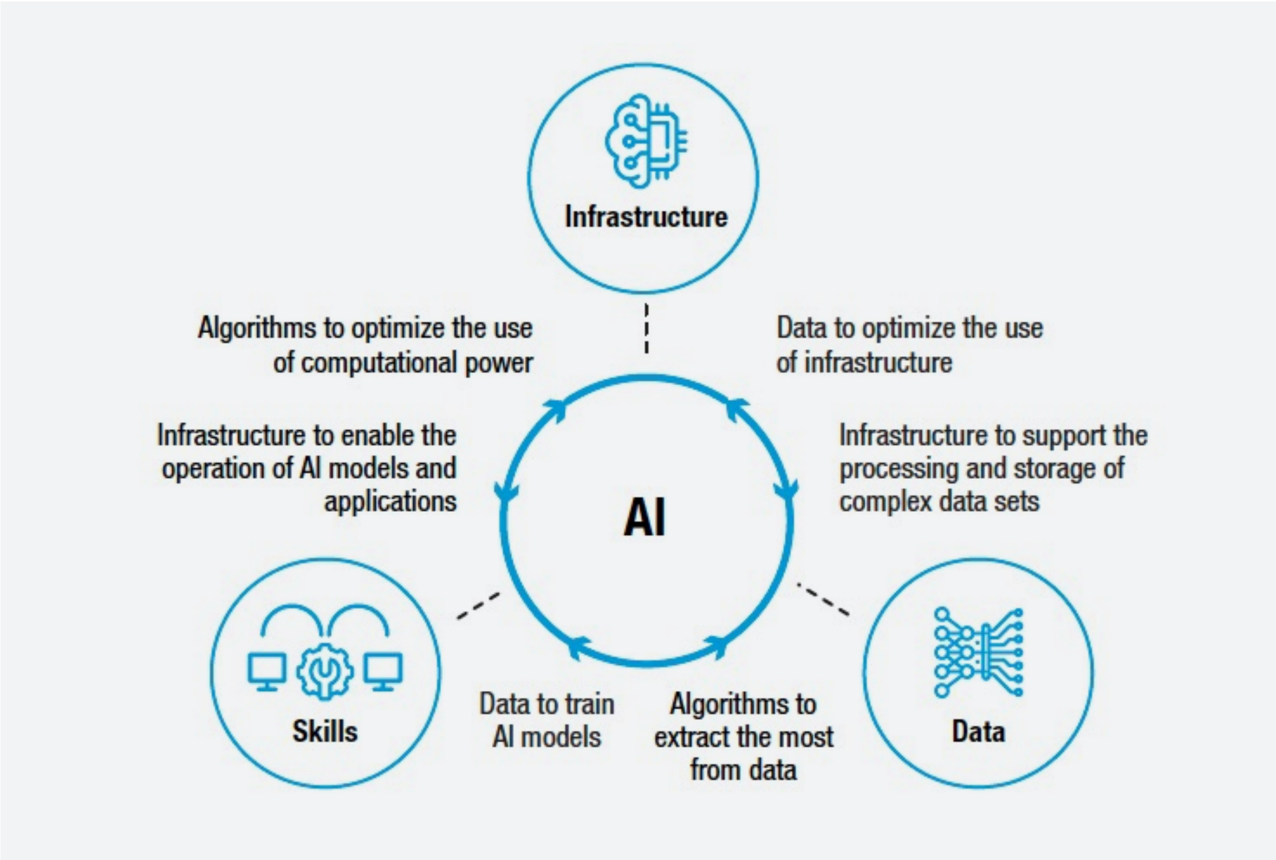
Platforms to provide access to computer hardware.

Computer hardware

Accelerator chips optimized for training and running the models.

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:

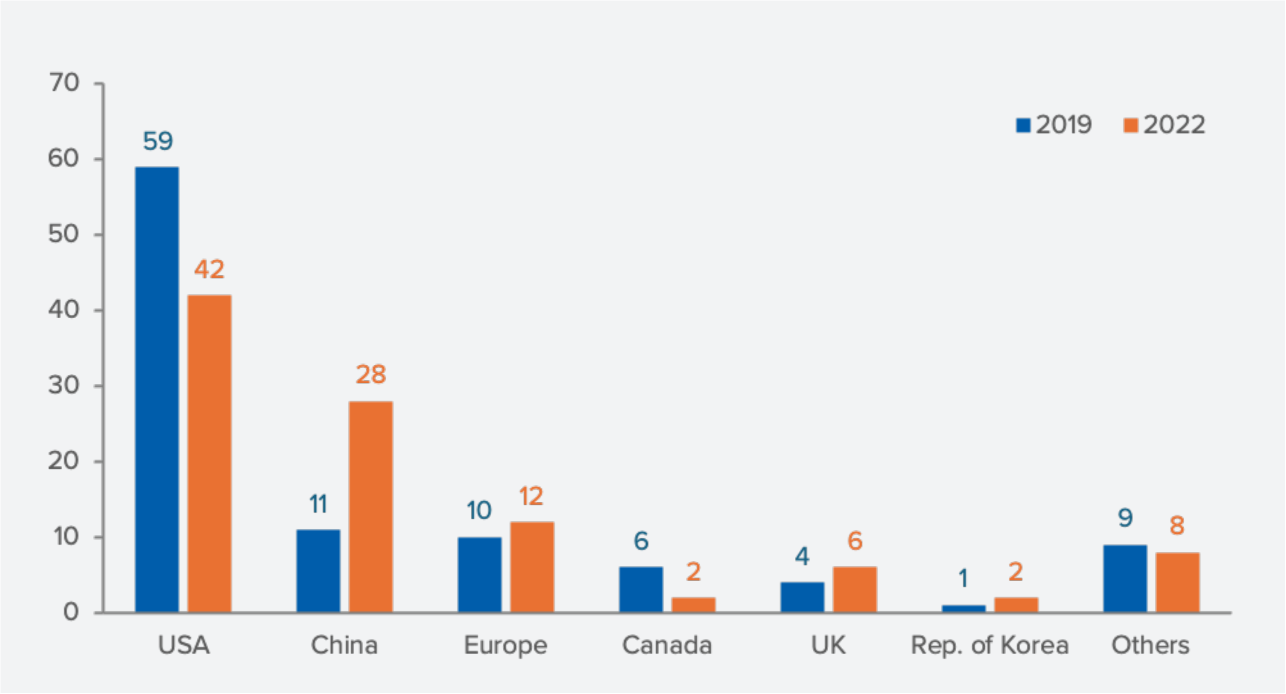
- *Customer Service* – Call centers are using AI to improve the productivity of the less experienced workers.
- *Software Development* – Engineers increasingly rely on AI for automated coding.[64]
- *Healthcare* – AI systems demonstrate growing proficiency in medical imaging and chart analysis.
- *Education* – 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

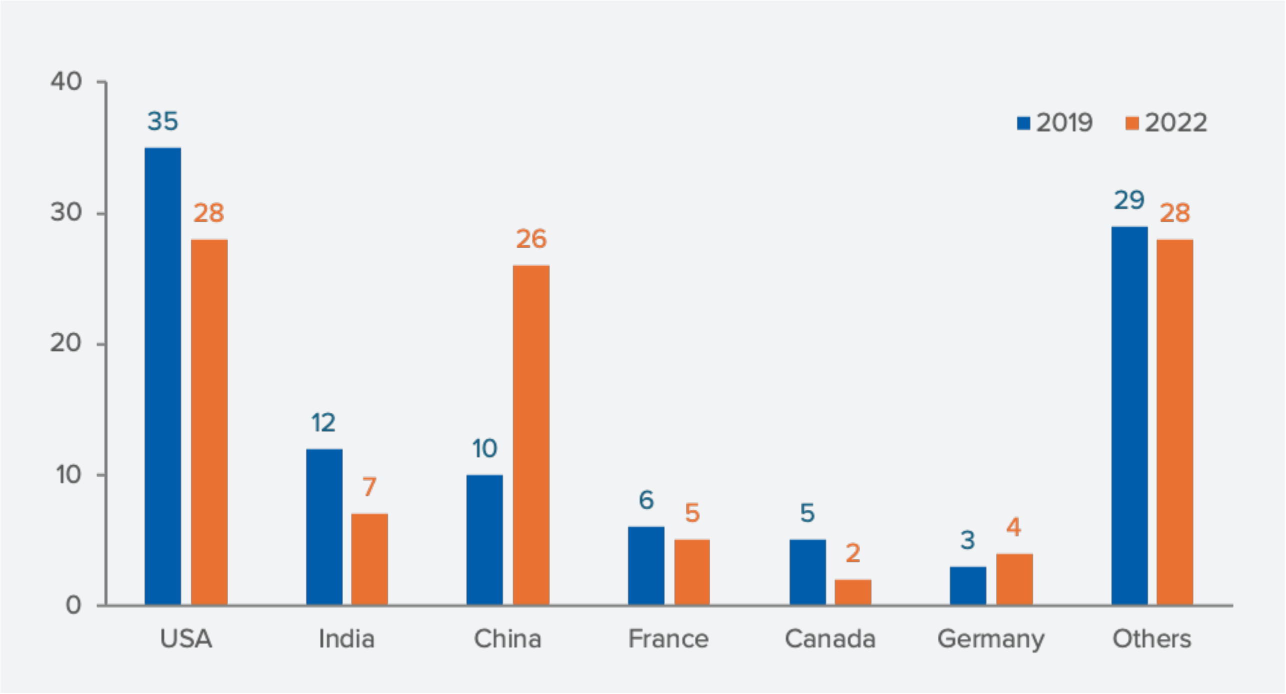
Figure 15 – Distribution of top-tier AI researchers



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]

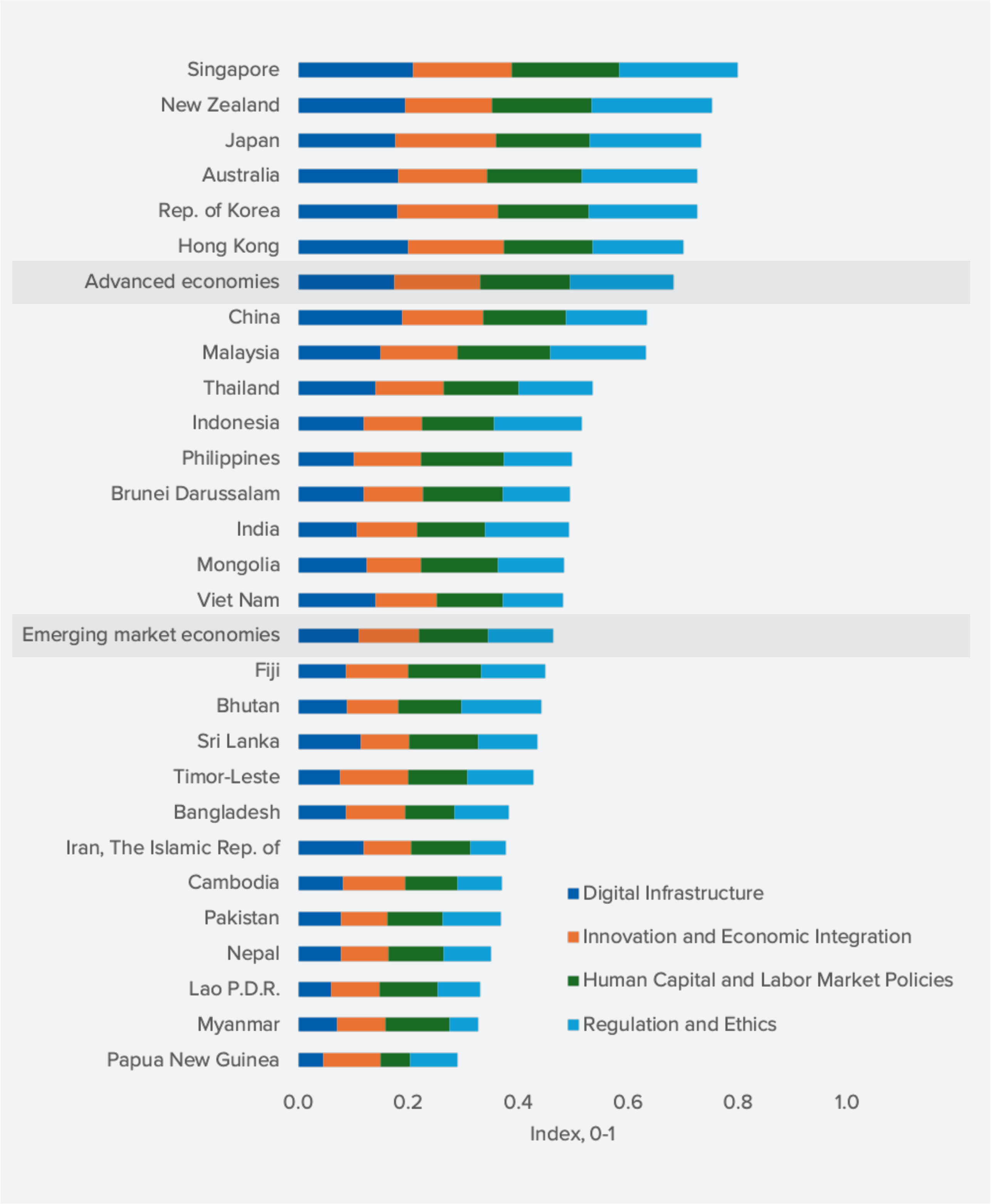
Possible outcomes, positive and negative

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)
89. (Khan, Umer and Faruqe, 2024)

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CHAPTER 7 — LESSONS FROM ONLINE GIG WORK IN INDIA AND INDONESIA

Sarayu Natarajan, Kunal Raj Barua, Supratik Mitra, Nighat, and Sagnik Sanyal, Aapti Institute

Generative artificial intelligence is transforming many global labor markets, especially in online gig work. Using information from India and Indonesia, this study examines AI's dual role, both as a substitute for routine tasks and as a complement to human skills. Based on existing quantitative analysis, it assesses its effects on economic inequality, including gender gaps. This is supplemented with interviews with online gig workers and experts. The chapter concludes with recommendations for governments, platforms and workers – aimed at creating an inclusive AI-resilient workforce.

The current preoccupation with the potential impact of new technology, especially AI, to replace people and cause a loss of jobs is not new. Throughout history, major technological innovations have profoundly reshaped global economies and labor markets.[1] Similar fears emerged during the Industrial Revolution with the advent of machines and factories and more recently again in the 1990s with the rise of computerization.[2] Historically, economists have countered anxieties by highlighting the compensatory effects of increased productivity, lower production costs, and rising demand.[3] And in practice technological advancements have often led to the creation of new types of job to replace those lost through automation.[4]

It is also important to consider the quality of employment. The deployment of new technology typically changes skill requirements, increasing the demand for some skills while making others less valuable, or obsolete.[5]

The new world of gig work

Online gig work has gained in popularity since the onset of COVID-19, particularly among workers outside the formal labor market.[6] Gig work is typically divided into two main categories: location-based platform work (offline) and cloud work (online). Offline gig work includes services such as food delivery, ride-hailing, and domestic assistance, whereas online gig work consists of tasks that can be performed and delivered remotely. This chapter adopts an expansive definition of online gig work that encompasses both offline and online employees as well as independent contractors, covering paid and unpaid tasks.[7]

In 2023, the global gig workforce was estimated to be 435 million, representing 12 percent of the global job market, with online platforms playing a crucial role in this expansion.[8] The gig economy market is projected to reach $1,847 billion by 2032.[9]

Both offline and online work offer flexibility and autonomy to workers while enabling businesses to access specialized talent on demand. Online gig work is typically carried out through marketplaces such as Upwork, Fiverr, Freelancer.com, and Guru.com – which allow gig workers or freelancers to bid for and complete projects posted by clients.

Both offline and online work rely on AI in the form of algorithmic management. In offline gig work, AI optimizes dynamic pricing, for example, or routes, but without directly replacing workers since GenAI cannot perform physical tasks such as food delivery and domestic services.[10]

In online gig work AI-based systems match freelancers with clients, and also monitor worker performance, and implement human resource decisions.[11] Since many online gig jobs can readily be automated there are likely to be continuing changes and a significant shift in workers' skill profiles.[12] AI systems are likely to amplify demand for advanced digital and cognitive skills while reducing the demand for routine and clerical activities. Also in greater demand will be skills that complement GenAI, such as critical thinking, creativity, and emotional intelligence.[13] Even highly skilled freelancers may see fewer jobs and declining incomes.[14] This could also increase the gap between high-skill, high-paying jobs and low-skill, low-paying jobs.[15]

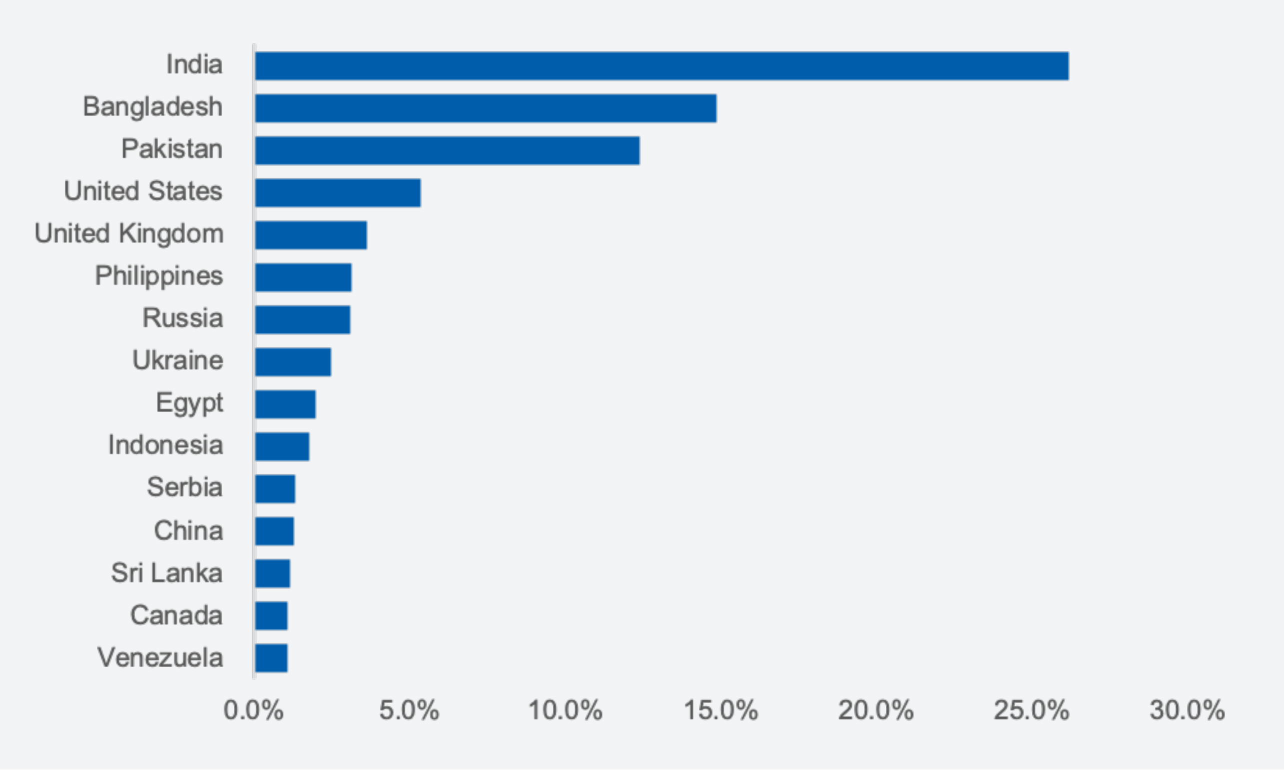
The workers most likely to be displaced are those in the formal sector, who may then need to transition to informal work.[16] This has serious implications for emerging markets and developing economies where employment is already highly dependent on informal labor markets.[17 18 19] Both forms of gig work share characteristics of informal employment in that they typically lack access to unemployment insurance, health benefits, or retirement plans.[20]

Measuring gig employment

Despite its rapid growth, online gig work remains under-researched and largely invisible.[21] Gig workers are a new workforce segment that is difficult to measure precisely. Gig workers are often categorized as independent contractors, self-employed workers, or day laborers. However, there have been some advances. Singapore, for example, in its 2023 labor force survey, accounted for gig workers. Australia has also added digital platform workers as a category in its labor survey. India's Code on Wages (2019) and its Code on Social Security (2020) have introduced definitions for gig workers, for workers participating in arrangements outside the traditional employee-employer relationships.[22]

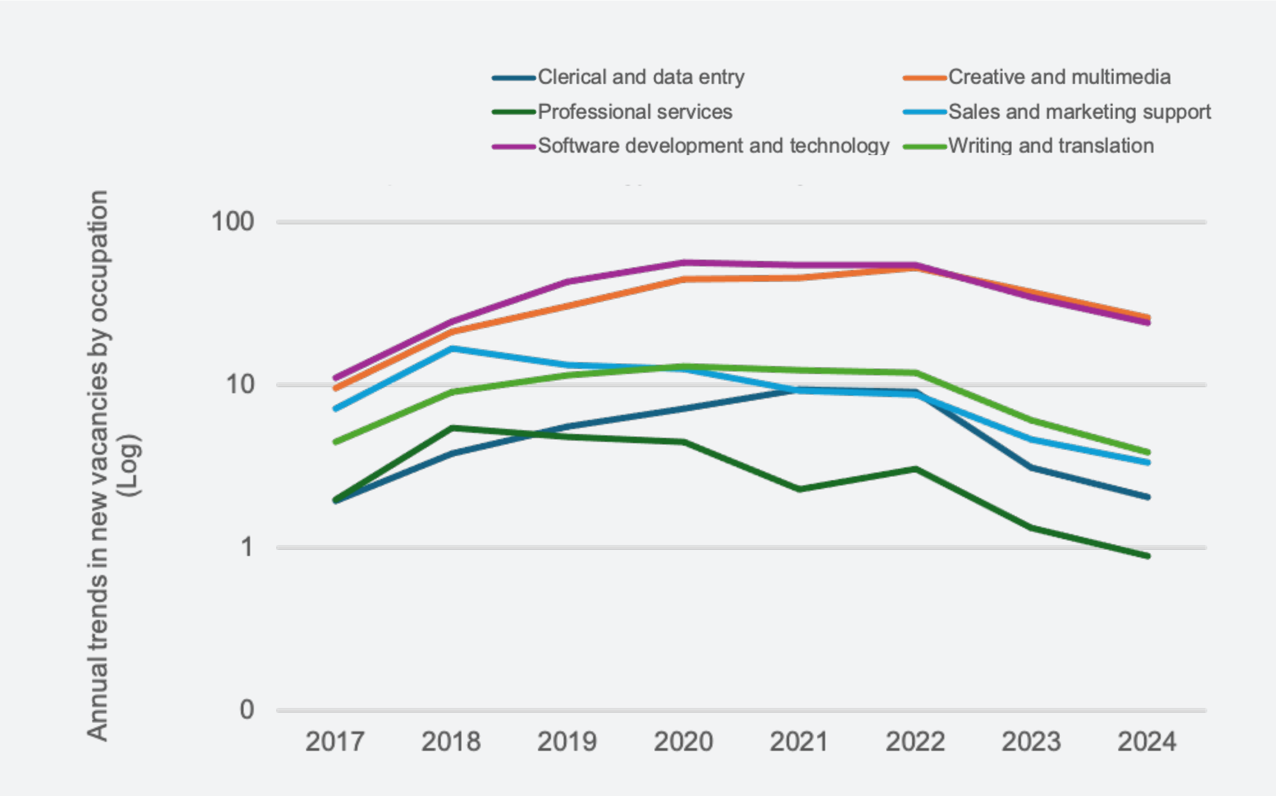
One important source of global data on gig work is the Online Labor Index (OLI), from the International Labor Organization with Oxford University. As indicated in Figure 1, the OLI indicates that a significant share of such workers are from India, Bangladesh and Pakistan.[23]

Figure 1– Percentage distribution of workers on online labor platforms – top 15 countries



Source: OLI database

Figure 2 – Annual trends in new vacancies by occupation, globally



Source: OLI Database; Aapti Analysis.

According to the OLI, since the introduction of ChatGPT the number of automation-prone online jobs declined more rapidly (Figure 2).[24] Nevertheless, between 2020 and 2021 the OLI also suggested an increase in demand for clerical and data entry work – including labelling and annotating data. Occupations like software development, creative and multimedia, professional services and sales and marketing have also seen a slight increase, while occupations like writing and translation have fallen.

Patterns of inequality in online gig work

In principle, seamless global access to work, combined with fewer requirements for certifications, should offer more equal access to employment.[25] However, gig workers face uncertain and unstable employment with a lack of benefits, and an overall precarious status,[26] and there are persistent wage disparities, particularly affecting women.[27]

In certain contexts, flexible working arrangements are attracting women, allowing for complementarity with other duty arrangements, like maternal and domestic care.[28] Indeed, there has been a notable increase in female participation in the online gig economy.[29] Yet this flexibility is often a double-edged sword. Gig work opens doors to economic participation, but it can also trap women in low-paid, unstable roles that lack clear pathways for growth and advancement. The flexibility that initially seems liberating may inadvertently entrench cycles of precarious work with limited benefits and job security.[30] Additionally, women tend to be clustered in roles that align with occupations historically dominated by women such as writing and translation, teaching, and clerical work.[31] Women often face a dual burden: the gender pay gap and occupational segregation, which are further exacerbated by algorithms.[32] Women in these occupations and in sales and professional services also face a unique challenge if they risk being replaced by machines.[33]

Field of study – India and Indonesia

To gain a greater understanding of online gig working, this chapter looks in particular at India and Indonesia. In some respects, labor markets in these countries are similar – both show significant disparities between formal and informal workers and between men and women.[34] These initial inequalities also seep into gig labor markets – and can then be exacerbated by the deployment of AI at scale.[35]

Both countries have high levels of job informality: in India in 2024, 88 percent; in Indonesia, 59.4 per cent as of February 2025.[36] And in both countries, legal protection in terms of safety and security and equality remains rudimentary.[37]

Nevertheless, there are notable differences between the two countries, with respect to formal employment. In India, with its dependence on service industries and IT-driven growth, fewer job opportunities have been created for the average worker. Between 1988 and 2022, growth in formal employment stagnated, increasing by only 10 percent. Indonesia on the other hand which has promoted labor-intensive manufacturing has encouraged workforce participation in the formal sector.

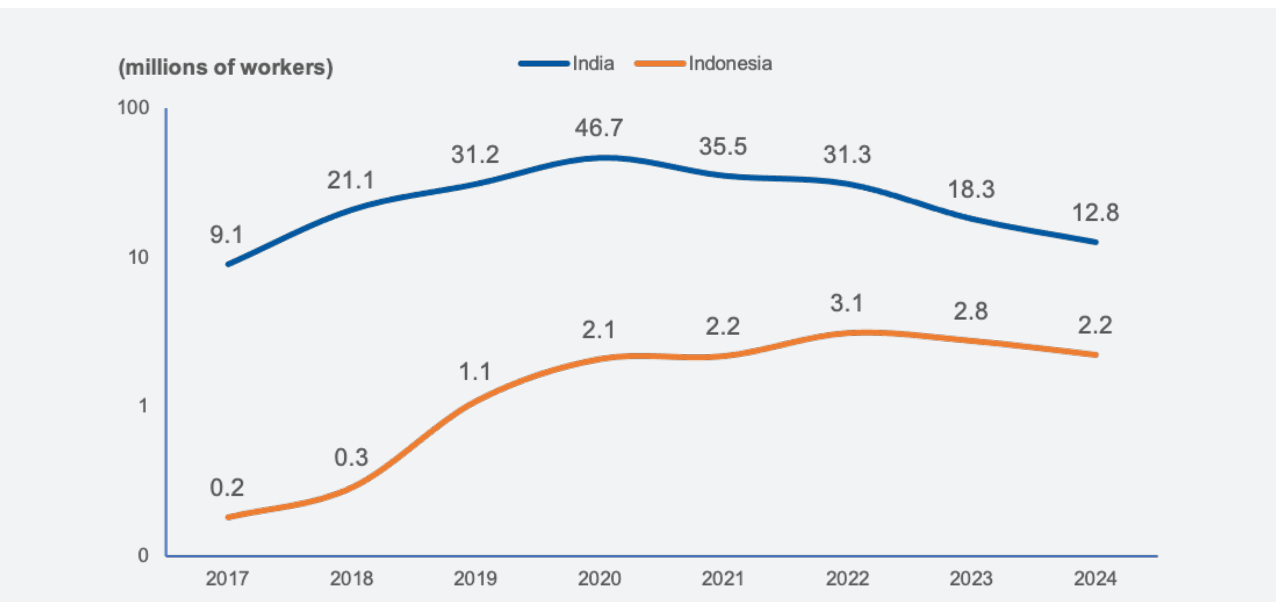
AI is thus likely to have different impacts. In India, the IT service-focused labor market is already seeing disruption.[38] In Indonesia, labor-intensive formal labor markets may see a more staggered impact, though with fewer productivity gains.[39]

In both countries labor protection for gig workers remains limited.[40] In India, social protection is gingerly being extended to offline gig workers,[41] but there is negligible consideration for their online counterparts.

Trends in online gig labor markets in India and Indonesia

India and Indonesia are at different stages of worker engagement for their online gig labor markets. India represents a more mature, saturated market for online gig jobs, while Indonesia is an emerging market with recent uptake and adoption. Between 2017 and 2024, India experienced a steady plateauing of workers registering on labor platforms, while Indonesia saw a significant rise (Figure 3).

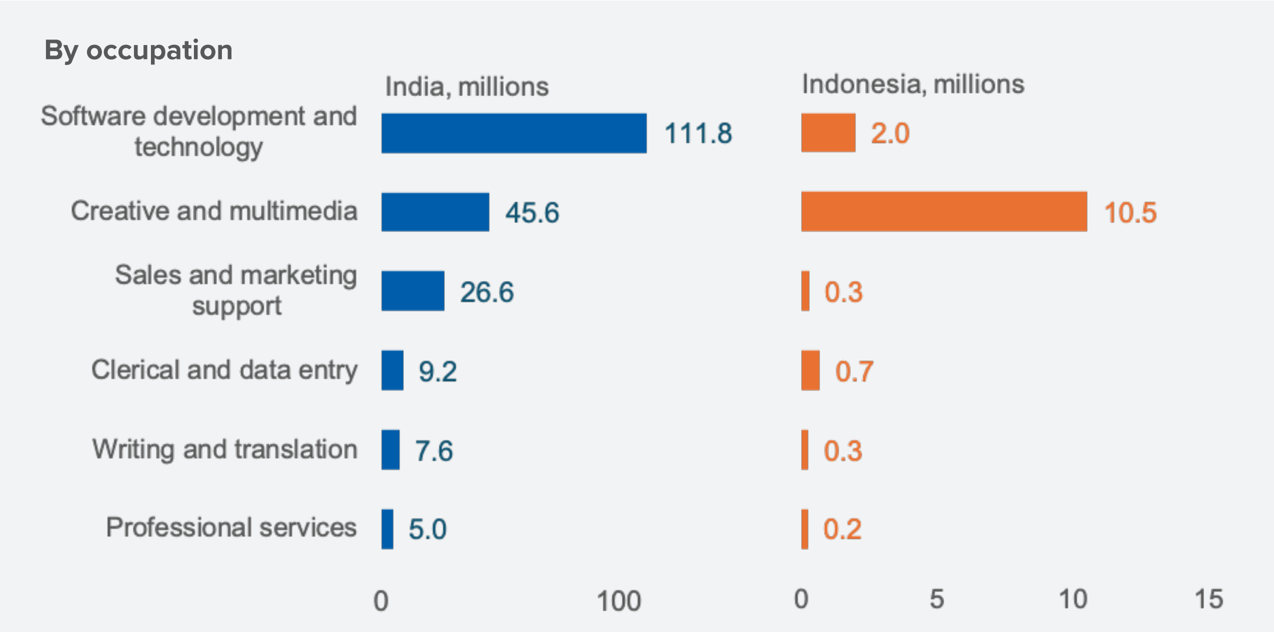
Figure 3 – Number of workers in online gig platforms, India and Indonesia, 2017–2023.



Source: OLI Database; Aapti Analysis.

Note: A logarithmic scale is employed to allow comparison between India and Indonesia. OLI data contains online workers only; ride-hailing/delivery are excluded. "Registrations" may include multi-platform accounts and inactive users; smaller values are produced when "active" workers are used.

Figure 4 - Gig workers in India and Indonesia, by occupation, 2016-2024 (millions)



Source: OLI Database; Aapti Analysis

There are also differences between the two countries in the occupations of online gig workers. As indicated in Figure 4, in India they are likely to be in software development and technology, while in Indonesia they are employed more in creative and multimedia tasks.

Substitution and complementary effects of AI

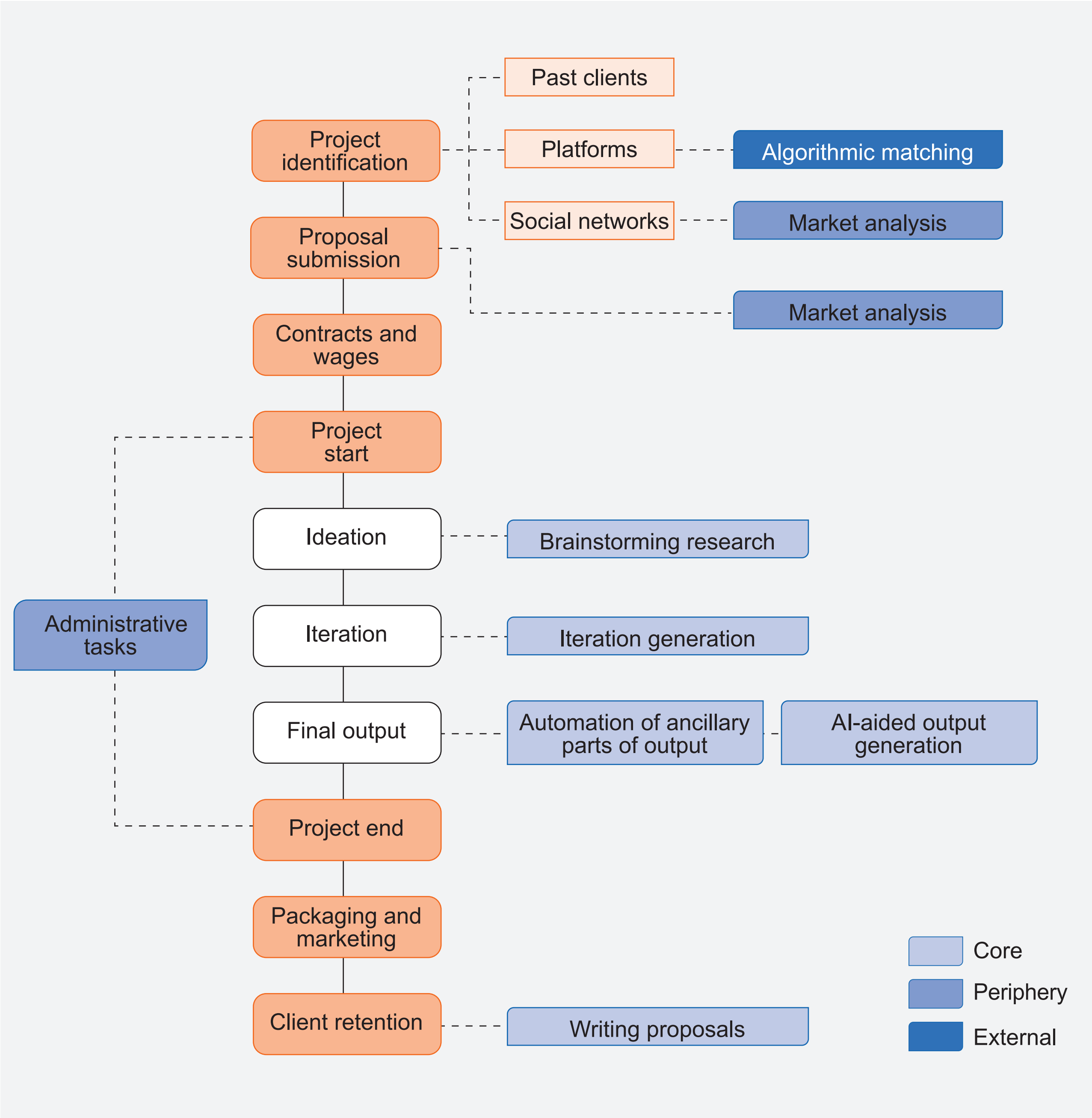
Figure 5 represents the project lifecycle of an online gig worker as well as the various touchpoints of AI interventions across three different categories, core, periphery and external.

AI can either substitute for or complement human labor. Substitution occurs when AI automates a substantial part of a task.[42] Complementarity emerges when AI handles repetitive tasks, freeing people to work on more creative or social aspects.[43] Generally, the effect of GenAI depends less on the sector or industry, and more on the composition of underlying tasks and skills and AI capabilities. For low-wage or low- cognitively intensive jobs, for example, GenAI skills can replace core and routine tasks. Tools like ChatGPT have already reduced the demand and wages for some freelance jobs.[44] In high-wage or high-cognitively-intensive jobs AI is more likely to complement existing worker capacities such as critical thinking, creativity, and emotional intelligence – which may in the long run become more valuable and enjoy greater demand.[45] Even here, however, some workers benefit more than others. Older workers are finding it more challenging than college-educated and younger people to move to roles complemented by AI.[46]

The study looks at changes in demand on online labor platforms in India and Indonesia. The first part of this analysis was quantitative, counting the postings on online labor platforms for two groups of jobs: AI-mature tasks where its tools produce high quality results that mimic human outputs; and less AI-mature tasks where the capabilities of the new tools remain nascent. This data was used to compare demand for labor before and after the release of publicly available GenAI tools.[47] This did show a weak effect, but it was not statistically significant.[48]

In addition, this study interviewed some online gig workers in India and Indonesia – three each from AI-mature and less AI-mature categories. There were also interviews with 12 experts, including researchers and clients, and businesses using gig labor platforms.

Figure 5 – AI use across a gig worker's project cycle



Source: Aapti Analysis

Impact of GenAI on online gig work

Table 1 summarizes how respondents said they were using AI tools. At the core, GenAI tools were primarily used in the ideation stage and for research; however, when these tools produce work of sufficient quality outputs, they are also used to aid the creation of the final output – workers reporting gains in both efficiency and quality. At the periphery, on the other hand, GenAI tools were being used to automate repetitive ancillary parts of the project cycle, enabling workers to focus on core tasks, leading to perceived gains in productivity.

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

Task category	Associated tasks	Use of GenAI
Core *The essential activities and processes that directly create a project's primary deliverables.*	Brainstorming and research support	Most respondents said GenAI tools were used for brainstorming and research. Such tools are typically used to understand the project at hand, often playing an assistive role in ideation, and in some cases, further probing to help strategizing and to deliver innovative outputs.
	Iteration generation	Respondents claimed to use GenAI tools to create multiple draft iterations of the output as part of the ideation process.
	Automation of ancillary parts of outputs	In some cases, AI models demonstrated the ability to produce quality outputs, but workers suggested the use of text and image-generating models to automate ancillary parts of the final output, such as background images or written copies for creative and design outputs.
	AI-aided output generation	A small cross-section of the respondents suggested the use of GenAI tools to generate outputs in some projects; however, these were never claimed to be final outputs, often needing human tweaking.
	AI-enabled product offering	Beyond the scope of a project cycle, some respondents claimed to be able to offer other services that they were previously unable to produce, using GenAI tools for support in such tasks.
Periphery *The supplementary tasks and support functions that facilitate or enhance the core work.*	Market analysis	Respondents were using AI-enabled search tools to conduct market research, particularly for identifying in-demand skills or exploring gig opportunities. They mentioned that these tools significantly enhanced the ease and efficiency of their research process.
	Proposal writing	Online gig workers often need to submit proposals for project opportunities. According to the respondents, GenAI tools have made this process more efficient and, in some cases, even improved the quality of the submission.
	Administrative tasks	Tasks like progress reports, presentations, and drafting emails form an important part of a gig worker's tasks within a project cycle. Such tasks were also seen to be either AI-automated or supported.
External *The outside systems, influences, or factors that lie beyond the worker but affect their functioning and experience.*		Online labor platforms, as seen in other gig labor platforms[49], also use AI models to algorithmically match clients to workers and rank workers.[50] One respondent suggested a lack of transparency on what factors are considered by such algorithms, restricting access to work opportunities. However, this lies outside the scope of the current study.

Source: Aapti analysis

Reports of users for core functions

For core activities, such as writing software or offering ideas, workers considered GenAI as a beneficial assistive technology. AI chatbots, for example, were used to brainstorm and ideate and enable workers to improve the quality of work. The tools also eased the process of making draft iterations, allowing workers to improve the quality of the final output. The benefits did, however, vary according to the maturity of AI models. For example, while AI chatbots produced relevant outputs for software development, and writing and translation, they were of less use in occupations like professional services, such as online help services.

Workers also reported negative impacts. Some suggested a shrinking demand for work on simpler tasks and projects. A similar decrease in opportunities was indicated in interviews with experts and employers, especially for repetitive tasks, with defined workflows and output requirements, for which AI models were mature enough to mimic human outputs. A few respondents reported AI's inability to comprehend or manage complex workflows, or to produce abstract outputs requiring contextual knowledge.

Reports of users for peripheral functions

For cognitive repetitive tasks like managing calendars, most respondents reported a gain in overall productivity: AI tools were helping workers either automate or aid in tasks like research and communication. A cross-section of respondents also reported using AI translators to overcome language barriers in international markets especially for platforms where the market remains dominated by global clients.

These responses also identified two crucial factors: AI-skill compatibility and the complexity of workflow and output.

- *AI-skill compatibility* – Where GenAI skills are mature and can mimic or better human skills they can substitute for them or be complementary. This also aligns with our tentative quantitative observation suggesting some reduction in employment as well as with international research.[51]
- *Complexity of workflow and output* – Where the work is more complex and dependent on contextual factors or experiential knowledge, GenAI has less to offer. Jobs requiring outputs with complex workflows are likely to see minimal disruption.

Table 2 shows how these two factors can be considered in four combinations, offering a starting framework considering the impact of GenAI.

Inequality analysis

In many cases, AI adoption deepens existing inequalities among gig workers by influencing employment structure, skill barriers, job quality, and digital preparedness, shaping who benefits and who is left behind in the evolving digital labor market. This section considers the aspects that will be affected, as summarized in Figure 6.

Employment terms and support infrastructure

Factors such as wages, labor regulations, taxation systems, and access to connectivity can leave workers in exposed and precarious situations.

Wages – The absence of a formal wage framework made it difficult to predict income and budgets. Monthly earnings fluctuated depending on whether working with local or international clients. One worker in Indonesia said that working with domestic clients could bring up to $200 to $300, whereas international clients might pay $600 to $900 for a similar task. Additionally, wages were also dependent on levels of experience. A worker with more than five years of work experience could make up to $1,000 a month.

Contracts – Respondents in India often worked with clients on retainers, allowing them to earn a baseline monthly income. Workers in Indonesia, on the other hand, were more likely to have a project-based relationship, so their income depended on the number of clients they

Table 2 – The impact of AI on different categories of work and tasks

When AI skill compatibility is high and complexity of workflow and outputs is low: There is a higher probability of GenAI tools substituting for human labor. *For example: AI text generators can produce high-quality writing work, particularly in areas like copywriting and search engine optimization, reducing the reliance on human labor.*	**When AI skill compatibility is high and complexity of workflow and outputs is high:** There is a higher rate of complementarity with existing human labor, helping workers not only increase their productivity but also the quality of outputs. *For example: tasks like product design require contextual awareness and experiential knowledge so there is limited automation; instead, AI tools assist workers, producing perceived productivity gains.*
When AI skill compatibility is low and complexity of workflow and outputs is low: Limited impact in terms of substitution or complementarity. *For example: for jobs within the online gig economy requiring physical presence, like photography or video production, the substitution impact of AI can be assumed to be negligible and there are also limited complementary effects.*	**When AI skill compatibility is low and complexity of workflow and outputs is high:** Workers use AI tools to automate or assist with peripheral tasks, resulting in minor productivity gains. *For example: in professional services AI can be used in the periphery to aid and assist workers, improving overall productivity.*

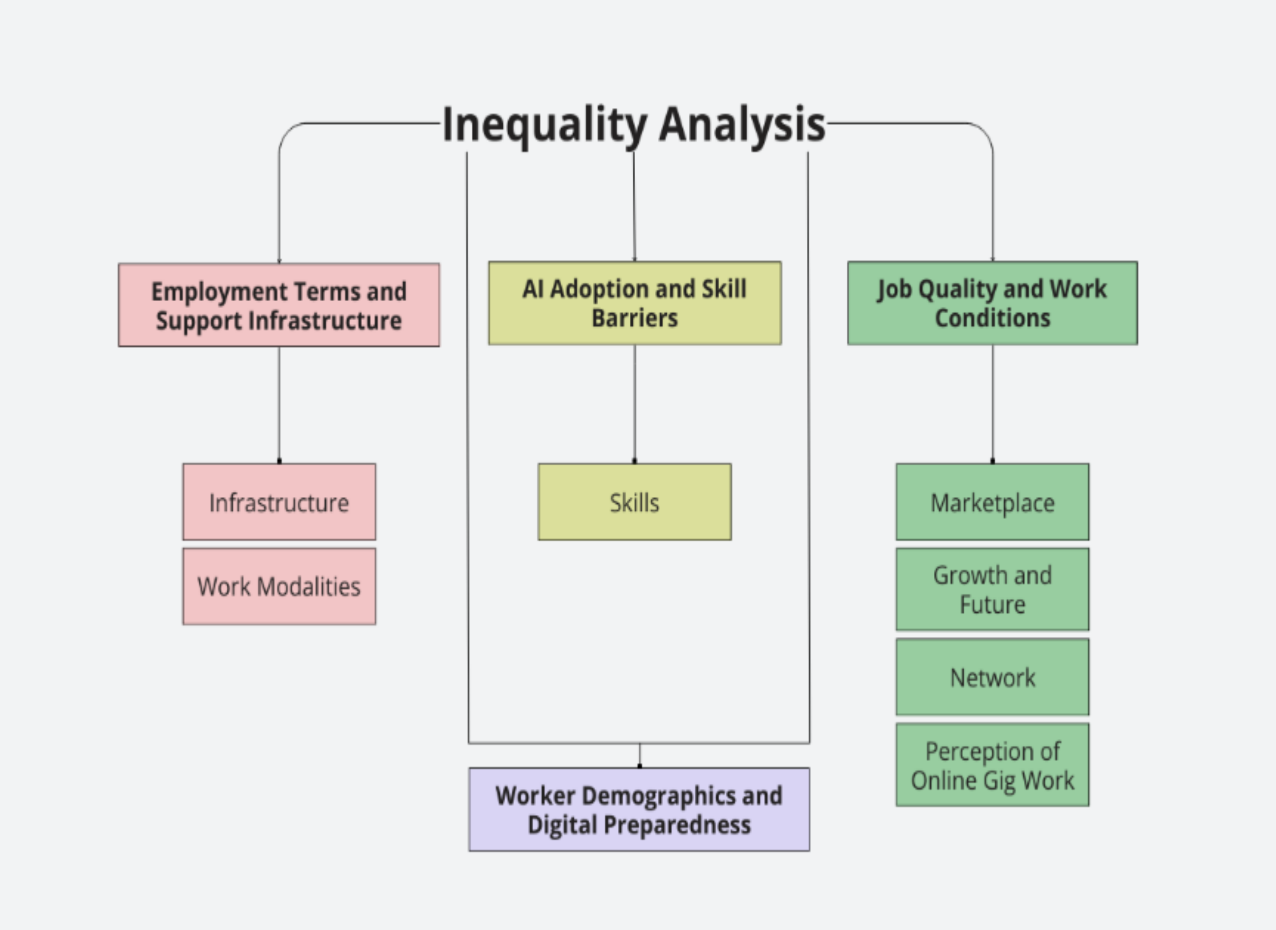
worked for. This also limited their capacity to work on multiple projects for the same client. Platform workers tend to operate with vague contracts that often lack clear payment schedules, indications of the scope of deliverables, or processes for dispute resolution. This leaves workers exposed to conflicts with clients, with minimal remedies at their disposal.[52]

Taxation – Given the unclear employment classification of online gig work, it may be difficult for workers to understand and fulfil their tax obligations. Indian workers often relied on chartered accountants, whereas Indonesian workers depended on assistance from personal contacts.

Infrastructure – Infrastructure includes access to the internet, hardware to perform the job, government support, and community support. None of the workers reported problems with hardware or software infrastructure. However, workers from Indonesia mentioned needing more support from the Government in terms of better job opportunities, access to social security and skill development programs. One worker mentioned the need for awareness campaigns by the Government around training and development on AI models for creative work. In terms of community support, workers from both countries said that they had taken up mentorship roles for those entering the workforce. Additionally, workers from Indonesia mentioned the value of community-based organizations that focused on skill development and network building.

Gender – Although our interview data did not capture the nuances of gender-based concerns, secondary research

Figure 6 – Structure of the inequality analysis



Source: Authors

indicates gender factors in online platforms though the impacts vary. In other contexts, early evidences suggest that wage gaps disadvantaging women are a feature of online platform too.[53 54] Another important factor in India hindering online women workers is lower smartphone ownership,[55] combined with lower digital literacy rates.[56]

AI adoption and skill barriers

Insights from the interviews under this theme comprise three dimensions of skills: skill types, job roles, and AI adoption.

Skill types – Workers and experts emphasized the growing importance of soft skills. While hard skills help workers perform the required tasks, soft skills such as communication, critical thinking, and creative thinking are essential for maintaining strong client relationships, both directly and off-platform. Soft skills cannot yet be entirely replicated by AI tools. One worker in Indonesia for whom AI had largely been unhelpful in expanding the business, underscored the necessity of soft skills in building a professional network. To thrive, workers need to strike a balance between hard skills and soft skills.

Job roles – These are categorized into six clusters based on the OLI database: creative and multimedia, software development and tech, writing and translation, clerical data entry, professional services, and sales and marketing support. Experience with AI can, however, be quite diverse. For example, one worker from the professional services cluster mentioned that many of their clients have been paying for the use of premium

AI models. On the other hand, another worker from the creative cluster mentioned that while AI can improve productivity, its outputs are too generic and lack the human touch and sensibility.

Effect on projects – Workers from Indonesia mentioned that, given the rapid integration of AI tools, most clients expected shorter turnaround times and have at times encouraged the use of AI to facilitate completion. Conversely, workers from India reported no such expectations from their clients; rather, they were happy to work through the creative process to arrive at the final output. Within creative work, workers mentioned that different types of projects offer different scope for AI use. For example, specific social media work that requires outputs to be generated quickly might utilize AI capabilities for final output generation. Contrastingly, an end-to-end brand strategy project which is largely abstract, might only require AI for brainstorming. It was also reported that in most AI-generated output processes, a trained worker's experience and perspective were still required.

Learning and skill development – All workers reported that their knowledge for AI tools was acquired through self-initiated exploration driven by curiosity. None had any formal training or structured skill development. This underscores a significant gap in support systems for upskilling within the online gig economy.

Gender – The interviews did not directly capture gender-based differences, which calls for exploration in future studies.

Job quality and work conditions

This theme considers work culture, job stability, and available benefits which are explored across four dimensions: marketplace, growth and future, network, and perceptions of online gig work.

Marketplace – Work was secured in diverse ways. In Indonesia, many gig workers relied on digital platforms such as Upwork and Fiverr. However, this dependence comes with significant drawbacks: high platform fees, commission-based earnings, and opaque algorithmic matching – which affected earnings, predictability, and job security. In India on the other hand, workers frequently relied on word-of-mouth referrals, which tends to result in more stable and repeatable business. Another crucial factor is client mentality. Two female workers from India recounted instances when male clients were dismissive and devalued their feedback, an unpleasant experience that can also damage long-term professional relationships, especially in environments with persistent gender stereotyping.

Growth and future – Gig workers follow various career trajectories. Some become full-time workers by joining their clients' organizations or building their own companies.[57] In Indonesia, freelancers often use their platform-mediated experience as stepping stones for launching their own agencies. In India, on the other hand, many workers preferred to build their clientele through traditional word-of-mouth channels while maintaining their independent status. Nevertheless, the inherent uncertainty of gig work often leads workers to combine freelance projects with part-time or full-time employment.

Networking – Networks are indispensable not only for acquiring new opportunities but also for obtaining guidance on navigating platforms. In Indonesia, the primary mode of community support was digital, operating through Facebook groups, Twitter, and Reddit. In India, on the other hand, workers followed a hybrid model where community support was both in person and digitally via WhatsApp groups.

Perception of gig work – Workers in both countries appreciated the flexibility and autonomy of remote work. These could however, be limited by traditional gender norms – with women largely concentrated in professional services, clerical and data entry, and creative and multimedia. One female worker from Indonesia who was involved in community skills teaching for gig work, mentioned that almost every candidate in the professional services cluster was female. Expert interviews suggested that this was because working remotely allows women to make time for their domestic work. This indicates the need for targeted interventions aimed at improving worker well-being and long-term career prospects.

Worker demographics and digital preparedness

Worker demographics can be analyzed through three dimensions: age, years of experience, and digital preparedness.

Age – All the workers in the sample were between 20 and 30 years of age. The experts indicated that gig work seems to attract a young workforce that includes recent high-school graduates, early-career professionals, mid-career individuals exploring new opportunities, and generally, those under the age of 30.[58]

Experience – A worker's adaptability and resilience will often depend on previous experience in the gig economy or related fields. Those with extensive experience may have developed an expansive portfolio and a deep understanding of client expectations. This typically gives them an advantage over those entering the market at junior positions, especially when AI tools are rapidly taking over many tasks. However, more experienced workers may also be reluctant to adopt new tools that fundamentally change established workflows. One worker with more than five years experience did not want to incorporate AI tools in any capacity beyond brainstorming.

Digital preparedness – This is defined as a worker's ability to navigate online platforms, master digital tools, and adapt to shifting technological landscapes. All workers in this small sample had a basic understanding of digital tools and maintained a minimum level of familiarity, and most were early adopters, and self-starters.

The preliminary analysis based on a small sample in India and Indonesia thus indicates potential challenges and emerging inequalities among workers in online gig economies. They indicate issues such as consistent wage structures and limited government support systems with skills and training barriers and opportunities influenced by traditional gender norms. Workers typically have to self-teach new tools potentially widening gaps between adaptable and less adaptable workers. Overall, these findings highlight the urgent need for inclusive policies and interventions aimed at improving digital labor rights.

Policy recommendations

Governments

Governments can improve worker well-being and aid the creation of an inclusive and AI-resilient online gig workforce, acting in areas including employment classification to address informality, including through stronger data and evidence-based, skilling and re-skilling, with a particular focus on vulnerable groups and women. In the specific,

- *Labor laws* – Update labor laws and codes to include online gig workers as a distinct category of workers. For example, India's Code on Wages (2019) and Code on Social Security (2020) have introduced definitions for gig workers, for workers participating in arrangements outside the traditional employee-employer relationships.
- *Social protection* – Create dedicated policies or social protection schemes for gig/platform workers that address their specific needs, including health insurance,
- *Labor force surveys* – To ensure visibility, include online gig work as a formal category in labor surveys. Ensure that data are disaggregated by gender, region, and level of skill. Singapore and Australia are among the countries that have added gig and digital platform workers in their labor surveys.
- *Skills training* – Integrate AI skill building into formal education and focus on holistic capabilities like problem-solving, communication, and strategic thinking – partnering with private and academic institutions to deliver diverse, adaptive and accessible training programs.

- *Retraining* – Offer subsidized access to reskilling programs for current workers affected by automation and AI substitution, along with interoperable and nationally recognized certifications that encourage worker participation. In Indonesia, for example, the Kartu Prakerja training program caters for the existing workforce as well as young workers without formal education. Partnering with enterprises and universities, it is also offering advanced technological skills, focusing on AI, data science, and cybersecurity.
- *Opportunities for women* – Foster flexible training and mentorship initiatives to help women develop technical skills and expand their options for gig work that take into account their domestic responsibilities.[59] Incentivize platforms to create a special program for female workers for proficiency in technical skills. In the Philippines' the SPARK programs for example, bridge digital skill gaps across genders. A similar targeted approach has also been adopted for workers with disabilities.
- *Opportunities for women* – Post-training opportunities and finance for female workers. Embed gender-responsive design in skilling and digital literacy initiatives.

Workers

The second set of recommendations outlines how worker unions and workers can take the initiative to advocate for their rights and equip themselves to succeed in an increasingly AI-dependent online gig-work market.

- *Collective bargaining* – This is an effective mechanism to voice worker demands. Regional or occupation-level collectives can bargain for wage levels and offer peer-to-peer support. In Serbia, for example, workers mobilized to form the Association of internet Workers to protest a new taxation regime and succeeded in gaining new rounds of negotiations with the President.[60]
- *Regional level organization* – Regional workers organizations can support gig workers using social media platforms like Facebook, Reddit, and Twitter/X. Digital communities with effective legal frameworks can play a key role in collective bargaining efforts.
- *Worker networking* – Workers will benefit from networking in digital communities to understand skill demands in the market, and for peer-to-peer learning. In the United States the Freelancers Union, a non-profit entity, offers a wide range of resources to freelancers – finance advice, tax advice, free legal clinics and insurance.[61]

Platforms

The third set of recommendations emphasizes platforms' accountability for worker well-being by addressing issues that directly affect the quality and experience of their work. This could be achieved through:

- *Transparent fee structures* – Platforms should make extra efforts to provide standardized, comprehensive and accessible information that can offer key safeguards for workers. Governments can support such activities, by providing transparency platform standards – concerning the disclosure of all fees, commissions, and hidden charges.[62]
- *Contract standards* – Platforms must work towards standards for clearly written and comprehensive contracts that establish work expectations, outline processes to protect against disputes, specify the scope of work, and detail payment terms. Governments can provide standardized contract templates that include guidelines on key elements like payment terms, deliverables and grievance-redressal mechanisms.
- *Enable worker interaction* – Platforms should allow workers to interact with each other. This can improve peer-to-peer support and information sharing and help build shared identities. To encourage worker-centric features for community interactions governments can incentivize platforms – through endorsements or public procurement partnerships.

The AI revolution for gig work is not therefore simply about job replacement or increasing human productivity but about a fundamental reconfiguration of work. At present, gig work is largely growing organically, offering flexibility and new opportunities to workers, but with most of the control in the hands of employers through algorithms. In future governments, platforms and workers will need to work together to build an inclusive and AI-resilient workforce.

END NOTES

1. (Graetz, Restrepo and Skans, 2022)
2. (Frey, 2019)
3. (Hötte, Somers and Theodorakopoulos, 2023)
4. (Acemoglu and Restrepo, 2019)
5. (Dachs, 2018)
6. (Fairwork, 2023)
7. (Koutsimpogiorgos et al., 2020)
8. (Datta et al., 2023)
9. (World Economic Forum, 2023)
10. (Möhlmann et al., 2021)
11. (Duggan et al., 2020)
12. (Demirci, Hannane and Zhu, 2023; Teutloff et al., 2025)
13. (Auer, Köpfer and Švéda, 2024)
14. (Hui, Reshef and Zhou, 2023)
15. (Demirci, Hannane and Zhu, 2023)
16. (Fernández and Meza, 2015)
17. Research looking at broader labor markets shift of formality to informality is limited. Additionally, micro-data study from Brazil and historical analysis of previous waves of automation, suggest minimal impacts.
18. (Cazzaniga et al., 2024)
19. (Elgin et al., 2021)
20. (Datta et al., 2023)
21. (Howcroft and Bergvall-Kåreborn, 2019; Hussein, 2023)
22. In 2022, India's Niti Aayog also conducted a one-time nationwide estimate, I and projections of gig workers based on existing data, but this is limited as it does not distinguish between online and offline gig workers.
23. (Stephany et al., 2021; Datta et al., 2023)
24. (Demirci, Hannane and Zhu, 2023)
25. (Graham and Anwar, 2019; Van Slageren, Herrmann and Frenken, 2023)
26. (Rodríguez-Modroño, Pesole and López-Igual, 2022)
27. (Galperin and Greppi, 2017)
28. (Rani, Gobel and Dhir, 2022)

29. (Palagashvili and Suarez, 2021)
30. (Rodríguez-Modroño, Pesole and López-Igual, 2022)
31. (Rodríguez-Modroño, Pesole and López-Igual, 2022)
32. (Rani, Gobel and Dhir, 2022)
33. (Korgul, Witczak and Święcicki, 2024)
34. (Sen, 2024)
35. (Schor, 2020; Salari et al., 2025)
36. (Shetty, 2022; Pratomo et al., 2024)
37. (Putri, Darmawan and Heeks, 2023; Chandra and Yadav, 2024; Sharma, 2024)
38. (Muneer, 2025)
39. (ILO, 2024)
40. (Datta et al., 2023)
41. (Mitra, 2025)
42. (Chen, Srinivasan and Zakerinia, 2024)
43. (Autor, 2015)
44. (Demirci, Hannane and Zhu, 2023; Teutloff et al., 2025)
45. (Demirci, Hannane and Zhu, 2023)
46. (Pizzinelli et al., 2023)
47. This invoved two-way fixed effects difference-in-differences analysis Detailed note on the methodology and limitations is available in the appendix
48. There was negative coefficient of -4.113 but not statistically significance (p-value = 0.265). Suggest a trend that needs further investigation.
49. (Kadolkar, Kepes and Subramony, 2024)
50. (Trautwein et al., 2025)
51. (Auer, Köpfer and Švéda, 2024)
52. (Filinovych et al., 2025)
53. (Adams et al., 2025)
54. (Liang et al., 2018)
55. (GSMA, 2024)
56. (Njikho, 2024)
57. (Permana, 2023)
58. (Datta et al., 2023)
59. (Ghosh, Ramachandran and Zaidi, 2023)
60. (Digital Platform Observatory, 2020)
61. https://freelancersunion.org/
62. The EU wants new rules to improve the working conditions of people working in the gig economy https://www.consilium.europa.eu/en/policies/platform-work-eu/

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PART 3

GOVERNANCE: STRENGTHENING OR ERODING TRUST?

CHAPTER 8 — EXPLORING THE POTENTIAL OF AI TO USHER IN A NEW GOVERNANCE PARADIGM IN ASIA AND THE PACIFIC

Urvashi Aneja, Aarushi Gupta, Sasha John (Digital Future Labs)

AI can enable anticipatory governance that is based on more collaborative leadership with greater civic engagement. It should also be more efficient, but efficiency alone is not an adequate metric; governance transitions must also be equitable and just. If political and societal trade-offs are not managed effectively, AI-driven efficiency could come at the cost of essential public values such as privacy, transparency and accountability.

This chapter explores the potential of AI for improving bureaucratic workflows, allowing governments to be more responsive and to build foresight capacities for complex policy environments. Governments could work with a wide range of partners to draw in diverse expertise and knowledge systems, while enabling citizen participation and deliberative policy making.

Achieving this new paradigm will not be easy. Some countries will be hampered by weak digital infrastructure, unrepresentative datasets, and the lack of enabling policy frameworks or national capacities for deploying AI safely. Many institutions are now expected to leverage technologies where institutional expertise is still developing.

Whether AI can usher in a new and more forward-looking form of governance is ultimately not a function of technology but of the political and social context in which AI tools are introduced. This chapter explores the potential for a new type of politics that shifts the balance of power, and advances more equitable political, social, and economic relations.

Public sector bodies across several Asia-Pacific countries have already experimented with advanced statistics and machine learning tools. In Thailand, for example, to improve the efficacy and responsiveness of urban services Bangkok has instituted Traffy Fondue, a citizen-facing, issue reporting platform. In China, Pingshan, a district in Shenzhen, illustrates the use of AI for administrative efficiency, assigning citizen complaints and queries to the appropriate agencies and frontline workers via an AI-based internal query management system; and Singapore has invested heavily in digital twin infrastructure for future planning.

Nevertheless, while digital administrative services are increasingly established, advanced machine learning is a relatively new technology in the region. Consequently, there is currently emerging information on the outcome of such specific algorithmic applications, with evolving data and analysis on their effects on governance systems or on human development as a whole.

Even more nascent are Generative AI (GenAI) models. Many interventions are limited to specific ministerial departments or are deployed through pilot studies.[1] Asia and the Pacific offers few documented examples with evidence over time: most are from high-income countries such as Singapore and the Republic of Korea, or well-resourced provincial administrations in China – making it difficult to build a region-wide narrative. This chapter is therefore necessarily partial and speculative – using examples to suggest how AI could support or transform governance.

Future 'imaginaries'

Government, technology companies and international organizations in the region can have socio-technical 'imaginaries' for AI – visions of what is good, desirable, and worth attaining.'[2] Importantly, these imaginaries are performative; they mobilize actors, direct resources and legitimate policy measures. In some countries, they are well developed, with formal political support and AI technologies embedded within governmental frameworks; in others, they are still emerging. Whatever the vision, there will not be a single Asia-Pacific model, rather a series of solutions that align with each political, social, and cultural context.

As an indication of what is possible, this section organizes current AI-based interventions according to 'good governance' dimensions – globally recognized values and principles such as participation, anticipation, agility, efficiency, transparency, and accountability (Table 1).[3]

For foresight

Today's global order faces a series of protracted problems – rapid technological advances, climate change, war, civil unrest, geopolitical tensions, and shifting societal needs. Governments need to gauge and pre-empt current and future trajectories. As expressed by the UNDP Asia-Pacific Human Development Report 2024, this can be achieved by "systematically and actively monitoring sources of information for early signs of emerging trends, disruptions, opportunities, and changes that may have significant future implications."[4]

In this way, governments can move beyond reactive policymaking and adopt anticipatory and resilient postures centered on systems thinking, strategic foresight, and cross-sector collaboration.[5] Developing such anticipatory muscle requires a significant shift in policymaking mindset – towards one that values futures thinking, with the ability, both technical and intellectual, to detect and monitor, and inform decision-making based on early signals and forecasts and maps of various scenarios.

Table 1 – Potential of AI in driving governance reforms

Pillars of good governance	Potential roles of AI	Specific tools/methods
Anticipation	Forecaster	Predictive analytics; risk scoring models; time-series forecasting
	Simulator	Generative AI; predictive analytics; machine learning
Agility and efficiency	Monitor for bureaucratic workflows	Rule-based decision trees; natural language processing
	Archivist	Case-based reasoning; semantic search
Participation	Citizen information desk	Large language models
	Architect of digital public squares	Large language models; sentiment analysis
	Sense-maker of situated knowledge	Multi-modal ai integrating text, spatial, and image data
Transparency and accountability	Public financial management tool	Natural language processing

In this regard, AI can act as a crucial enabler, making sense of vast and disparate datasets. Tools such as predictive analytics, and nowcasting and forecasting models, can identify emerging risks and disruptions, along with opportunities for public value creation in the near and far futures.

As a nowcaster and forecaster

AI-based forecasting models can help in decision-making in highly uncertain scenarios – by tracking real-world events and complex data trends to anticipate the likelihood of instability or social unrest or conflict.[6] By making sense of large volumes of historical and current data, AI-based predictive analytics can enable "decentralized prediction at scale"[7] for crisis preparedness. Such models can also be valuable at lower levels of administration where local governments may lack the institutional capacity or resources for such planning, provided that outputs are treated as probabilistic and subject to meaningful human judgment to mitigate potential biases.

Climate models, for example, can forecast which micro-regions will experience drought,[8] and disease surveillance algorithms can track real-time outbreaks. The Asian Development Bank, for example, has employed AI and satellite imagery in the Philippines and Thailand to track poverty patterns at highly granular geographic scales – to detect early signs of economic distress or deepening pockets of inequality before they appear in traditional surveys or national statistics.[9]

At the global level, UNCTAD uses AI models to analyze data on shipping and customs to offer near real-time projections of trade volumes, helping governments adjust their fiscal and trade policies with minimal lag.[10]

As a simulator

A valuable tool for planning any physical environments cities, transport networks, ecosystems is a 'digital twin' – a virtual replica that can integrate real-time data, predictive models, and simulation tools. Digital twins offer data-rich, dynamic mirrors of complex systems and can be used to simulate potential futures, test policy scenarios, and proactively manage interdependencies. Digital twin architectures are increasingly being combined with machine learning, natural language processing, or decision-support algorithms to transform static models into adaptive tools for foresight and future-readiness.

For instance, Singapore's Virtual Twin integrates spatial and sensor data, allowing planners to simulate sea-level rise, test disaster response strategies, and model infrastructure impacts.[11] In China, the city of Haidian's "brain"[12] analyzes data from over 14,000 CCTV cameras and 20,000 sensors to oversee functions such as traffic, public safety, and environmental health, and uses LLMs to generate visions of urban futures.[13]

Digital twins can also enable participatory governance. Citizens and communities who engage with simulation models can better appreciate the complexity of the issues, understand the value of good data, and recognize the range of influences on policies and decisions.[14] This can help them visualize the impact of long-term visions and planning decisions, provide feedback, and contribute to the co-creation of alternative futures.

However, it should be emphasized that the implementation of forecasting and simulation tools is neither politically nor ethically neutral. These technologies raise urgent questions about surveillance, data governance, accountability, the interpretation of information, and the capacity and willingness of users to act on insights revealed. To serve the public good, the data must be truly representative and used transparently, and the models should be designed to expand the civic and democratic space within which governments imagine and navigate the future.

For agility

AI can harness vast amounts of data about citizens' feedback. Based on this, governments can customize public services,[17] leverage advanced computational techniques to improve the management of public agencies",[18] and streamline bureaucratic processes and operations.

These ideas resonate with the "public project management paradigm",[17] which envisages moving away from linear and rigid workflows towards dynamic approaches that are more amenable to swifter shifts in strategy.[18] Often referred to as 'agile governance', this privileges adaptive structures over hierarchies and silos, emphasizing the virtues of flexibility and responsiveness. UNDP and other development agencies in Asia and the Pacific are increasingly endorsing agile governance as a framework for tackling rapidly evolving policy challenges.[19]

Nevertheless, many countries have been slow to adapt. Their digitization efforts may display veneers of modernity and efficiency but fail to address the underlying constraints on transparency, accountability, and public integrity—often retaining a culture of secrecy and top-down control.

With the use of AI on the other hand, interventions can be more sophisticated and intentional. Unlike generic digitization or datafication, AI tools can be more purpose-driven and target specific bottlenecks in public sector workflows – guided by a theory of change that uncovers and addresses the root causes of inefficiencies. Design and deployment can also be more participatory. Used in this way, AI can not only speed up bureaucratic processes but also reconfigure or reengineer them to make them more comprehensible to citizens.

As a monitor for bureaucratic workflows

AI can be used to develop real-time monitoring tools for bureaucratic workflows, responding to citizen queries or grievances, overseeing project implementation pipelines, or managing service delivery timelines. AI can help bureaucrats and beneficiaries by tracking progress, assigning responsibility to officials or departments, collating status updates, and flagging urgent, exceptional, or priority cases.

Governments in India, Japan, China and Malaysia, for example, have been building online unified digital public service portals and citizen interfaces to enable advanced workflow management. AI can add sense-making layers to these, synchronizing data platforms so as to break down departmental silos.[20]

In China, for example, in Pingshan (Shenzhen) the local government has implemented an AI-based "unified management in one network platform" which collates queries and complaints from citizens on transport and environmental protection, for example, and from the private sector on issues such as taxes and licenses.[21] To prevent "passing the buck" between government departments, the platform directs requests to appropriate agencies and frontline workers, setting deadlines for resolution. It also tracks progress by the designated official, recording each action while updating citizens. If multiple citizens continue to report or raise the same issue, it flags this as a priority and sends the relevant agencies reminders to improve their solutions, and alerts higher-level officials to monitor progress. As well as using AI as a taskmaster, the Pingshan Government also uses it to analyze video data and detect problems related to city traffic and waste disposal.

As an archivist

An often-overlooked component of agile governance is institutional memory. Much historical information is lost through a high churn of civil servants, poor documentation practices, and inadequate coordination across and within departments. When confronting recurring policy dilemmas, new officials may struggle to access relevant precedents while even experienced staff may be unable to retrieve relevant lessons from the past.

Bureaucrats, legislators, and executives can use AI as a digital archivist or knowledge manager to build on accumulated institutional learning – including past experiences and experiments. AI agents can organize, analyze, and retrieve information that often remains unstructured and scattered across departmental reports, circulars, notices, training manuals, and internal policy memos. With natural language processing and information retrieval algorithms, public servants can more effectively preserve, structure, and reuse valuable institutional knowledge.

Such tools can build continuity and consistency during bureaucratic transitions, reduce duplication, and provide better decision-making support; for example, through case-based reasoning (CBR) systems, which analyze comparable prior cases or problems.[22] City planners can, for example, use CBR to quickly retrieve case histories and flag past policy failures or successful strategies as a basis for future urban planning.

Parliamentarians and parliamentary staff can employ CBR systems or sectorally trained LLMs for legislative research. Judicial officers or legal clerks can speed up judiciary workflows by performing AI-assisted precedent analysis.[23] Some jurisdictions, for example, uses LLMs to analyze past cases, and help judicial officers write judgements and orders more efficiently.[24]

In India, another example of AI as an archivist is through the Kunji (Hindi for "key") chatbot. Developed by a social-impact organization, Kunji responds to text and voice commands in multiple languages to help local officials retrieve relevant policy documents. It can also regularly upload new information, sustaining the archive as a living repository of policy frameworks and regulations.[25]

Also in India, the Parliament is aiming to use AI to revolutionize parliamentary documentation, by making parliamentary documents, debates and notes available in multiple Indian languages.[26] AI systems – especially those that combine traditional information retrieval methods with relatively newer forms of LLM-based conversational agents – can strengthen and develop the evidentiary, analytical and predictive reflexes of public officials.

For participation

The new public management approach has been criticized for merely offering states ways to increase efficiency by emulating private corporations. But, while boosting efficiency, AI systems should also be able to help governments in their much broader mandates. Unlike privately-owned entities the states must be accountable to the public, always serve the public interest, safeguard and uphold a wide array of citizen rights, respond to public needs, and focus on the most vulnerable and marginalized even when doing so may not always seem efficient.

As a citizen information desk

AI interfaces can help bridge state-citizen gaps. Government programs often have complex eligibility rules and opaque application processes. Citizens also struggle to get accurate information from officials. As a result, they are forced to make multiple trips to government offices or service centers, incurring high search costs in the process.

AI-driven chatbots offer useful alternatives, particularly for people living in places where it is difficult to access government officials or reach public service centers. Governments have already been using chatbots that enable citizens to get information on public services and report grievances.[27] Such interfaces allow citizens to submit queries in their local language and through their preferred medium – whether text or voice. The AI model then leverages these with advanced natural language processing and the latest GenAI techniques to access diverse data sources, retrieve relevant information, and respond in the appropriate language.

In India, for example, Jugalbandi, is an LLM-based chatbot designed collaboratively by Microsoft, OpenNyAI, and AI for Bharat, a government-backed initiative. Jugalbandi collects citizens' queries in their local languages, retrieves the necessary information from government databases which are primarily in English, and responds in the users' language.[28] Jugalbandi aims to bridge the chasm between the state and the citizen and also make public information more consistent while allowing interactions to be personalized to the needs of citizens. For example, if a user informs Jugalbandi of their current educational qualifications and asks, 'What kind of government scholarships are available for me?', it replies in clear and simple terms with a list of applicable central and state government scholarship opportunities, along with their eligibility criteria and the documentation they require.

This can be of tremendous value to governments at district or city levels. In Thailand, for example, the Bangkok Metropolitan Administration (BMA) in 2024 launched an AI-enabled citizen platform called Traffy Fondue through which citizens can report local issues – such as broken streetlights or trash accumulation. Within two years, BMA had received almost 600,000 complaints, mostly related to roads.[29]

As an architect of digital public squares

A critical component of effective governance is enabling and encouraging civic input. Many governments use digital portals, public assemblies, and feedback forms but find it difficult arrive at a consensus, especially when staff need to sift through large volumes of input along with related documents and notes.[30]

AI can enable and manage mass online deliberations, such as hybrid citizen assemblies, consultations, virtual town assemblies, and mini-publics – as has happened in France,[31] and Spain[32] where randomly or self-selected citizens have shared their perspectives on policy issues as part of democratic decision-making.[33 34]

Similarly, civic technology initiatives have established vehicles for opinion-mapping and consensus-building amongst citizens and government officials .[35] An open-source survey research tool – Pol.is – uses advanced statistics and machine learning to gather, analyze and digest large amounts of text, and visually maps disagreements amongst groups. Project facilitators use this in conjunction with Typeform, a data-gathering tool for stakeholder dialogues that uses rolling questionnaire supplemented by direct personal contact. For this purpose, staffers receive special training, to gain the title of "participation officer."

In 2015, a digital consultation on the ride-sharing company Uber asked: "What are your feelings about occasionally using personal vehicles to transport passengers and charging for this?" Opinions coalesced into two overall groups: pro-Uber and anti-Uber, with the latter twice as large. Pol.is was used to cluster and visually map the gaps between participants' opinions. Each group was then invited to refine their remarks to appeal more to their opponents – resulting in seven comments that received almost universal approval. The insights were presented to stakeholders, including government officials, Uber representatives, taxi association representatives and leading scholars. All data is available on a public platform for individuals to run their own independent analyses.[36]

As a sense-maker of situated knowledge

As well as using formally curated data, AI systems can also be trained to interpret and synthesize hyper-local knowledge, which is particularly valuable in Asia-Pacific countries that have very diverse populations whose community knowledge and perspectives often remain undocumented and marginalized.

A notable pilot initiative is in Indonesia. As part of its Social Innovation Platform, the Ministry of Villages and Development has introduced an AI-based 'digital listening tool' Disadvantaged Regions (Kemendesa PDT). Developed in collaboration with UNDP and the International Fund for Agricultural Development, this is designed to allow local communities, to participate through voice, text, and images to share their opinions for village-level planning.[37] The tool uses AI to distil key concerns and opportunities and can also create 'digital profiles' for different demographic groups to facilitate solutions that respond to specific concerns. The data from the digital listening tool is also expected to be utilized for future planning.[38]

Similarly in Malaysia, the Government is using geospatial AI to simulate flood risks and support climate-resilience planning through community-centered approaches. Unlike earlier analyses that relied solely on satellite data, this initiative also incorporates insights from local communities – for example, information about the social value of flood-prone land. This helps the AI model account for cultural, historical, aesthetic, and emotional attachments that are often missing from conventional planning datasets. Additionally, the model can help validate satellite data by factoring in site-specific variables and indicators that only local knowledge can provide.

The result is a spatially rich, socially grounded dataset that reflects the priorities of the communities most affected. Rather than treating citizens as passive data subjects, the system reimagines them as active informants and participants for climate-resilience planning.[39]

For transparency and accountability

Transparency and accountability are the building blocks of participatory and deliberative democracies, enabling citizens to monitor government actions and hold public institutions to account, and prevent corruption. Yet, in practice these processes can face challenges regarding opacity, and public bodies may be subject to entrenched ideological positions, intensive lobbying, and other political pressures. Meanwhile, efforts to understand political actions and government initiatives are often complicated by bureaucratic complexity.[40]

AI opens up the prospect of greater accountability with new tools for scrutinizing political actions and holding officials accountable – for supporting investigative journalism, for example, watchdog organizations, and human rights advocates. Similarly, AI tools can monitor political campaign financing, identify irregularities, and flag potential conflicts of interest.[41] AI can also empower citizens and civil society actors to hold public officials accountable by collecting and analyzing data that otherwise might remain scattered and unstructured. In Brazil, for example, AI-enabled bots have used data mining and analytics to identify anomalies in public procurement, in the utilization of public revenues, and in the functioning of the judiciary.[42]

Machine-learning models could also help identify corruption in public procurement contracts – though their value and real-world impact for this have yet to be explored.[43]

Unlike earlier e-government initiatives, which had finite goals and fixed timelines, today's digital transformations are – and, more importantly, have to be – continuous, adaptive processes with no clear endpoints, requiring constant recalibration of public services, tools, and institutional norms in line with citizen and state capacities and the external needs of the moment.[44]

The risks ahead

As governments across the Asia-Pacific region increasingly adopt digital tools, they will see promising opportunities but also serious risks. While AI may enhance state-citizen interactions and responsiveness, it also risks heightening exclusion, enabling surveillance, obscuring lines of accountability, and reinforcing specific visions of development.

Moreover, unless these technologies are embedded within stable legislative and executive frameworks, they will always remain vulnerable to shifts in leadership and funding cycles – jeopardizing their long-term impact and the return on investment.

The true challenge lies not just in adopting AI, but in sustaining its deployment, oversight, and integration into public institutions. Governments must proceed with caution. Despite the compelling narrative surrounding AI, evidence of its consequences in the public sector remains limited, and there are significant risks. These include:[45]

1. Mission-creep into mass surveillance

AI-driven systems can generate real-time insights but gathering sufficiently dense data can entail a form of 'panopticon' monitoring of the citizen body, their movements and behaviors.[46] In countries that have less technical, administrative or political capacity, or in contexts characterized by political instability or limited checks and balances, such monitoring can easily become a tool of surveillance and repression.

Even in more democratic countries, public service chatbots often process sensitive personal data, including political opinions, demographic information, and behavioral patterns. Such data extraction can become a routine part of administrative 'backend' infrastructure that is too mundane or opaque to attract public attention or concern.[47] Nevertheless there can be grave implications for citizens and their freedom of movement and action in public spaces. Under the guise of public safety or stability, audio-visual, spatial and motion data can be used in combination with predictive analytics, to pre-empt dissent, or track individual movements, or target civil society and marginalized groups.[48] The potential for misuse, such as sharing with law enforcement or combining datasets for profiling, is real and significant. This can create a chilling effect, where citizens start to self-censor or withdraw from participation in everyday civic life, fearful of over-surveillance and data misuse.[49]

These systems also systematically monitor the historical actions and decisions of government officials. Such oversight may constrain individual autonomy, diminish opportunities for decentralized governance, and foster a culture of fear and subordination. Additionally, this information can facilitate politically motivated appointments. For instance, within the judiciary, AI technologies could be used to strategically select judges whose views align with those of the ruling party.

Without adequate and transparent data governance protocols, AI systems envisioned to bolster response governance may intentionally or unintentionally creep into the territory of citizen surveillance.

2. Opaque algorithms

AI systems typically operate as black boxes using complex algorithms that are difficult to follow and making choices whose steps cannot be retraced.[50] This is a precarious foundation for policy making. For example, the "thinking" of the Haidian "city brain" happens in a digital cloud and a physical computing center, where it "[analyzes] the variegated pieces of information at its disposal, finding patterns and reaching a situational awareness". It is then "up to the city brain" to assess the gravity of a situation and determine the appropriate course of action.[51]

In some countries such responsibility is also offloaded for systems of welfare or policing that use predictive algorithms.[52] Such logic can accelerate action in the wrong direction, as has happened with AI-enhanced algorithmic welfare systems. In Australia, for example, Robodebt was an automated government scheme that incorrectly demanded welfare recipients pay back benefits and then issued debt notices, wrongfully collecting AUS$746 million from 381,000 individuals,[53] many of whom experienced severe mental health crises; some died by suicide.[54] In one integrated service platform in the region, for example in Telangana, India, reliance on automated eligibility systems during the pandemic reportedly led to unintended exclusions, which in some cases left vulnerable households without recourse.[55] Neither the state government which implements the Samagra Vedika technology, nor the private company that owns the rights, placed the source code or any verifiable evidence of its efficacy in the public domain.[56] In these circumstances it becomes easy to "pass the buck" back and forth when something goes awry.[57]

3. Epistemic bias

Epistemic bias is a bias around what or who is recordable and therefore knowable or worth knowing. In AI systems, this occurs when an activity such as research or modelling is influenced by pre-existing beliefs and perspectives. Anticipatory governance processes can, for example, privilege certain world views or priorities over others. Often, they support mostly technocratic and linear planning strategies, and privilege the social frames of more powerful actors and certain types or forms of knowledge.[58]

Officials building digital twins, for example, when faced with complex and messy social reality tend to favor those aspects that can be captured by discrete data or which reflect the officials' own perspectives and priorities. Other people might come up with different versions. For example, in a pilot in London three distinct social groups with different interpretations of their environments gave input that led to three different twins.[59] In complex processes, in order to achieve stable outcomes some interpretations are likely to win over others, thereby privileging certain priorities or perspectives. Digital twins are thus not mere representations but can also be 'steering techniques' for arriving at certain goals.[60] It is important therefore to interrogate their goals and logic and consider the potential for bias and exclusion.

Moreover, government staff making use of AI innovations might not be able to identify exclusionary bias or have the capacity to address it. The more complex the model, the more difficult this becomes.

A broader problem with such systems is that they assume that our futures are objectifiable and quantifiable – they therefore assess political and socioeconomic realities algorithmically, and view governance itself as a series of optimization problems.[61] This linear approach leaves little room for contestation, plurality, and complexity. There will always be questions around what future to prepare for and whose values and voices are included in the imagination of that future. It is vital therefore also to have procedural safeguards and to enable civil society collaborators and the larger citizen body to add necessary nuance and color to data-driven insights.[62]

4. Engineered inclusivity

Incorporating AI into flawed participatory processes risks exacerbating existing biases. Rather than enabling genuine deliberation, AI can codify a superficial "engineered inclusivity" that is used to manipulate public opinion. For instance, automated moderation or summary tools might systematically amplify mainstream viewpoints while downplaying dissenting or minority voices. This not only undermines the quality of the debate but also further marginalizes groups who are already underrepresented.These risks are particularly high in some countries of South and South-East Asia which have lower levels of digital literacy.[64]

Even efforts to widen participation to some of the larger excluded groups tends to involve unelected representatives who themselves are in relative positions of power and might not accurately represent the needs of the group, or might focus on issues that are not generalizable or pertinent to the larger citizen body.[65]

There can also be a technocratic bias if officials primarily seek participation on issues with a digital or online component such as ridesharing, AI development, revenge porn, and online alcohol sales, leaving out many other issues and communities.[66]

As with any exercise in participation there is the risk that it may be performative rather than transformative – mere "open washing". In many digital consultation initiatives, for example, one of the biggest shortcomings is that the public authorities are not required to pay heed to the outcomes.[67] Without political buy-in and legal mandates AI-enabled participation can become detached from the real levers of governance.

Another crucial concern is citizens' perceptions of AI and of the value of their input in decision-making.[68] If these are negative or skeptical this will increase mistrust not only in the process but in governance itself.

5. Automation bias

On the other hand, there can also be too much trust in automated systems. Research shows that people tend to defer to the judgment of algorithmic and automated systems a tendency that is accentuated with LLM-based conversational chatbots whose interfaces are designed to duplicate the experience of talking to an actual human. This is a cause for concern when AI becomes the sole basis upon which decisions are made. In emerging economies like China, Indonesia, and India – where trust in AI is relatively high – there can be excessive reliance on AI models.

Mesmerized by the productivity and efficiency gains, it is easy to forget the brittleness of this technology. LLMs may work properly most of the time, but most of the time is not good enough for systems on which people are heavily reliant. LLMs are prone to inaccuracy and hallucinations, so following their advice uncritically can have grave consequences. For example, MyCity in New York provided citizens with legal guidance that was not in line with the city's legal frameworks.[69]

Errors are particularly troubling when these systems are deployed in developing countries to fill information gaps between citizens and states. Individuals in these countries may not have access to alternative sources of information and may rely overly on these systems.

Compounding automation bias is "expert bias". Faced with complex issues, governments may put their trust in expert-driven predictive models that treat problems as "solvable given enough time, resources, and expert advice".[70] This tends to sideline the less quantifiable community-based insights and grassroots realities and to reinforce technocratic approaches – limiting the potential of AI-enhanced governance to support more holistic and imaginative approaches to policymaking.

Even when decision makers know that AI systems can produce erroneous results, they may still assume that their system is prescribing the best course of action. For a busy public official not well versed in the technology it takes courage to defy the AI recommendations, and venture on their own path, painfully conscious that, if the plan fails, they might later be questioned and shamed for not heeding the AI's guidance and presuming to know better.[72] Added to this is the danger that outsourcing AI to all processes for information gathering, synthesis, and decision support could reduce the number and capacity of essential government officials.

Widening inequality

The introduction of AI is likely to widen existing digital divides. Developing AI models demands advanced computational power along with high-quality data. Even deploying AI models requires extensive financial and human resources and adequately trained personnel.

Several Asia-Pacific countries are boosting their AI capacities in these directions. Indonesia, for instance, is investing in a local network of data centers.[73] India's IndiaAI program is geared towards boosting investment into domestic data and compute infrastructures.[74] Thailand's is aiming to scale up AI education and training.[75] Nevertheless, these investments are often unaffordable for governments in lower-income countries, or provinces.

A major concern is data quality. To perform effectively, AI systems need regularly updated and representative data that is sufficiently granular and contextually nuanced. Digital twins, for example, that require high-quality and interoperable data have so far only been developed and deployed for data-rich, highly digitized environments as in Singapore or China.

Elsewhere in Asia and the Pacific, data may be patchy, outdated, or riddled with errors. In Nepal, for example, creating reliable predictive models for the national public health system will be hindered by infrequent collection of data which is not disaggregated at the local level.[76] In some cases, critical data points may only be collected once a decade.

Poor-quality data used in AI models often reflects underinvestment in digital infrastructure as well as the limited technical capacity of local officials and frontline staff. These actors – and even senior bureaucrats – may lack the skills or tools to evaluate whether the data they rely on is biased. This challenge is further intensified by misalignments in values, priorities, and technical expertise between government institutions and the private firms that develop these models, making it harder to identify and correct harmful data practices.

There are also likely to be gaps between different levels or branches of government. Many AI tools such as early-warning systems or archival systems may require data pooling across sectoral ministries and across different tiers of government. In countries with fragmented federal structures or weak central-state cooperation, national-level AI initiatives may also fail to trickle down to regions that are geographically remote or economically marginalized – further entrenching existing inequities in digital and infrastructural capacity.

It is important to recognize that anticipatory governance demands significant state capacity. For many government departments – already stretched thin and under-resourced – it may be an unaffordable luxury, especially when immediate, day-to-day challenges dominate their focus.

In a similar vein, citizens and other non-state actors – especially from marginalized communities – may lack access to digital tools or have insufficient literacy to engage with AI-mediated processes. In many countries, some civil society groups are already leveraging advanced technologies while others are struggling to establish basic digital processes. And even if they are offered greater access to information, they may not have the skills or capabilities to take advantage of it.

Inequality from using AI in governance

Both predictive and generative AI systems are susceptible to discriminatory patterns and bias. Local communities and marginalized groups that are underrepresented or missing from training datasets risk being excluded or discriminated against. This challenge is especially pronounced in geographically vast and socio-culturally diverse countries where rural regions, informal settlements, or ethnically marginalized communities remain underrepresented in administrative records as well as in digital spaces – as in India, for example, Indonesia, Australia, the Philippines, Malaysia or Timor-Leste,

The tools discussed in this chapter offer promising solutions, but they also carry the risk of deepening existing digital and socioeconomic inequalities – which are often complex and interwoven. For example, an AI-powered system designed to monitor bureaucratic workflows might identify bottlenecks in public service delivery or grievance redressal processes. Yet, it may overlook the underlying causes of these delays, such as staff shortages, limited technical capacity, or the absence of legal authority to address certain issues. By failing to account for their lived realities, the system risks unfairly penalizing already under-resourced departments and personnel.

Similarly, AI-driven archival platforms that digitize and curate institutional memory may reinforce dominant narratives. These systems often prioritize formal documentation and the perspectives of powerful actors, while neglecting oral traditions, informal practices, and local knowledge – forms of understanding that have long existed only on the periphery of official records. Digital twins, for example, depend on granular, high-frequency data collection. If certain parts of the population are data-invisible, these simulations can perpetuate their invisibility, leading to biased policy decisions and unfair resource distribution.

Inequality in ability to mitigate AI harms

As well as having different capacities to implement AI systems, governments can also differ widely in their capacities to recognize and respond to potential harms. Some have mature policy and regulatory environments. The Republic of Korea, for example, has developed comprehensive legislation on AI investment, oversight, and enforcement, set to take effect in 2026.[77] China, too, has introduced formal regulations around GenAI.[78] In contrast, countries such as India and Bangladesh are still in the process of drafting national AI strategies and currently lack enforceable laws to prevent or address AI harms.

The lack of regulatory frameworks can have serious repercussions for both citizens and government officials. For citizens, regulatory gaps leave them with fewer means of challenging AI-related harms and seeking redress. This is compounded by the lack of AI literacy, making it difficult for citizens even to recognize the harms, let alone demand accountability. But the lack of regulations also exposes public officials: unclear liability structures can leave them vulnerable to disciplinary action, even when failures are the result of design flaws or systemic issues beyond their control.

There is also the concern that state institutions are being tasked with regulating technologies they scarcely understand.[79] The problem extends beyond technical capacity – it involves the ability to make informed decisions about where AI should be applied and what protections are necessary. This demands that government officials possess a nuanced understanding of the risks specific to their context, the limitations of the AI tools they deploy, and the ability to avoid using

AI indiscriminately as a blanket solution for all policy and governance issues. Some governments in higher income countries or districts have the resources to hire technical advisors and build in appropriate safeguards; other are less equipped to either to leverage AI or deal with any harms.

Policy recommendations

AI can extend state capacity and bend bureaucratic systems toward efficiency, but efficiency is not the same as public value. Where there are major gaps in infrastructure, data, or policy, the benefits of AI are likely to be distributed unevenly – amplifying existing inequalities rather than closing them. Moreover, the state is not a private firm; efficiency cannot be its guiding principle, especially if it undermines public values. Making government more efficient can also accelerate the harms: from top-down bureaucratic hierarchies that strip autonomy from officials, to opaque welfare systems that penalize the most vulnerable.

AI should not simply be automating existing processes, it should also be optimizing bureaucratic workflows and stimulating new forms of governance: deliberative rather than legalistic norms; distributed rather than centralized authority; citizen agency rather than engineered inclusivity.

Governments need therefore to think more broadly – guided by a theory of change that analyzes the root causes of the problems, outlines what is needed for system change, and then shows how AI can support this.

History reminds us how technology could be mobilized toward more democratic ends. Experiments in the early 1970s, for example, sought to redistribute economic decision-making—conveying simple economic information to workers in real time to support them in self-regulating their industries.[80] The experiment was short-lived, as Allende's government was brought down in 1973. While short-lived, such initiatives remain important examples of how to inject a new rationality into the design and production of technology.

More recently, political scientist Akshay Mangala has shown how bureaucracies constrained by rigid legalism could better respond to citizens' needs by orienting around deliberative norms.[81] With some political reconfiguration, AI could serve not just as a technical tool, but as a catalyst for new forms of governance. The following recommendations are grounded in practical examples drawn from initiatives and experiences across the Asia-Pacific region.

A. Build AI literacy

To use AI effectively and safely, those within government must understand how the technology works and what it can and cannot do – able to judge when machine learning is appropriate, or where other policies or tools may be more effective.

Government will also need the knowledge and capacity to query the claims of vendors who tend to oversell their technologies, obfuscating critical questions with technical jargon. Experience from various countries in Asia and the Pacific illustrates the risk of such capacity gaps: automated eligibility systems in the region, for example, reportedly led to unintended exclusions from welfare benefits without recourse, while similar programs globally have wrongfully demanded repayments from large numbers of citizens. In both cases, algorithmic harms were amplified by the lack of technical literacy and foresight in government.

When introducing systems, governments often have too much recourse to management consultants rather than focusing on building in-house skills.[82] Some outsourcing may be necessary, but this can also erode state capacity and reduce accountability; external consultants may feel more accountable to their technical communities rather than to the public at large.

AI literacy training should also be tailored to different roles and responsibilities. Officials in charge of procurement, for example, may need a higher level of technical knowledge, while those communicating with citizens will require the knowledge and skills to explain the technologies, and how citizens can voice grievances. Once AI is embedded within governance, this will also raise new questions for judicial oversight; judges will thus also need training to manage these new complexities.

It will be difficult to foresee all the potential harms and risks of AI systems, or to identify individual instances of damage; harms may only become apparent in the aggregate. To navigate this uncertainty, governments need to cultivate 'futures literacy' to be able to evaluate the near-to-medium-term implications of AI from both a systems perspective and from the vantage point of diverse social groups.

These efforts can be reinforced through regional collaboration. The Association of South-East Asian Nations (ASEAN) or the Pacific Islands Forum could stimulate peer-learning networks to pool scarce expertise for the benefit of lower-capacity states. Regional development institutions such as the Asian Development Bank (ADB) or the UN Economic and Social Commission for Asia and the Pacific (UNESCAP) could build foresight hubs to ensure that AI use in governance is shaped by local priorities and region-specific development goals.

B. Institutionalize transparency and accountability

In many countries in the Asia-Pacific region, the state is one of the largest procurers of digital technologies. This provides states with opportunities to steer innovation and shape markets and in particular to specify that technological design should uphold certain public values. Well-designed public procurement can also improve trust and confidence in the use of AI in public services.

Where AI is used as a tool of governance, its outputs should be explainable. Governments should thus insist on understandable or interpretable models. Concerns regarding whether this is technically possible or whether it might hinder innovation should not deter progress; it should be up to technology providers, to figure this out. In this way, governments can play a critical role in setting norms and standards.

Governments also need clear information on the provenance and selection of data, and on feature choices and algorithmic models. At all stages there are likely to be mistakes. Officials overseeing the introduction of AI systems should be able to interpret the results of tests, including error rates, and take measures to correct these, while addressing data gaps and mitigating other risks including those related to privacy and data security.

AI systems ought first to be tested in isolated 'sandboxes' before being introduced into public institutions. In Singapore, for example, the Infocomm Media Development Authority has a Generative AI Evaluation Sandbox, which provides a controlled space where developers, regulators, and independent testers jointly assess generative AI systems, creating common evaluation standards. Smaller or less digitally mature governments could instead be supported through shared regional sandboxes alongside mechanisms for regular peer learning between governments.[83] Learnings and outcomes from these initiatives must be well-documented and independently audited.

Alongside this, there will need to be robust systems for continuous monitoring and evaluation along with mechanisms for independent oversight that report on the impact of AI systems on social systems and individual rights. These evaluations should be available for public audit and scrutiny. In addition, governments, at all levels, will need to maintain online AI dashboards which assemble information on how AI is being used and performing, and the corrective measures taken in response to any known errors or reported grievances.

In China, for example, the Cyberspace Administration requires all GenAI tools to be registered in a publicly accessible algorithm registry. This system provides a high level of transparency and traceability by logging key metadata such as approval dates, developer identities, tool functions, and system scope. However, it must also be noted that although the registry is publicly accessible, the disclosed information is often at too broad or high a level to offer insights into how specific AI systems operate or were trained. Information on the sources of training data or on the measures for mitigating risk are not disclosed – highlighting a gap between formal compliance and substantive accountability to the public at large.[84]

C. Seed new financing models and cultures

Often, private 'AI for good' ventures build products or applications for public or social purposes without sustainable revenue models or clear pathways to monetization. After the pilot stage such initiatives can fail to gain momentum. For those that make it past the pilot, there are typically two options: either monetize the data that has been collected or sell out to Big Tech companies. The first option violates privacy norms, and the second only further entrenches the power of Big Tech.

Governments may be willing buyers of AI tools for governance, but civil society organizations may be unable to afford to make, deploy or maintain the tools for 'Civic Tech'. Market dynamics are thus likely to widen power imbalances.

Startups building AI interventions often rely on venture capital. This creates perverse incentives that can be unaligned with social good or the public interest.[85] Venture capital (VC) demands exponential growth and global market capture, while social initiatives may require gradual and cautious approaches, and may only cater to specific national or local needs.

VCs also operate within a 'fail fast' culture that encourages short-term thinking and shallow innovation. For a social or development initiative, failing fast can cause grave or irreversible social harm and endanger the lives or livelihoods of people who are already vulnerable and marginalized. Not all innovation is worthwhile, useful or socially beneficial.

Technology startups typically envisage that a successful product can eventually be extended without requiring significant changes.[86] This 'scalability' is an essential criterion for investors but is antithetical for equity-driven social change that needs to be adapted for specific contexts.

AI-for-governance initiatives will need alternative financing models. With high fixed and ongoing costs and low prospects for cost recovery, they are usually a poor fit for short donor cycles or VC incentives. Instead, regional development banks, such as ADB or the Asian Infrastructure Investment Bank, or philanthropic funders, could create multi-year, outcome-linked funding windows.

Moreover, funding isolated projects is not sufficient. Investment is also needed to strengthen the broader knowledge economy and to build the capacity of civil society institutions– so they can contribute to interpreting, evaluating, and shaping how technology transforms governance functions.

Although many Asian economies boast thriving tech sectors and a growing number of unicorns, this alone is not enough to advance a meaningful 'tech for good' agenda. Globally, scholarship from leading universities and thinktanks has played a key role in shaping technology toward the public interest – by analyzing its impact, challenging dominant narratives, and expanding the vision of what kinds of technologies should be built. Asia and the Pacific need comparable investments in research and critical inquiry. Currently, there is a reliance on frameworks originating externally, which are often applied to their local contexts, even when the nature and histories, and the capacities of their states differ significantly.

D. Grow the AI commons

Current AI ecosystems are dominated by commercial entities whose narrow interests are shaping the technology's ethical and social trajectory. The 2025 AI for Good Global Summit exemplified this: of 82 featured speakers, nearly half were from industry, compared to only three from civil society. Consequently, the definition of "good" is being curated by dominant technology firms, which have a vested interest in promoting adoption while downplaying potential harms.[87] This influence is compounded by the industry's reliance on dominant technology firms' infrastructure, from cloud services to developer tools, giving a few companies inordinate control over the direction of innovation. This dynamic widens the accountability gap and elevates the prospects for social harm. Embedding these commercial systems into state infrastructure only serves to legitimize and entrench this power.

What is needed are public and decentralized alternatives to Big Tech. Many Asia-Pacific countries such as India, Indonesia, and Thailand are already moving this way, building their domestic cloud infrastructures, creating platforms for sharing public data, and incentivizing local startups.

However, such initiatives alone will not be enough, as the capital required is likely to be beyond the reach of many governments. Even if it were within reach, this may not be the best use of public capital. Instead, there should be alternative models of AI development that work with smaller, more curated datasets, and are optimized for task-specific ends, and that do not rely on access to Big Tech cloud infrastructure. Alongside, there should be "small AI" investments that support and maintain open-source tools for building AI, as well for ensuring trust and safety.

Several organizations in the Global South are developing infrastructure for a decentralized AI commons; these efforts need to be further supported and amplified.[88] This can be done by prioritizing such initiatives in government procurement contracts, but even more importantly, it will require dedicated and sustained funding. This would not only accelerate civic engagement in an instrumental sense, enabling more efficient governance, but also transform the logic of governance by distributing power to citizens and developing AI solutions to address problems identified from the bottom up.

E. Put people in charge

Better governance offers citizens more decision-making power. As the examples in this chapter highlight, AI could facilitate such collective deliberation and policy planning. Similarly, AI can support better service delivery and forward-looking policy making.

Nevertheless, these systems carry significant risks: algorithmic bias from flawed data, threats to personal privacy, and increased surveillance. To mitigate these, there should be clear regulations on data minimization and on purpose limitation, along with new institutional capacities. Technical solutions like "privacy by design" and the use synthetic of data to fill gaps are also being explored.

Beyond these measures, there could be "people's councils." These bottom-up, confederated citizen assemblies would verify AI data sources and contribute new data to create more just and equitable systems. They would also serve as arbiters, deciding if, where, and how AI should be deployed. For example, Manchester, UK, has created a People's Panel for AI to incorporate the perspectives of marginalized communities into AI service design.[89] While such councils raise valid questions about representation, these challenges should not prevent their creation.

END NOTES

1. (Francis, 2024)
2. (Kuchler and Stigson, 2024)
3. (UNESCAP, no date)https://www.zotero.org/google-docs/?broken=eucHdi
4. (OECD, no date)
5. (Vervoort and Gupta, 2018)
6. (Murphy, Sharpe and Huang, 2024)

7. (Muggah, 2025)
8. (Lentze, 2025)
9. (Hofer, 2020)
10. (Hopp, 2021)
11. (Government of Singapore, 2017)
12. (Cugurullo and Xu, 2025)
13. (Cugurullo and Xu, 2025).
14. (Loblay, Freebairn and Occhipinti, 2023)
15. (Margetts and Dorobantu, 2019)
16. (Valle-Cruz et al., 2019)https://www.zotero.org/google-docs/?broken=0t5F7U
17. (Li, Fan and Nie, 2025)
18. (Meyer, Weigelt and Kreft, 2016)
19. (Paddison and McCollin-Norris, 2023; Liu, Lee and Goh, 2024)
20. (Engin et al., 2025)
21. (Li, Fan and Nie, 2025)
22. (Anthony Jnr, 2021)https://www.zotero.org/google-docs/?broken=b78exX
23. (Mahari, 2021)
24. (Liu and Li, 2024)https://www.zotero.org/google-docs/?broken=0xjSDS
25. (Veddis Foundation, 2025)
26. (Dharmaraj, 2025a)
27. (Makasi et al., 2022)
28. (Thoughtworks, no date)
29. (Wancharoen, 2024)
30. (Berliner and Economics, 2024)
31. (Combaz et al., 2025)
32. (Barcelona City Council, no date)
33. (Tessler et al., 2024)
34. (Chirigati, 2024)
35. (Computational Democracy Project, no date)
36. (Fork the Government (3/3), 2016)
37. (Shimomura and Salem, 2023)
38. As of September 2023, the tool was yet to be deployed in a real-world setting and was due to be field-tested in three Indonesian provinces.
39. (Richards and Zahidi, 2024)
40. (Li, 2025)
41. (Aarvik, 2019)
42. (Odilla, 2023)
43. (Aldana, Falcón-Cortés and Larralde, 2022)
44. (Mergel, Edelmann and Haug, 2019)
45. (Mergel, Edelmann and Haug, 2019).

46. A panopticon is a circular prison in which single guard in a central tower can observe all the inmates, who cannot see the guard – a system of control where visibility is a form of power, and the inability to know if one is being watched leads to continuous, self-imposed discipline.
47. (Törnberg et al., 2025)
48. (Amnesty International, 2025a)
49. (ECNL, 2024)
50. (Kaufmann, Egbert and Leese, 2019)
51. (Cugurullo and Xu, 2025)
52. (Amnesty International, 2025b; Ciston et al., 2025)
53. (Chiraag Shah, 2023)
54. (Frances Mao, 2023)
55. (Tapasya, Sambhav and Joshi, 2024)
56. (Tapasya, Sambhav and Joshi, 2024)
57. (Tapasya, Sambhav and Joshi, 2024).
58. (Muiderman et al., 2023a)
59. (Nochta and Oti-Sarpong, 2024)
60. (Korenhof, Blok and Kloppenburg, 2021)
61. (Muiderman et al., 2023b; Törnberg et al., 2025)
62. (Jasanoff and Kim, 2015)
63. (Zidouemba, 2025)
64. (UNICEF, 2021)
65. (Muiderman et al., 2023a)
66. (Hortonarchive, 2018)
67. (Muiderman et al., 2023a)
68. (ECNL, 2024)
69. (Richard, 2024)
70. (OECD, 2020)
71. (Tapasya, Sambhav and Joshi, 2024)
72. (Tretter, Ott and Dabrock, 2025)
73. (Tan, 2025)
74. (Government of India, no date)
75. (Government of Thailand, 2023)
76. (WHO, 2021)
77. (Shivhare and Park, 2025)
78. (Xu, Lee and Goggin, 2024)
79. (Lokanathan, Siddiqui and Oprunenco, 2025)
80. (Morozov, 2024)
81. (Mangla, 2022)
82. (Mazzucato and Collington, 2023)
83. (Government of Singapore, 2023)
84. (Sheehan and Du, 2022)
85. (Bracy, 2025)

86. (Hanna and Park, 2020)
87. (Birhane, 2025)
88. (Varon and Costanza-Chock, 2024)
89. (Local Government Association, 2025)

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CHAPTER 9 — AI FOR THE NEXT GENERATION OF PUBLIC SERVICES

Zheng Liang, Shuyang Sheng, Zhenming Huang, and Shangrui Wang Institute for AI International Governance (I-AIIG), Tsinghua University

Artificial intelligence can transform public service delivery – across all sectors including healthcare, education, welfare, transportation, and public safety. Machine learning, data analytics, and natural language processing provide promising opportunities to make services more responsive and efficient and improve citizen services. But there are also serious risks, notably of entrenching and deepening inequalities, with most of the benefits going to the more digitally equipped citizens, stranding more vulnerable groups and communities even further behind. This chapter explores the potential dual effects – either creating more efficient, flexible, and inclusive governance and services, or exacerbating structural inequalities both between and within countries.

Background and context

AI has become increasingly widespread in public service delivery and is already reshaping the organizational and operational dynamics of government. AI technologies are being integrated into many sectors, including healthcare, education, welfare administration, transportation management, and public safety. Governments are using AI to streamline bureaucratic processes, automate administrative workflows, and enhance the accessibility and responsiveness of citizen services.[1]

The patterns of AI deployment do, however, vary widely across countries and regions, shaped by differences in technological infrastructure, regulatory environments and institutional capacities. The effectiveness and inclusiveness of AI applications will thus vary significantly based on institutional readiness, regulatory safeguards, and the broader digital ecosystem.

Efficiency gains

For many governments in Asia and the Pacific, AI-enabled systems are already being used to automate routine administrative tasks. These systems help support decision-making in public agencies and process applications, verify eligibility for public benefits, and manage digital records more efficiently. By integrating machine learning, data analytics, and natural language processing, such tools are reshaping bureaucratic workflows, enabling more data-driven and streamlined operations and improving the quality of decision-making.

AI also supports the personalization of public services so they are more responsive to citizens' needs, allowing intervention to be tailored to the requirements of diverse social groups. AI-powered chatbots and virtual assistants have been widely adopted in citizen-facing interactions across many countries, offering 24/7 support and alleviating the burden on human service staff.[2] Based on integrated and continuously updated data profiles, AI systems can make public service delivery more personalized by adapting policies and services to the specific needs of individuals and communities.[3]

In addition, AI is enhancing risk-monitoring capacities by enabling more dynamic forms of governance through real-time data analysis and pattern recognition. Compared with traditional monitoring mechanisms, AI-powered predictive analytics can provide more timely and granular insights into emerging social, economic, and environmental trends. This strengthens governments' abilities to anticipate potential risks and implement early interventions. In sectors such as healthcare, disaster management and urban planning, AI-driven insights allow for early warning systems, better preparedness, and more targeted policy interventions. AI thus has the potential to fundamentally upgrade the agility and precision of public administration.

Risks of opaque and discriminatory systems

But throughout all these processes there are also substantial risks. One is that of opaque algorithmic decision-making – the "black box" phenomenon – raising serious concerns about transparency, accountability, and democratic oversight. Citizens and even officials may find it difficult to understand or challenge AI decisions. AI systems trained on historical or biased data can perpetuate or even amplify existing inequalities in service delivery, leading to discrim inatory outcomes that will undermine trust in public institutions.[4]

Another concern is the uneven impact across different regions and population groups. AI can exacerbate existing digital divides and create new forms of discrimination – systematically disadvantaging vulnerable or marginalized communities and further deepening social inequalities,[5] as well as widening inequality between more developed economies and the less developed.

From the perspective of public service delivery, this chapter will analyze the opportunities and risks of AI deployment on inequality – including urban-rural divides, gender disparities, the technological exclusion of aging populations, and gaps in digital literacy. It will also explore inter-country inequalities. Most of the benefits may well be captured by wealthier nations and regions that have advanced digital infrastructure and institutional capacities. The chapter will highlight how AI uptake across the Asia-Pacific region is likely to be shaped by structural differences in fiscal space, institutional readiness, and digital infrastructure.

Finally, the chapter will explore how to maximize the inclusive potential of AI – identifying the most effective institutional arrangements, regulatory frameworks, and accountability mechanisms that mitigate risks such as bias and exclusion, while promoting AI's positive contributions to inclusive development. This includes examining normative frameworks for ethical AI use in the public sector, mechanisms for citizen participation in algorithmic decision-making, and dynamic regulatory strategies aligned with technological change. The chapter uses case studies that illustrate how AI is reshaping public service delivery in the region, and how policymaking can achieve more inclusive and equitable public services.

AI involves not just a technological shift but a fundamental rethinking in governance structures. The following discussion explores the impact of AI in two key areas: reshaping governance concepts and enhancing governance capabilities on the one side, and the ethical challenges and social inequality effects on the other side.

Promise of AI for public services

Impact on government bureaucracy

Traditional bureaucratic systems have hierarchical structures and formalized procedures and focus on predictability and stability.[6] While efficient in their own right, they can, however, often become encumbered by rigid hierarchies and slow decision-making processes.

AI enables governments to bypass the traditional hierarchical bottlenecks using human-led algorithmic authority guided by large datasets and predictive analytics.[7] AI systems offer real-time insights and opportunities for quicker, more informed decisions that are more flexible and precise and aligned with current realities.

Data-driven governance

AI can collect and analyze vast amounts of data that enable governments to understand societal needs and respond to them with unprecedented speed and precision. AI can also monitor policy performance dynamically, forecast emerging challenges, and optimize resource allocation to prioritize urgent issues. The result could be faster and more evidence-based decisions and more proactive, and precisely tailored policy interventions.

In Singapore, for example, the Ministry of Health uses AI-powered analytics to monitor infectious disease outbreaks and tailor rapid public health interventions. In megacities in China, such as Shanghai and Shenzhen, smart city initiatives employ AI to optimize traffic flow and enhance urban management.

However, if such activities are to be inclusive, transparent, and accountable they will need to be grounded in sound governance frameworks and be using high-quality data. In countries with more limited digital soft and hard infrastructure such as Cambodia, pilot projects are using AI-powered mobile platforms for agricultural extension services though these efforts face significant infrastructural and capacity challenges.

AI is redefining governance

AI is redefining governance across three interconnected spheres: internal administrative efficiency, data-driven policy formulation, and transformative public service delivery. For administration, AI can automate repetitive and time-consuming tasks, and thereby increase efficiency and reduce human error. AI-driven task management systems can automate scheduling, generate reports, and send reminders, freeing up human resources to focus on more complex and strategic activities. In medicine, for example, doctors save time on clinical documentation by automating appointment scheduling, billing coding, and clinical documentation freeing them to focus more on patient care. This automation not only improves productivity but also ensures greater consistency and accuracy.

Singapore has been a pioneer in leveraging AI for governance and public service delivery. In 2019, the Government launched its National AI Strategy, aiming to deploy solutions across key sectors by 2030.[8] The strategy focuses on five critical ecosystem enablers:

- *Trustworthy AI* – Establishing robust governance frameworks and ethical guidelines.
- *Talent* – Investing in AI workers through specialized training programs and partnerships with educational institutions.
- *Collaboration for innovation* – Driving close cooperation between government, industry, and academia.
- *Data infrastructure* – Creating a robust foundation for AI applications.
- *Global engagement* – Participating in global AI initiatives to stay at the forefront of technological advancements.

An important achievement in Singapore is the Moments of Life platform which integrates 15 cross-agency services, including birth registration and childcare subsidies. In less than 15 minutes, new parents now complete paperwork that previously took two hours, reducing administrative time by 70 percent. Another success is the OneService chatbot which handles more than 500,000 queries annually on issues ranging from noise complaints to road repairs. Through automation, query resolution efficiency has improved by 50 percent, with 90 percent of cases addressed within 48 hours.

Another example is Viet Nam's National Strategy on Research, Development, and Application of Artificial Intelligence, launched in 2021. Aiming to integrate AI into socioeconomic development it fosters innovation and competitiveness and positions the country as a regional leader in AI. Key objectives include advancing AI research, developing robust digital infrastructure, and reforming education for training a skilled workforce. This should enhance efficiency, productivity, and decision-making in priority sectors such as healthcare, agriculture, education, smart cities, and national security. The strategy emphasizes ethical practices, risk management, and establishing legal frameworks to ensure responsible use. Between 2022 and 2023, Viet Nam's ranking in the AI Readiness Index, jumped from 55 to 39 – No. 4 in ASEAN. In 2024, Viet Nam issued the National Data Law, mandating data sharing between government bodies and enterprises.

Policy and action driven by data

AI models can analyze large datasets to forecast demand and optimize resource distribution. In IT infrastructure management, for example, AI can predict system performance and allocate resources dynamically to where they are needed most. This reduces costs as real-time data analysis improves system performance and enables quick and informed decision-making.

In Thailand, the convergence of advanced machine-learning algorithms, robust digital infrastructure, and a progressive healthcare ecosystem is creating unprecedented opportunities for AI-driven medical solutions for patient care, diagnostic processes, and operational efficiency.[9] Applications include diagnostic systems for rural areas and AI-driven solutions to optimize resource allocations for marginalized communities. Key applications include automated X-ray and CT scan analysis, predictive risk assessment for potential malignancies, and comparative image recognition for tracking disease progression. Between 2021 and 2026, Thailand's digital health market is projected to grow at a compound annual rate of 15 percent, with artificial intelligence playing a pivotal role in this expansion.

Two key ministries for AI innovation in Thailand are the Ministry of Digital Economy and Society and the Electronic Transactions Development Agency – which have launched six projects to accelerate AI adoption. In 2022, the Government launched the AI Governance Clinic which provides governance toolkits, interdisciplinary fellowships, and executive training to operationalize UNESCO's AI ethics principles, emphasizing transparency and risk mitigation.

In China, on the other hand, cities are at the forefront of piloting innovative solutions for more effective public services delivery. The city of Shenzhen has embraced AI for several critical systems:

- *Environmental monitoring* – AI systems track air and water quality in real time to quickly identify pollution sources, enabling authorities to take prompt corrective action.
- *Public safety* – Shenzhen is one of the most monitored cities in China. Over 300,000 CCTV cameras are equipped with AI capabilities for facial recognition. This enables behavior analysis, and anomaly detection with real-time identification of suspects. At the same time crime rates have fallen and overall security has improved with a 15 percent decline in certain criminal activities since 2018.
- *Emergency response* – AI algorithms analyze data from social media, sensor networks, and surveillance feeds to detect emergencies such as fires, flooding, or crowd surges. Since 2021, an AI-based early warning system for urban disasters has decreased average response times by 25 percent.

Smart city initiatives

AI can enhance urban governance and quality of life by integrating technologies across key sectors. In transportation and urban planning, for example, AI can facilitate smart traffic management that analyzes data in real time to reduce congestion, cut emissions, and boost public transit efficiency. Similarly, predictive policing models – when designed ethically – help law enforcement address biases in traditional methods and deploy resources more strategically to prevent crime. AI also offers opportunities for more precise environmental monitoring, processing satellite imagery and sensor data to forecast natural disasters, track deforestation, and optimize energy use in smart grids. Such applications not only improve public safety but also foster sustainable urban development.

Pacific Island opportunities

The Pacific Islands confront unique challenges – including geographic isolation, climate vulnerability, and resource constraints. For these states, AI offers transformative opportunities for sustainable development. By leveraging early warning systems and climate modelling, AI enhances disaster preparedness, while precision agriculture and fisheries-monitoring tools improve resource management. Beyond resilience, AI bridges geographical barriers through telemedicine and education, while tools for local language preservation and economic empowerment enable local communities to drive inclusive growth.

Vanuatu – AI is analyzing satellite imagery to track rising sea levels and flooding risks to inform infrastructure planning and early interventions.

Papua New Guinea – In regions with few specialists, AI-powered telemedicine platforms are enabling remote diagnostics, such as interpreting X-rays or detecting skin conditions.

Fiji – AI is being used to strengthen disaster response and recovery and reduce vulnerability to natural disasters. A notable collaboration is between the United Nations Capital Development Fund and the AI tech company Tractable. This has two key programs. One is a Smartphone App for Disaster Reporting which residents can use to report property damage, accelerating emergency assessments and the support needed. This is combined with AI Damage Assessment through which algorithms analyze images and data to evaluate damage and streamline the allocation of aid.

Risks and costs – disruption and exclusion

When leveraged appropriately, AI can enhance administrative efficiency and streamline processes. However, improper use may increase administrative costs and heighten social risks. AI does not operate in a homogeneous space but within uneven social, economic, and technological landscapes. Structural inequalities within countries – such as urban-rural divides, gender disparities, the exclusion of aging populations, and gaps in digital access and literacy – will shape how different population groups access and benefit from AI-enabled public services.

As AI becomes increasingly embedded in healthcare, education, and social welfare, there is a danger of excluding many citizens. Low-income groups, rural residents, and marginalized communities may have limited digital infrastructure, low digital literacy, and insufficient access to necessary technologies, thus being unable to benefit from AI-driven services. In healthcare, for example, rural areas may not have the advanced AI-powered diagnostics available in urban centers.

On the supply side, spatial disparities in infrastructure and investment often result in limited AI deployment in rural or underserved regions. Rural areas often suffer from incomplete data and unstable connectivity, rendering algorithms ineffective. They are likely to have slower response speed, lower service quality, and less personalization, widening the gaps between urban and rural areas. At the same time, institutional blind spots – such as the lack of gender-sensitive data or inclusive service design – can embed bias into algorithmic systems.[10]

There are also problems on the demand side – notably with aging populations and citizens with low digital literacy. They find it difficult to navigate AI-based services so risk being excluded from public benefits. In some cases, these issues are exacerbated by the way technology is designed and applied.

Algorithmic bias

AI systems can be prone to algorithmic biases that perpetuate social inequalities. In addition, the historical data used to train AI models is likely to embody societal prejudices. This will perpetuate and even amplify discrimination particularly in sensitive areas such as employment, lending, and criminal justice.

In 2022, an algorithm used to detect welfare fraud in the United Kingdom erroneously flagged dozens of Bulgarians, raising concerns over potential nationality-based bias.[11] Although the authorities stated that the algorithm does not take nationality into account, no one can say with certainty how it processes and balances the data it receives. Such cases demonstrate how AI-driven systems can skew resource allocations.

The 'black box' problem

AI often uses complex and opaque machine-learning algorithms operating within a 'black box' whose processes are hidden or incomprehensible, even to developers. This lack of transparency undermines public trust, particularly when AI is applied in sensitive areas such as social welfare, law enforcement, or healthcare. Overdependence on AI will reduce the scope for human judgment and discretion which is often essential in complex or sensitive contexts. Without clear explanations of how AI arrives at its decisions, citizens will feel excluded and doubt the fairness and legitimacy of outcomes.

The algorithmic illiterate

Effective access to AI-powered public services depends not only on hardware and the availability of internet services, but also on users' ability to understand and operate these technologies. Individuals with limited education, non-technical backgrounds, or language barriers often struggle to navigate interfaces, comprehend algorithmic logic, or respond to system errors. AI-driven systems frequently use standardized processes that lack explanatory mechanisms or human-centered support – raising the threshold for participation in subtle ways, and excluding certain groups from full participation in the digital world.

For example, in Malaysia after AI systems were introduced for social security, many low-income users, especially in Sabah and Sarawak, struggled to apply for unemployment benefits due to unfamiliarity with the system's language and operations.[12] Thai AI-assisted educational platforms similarly faced adoption barriers as digitally illiterate parents were unable to register their children, exacerbating educational disparities between urban and rural students.[13] Experience from Bangladesh showed that while AI platforms offer precision farming advice, many farmers could not interpret the data and rely on word-of-mouth communication, resulting in "reverse digital exclusion."[14]

These examples showcase the multiple governance risks stemming from the integration of AI into public services. Algorithm design must go beyond merely avoiding negative biases against specific groups. It should proactively identify and address the unique challenges and needs these groups face, ensuring that they receive tangible support and opportunities.

Rural populations left behind

Technology systems are primarily introduced in urban and economically developed areas, while rural and underdeveloped regions are often left behind. This can contribute to inequalities in public service access, particularly in healthcare and social welfare sectors. These disparities are often rooted in structural deficiencies in data infrastructure, technical expertise, and governance capacity in rural regions, highlighting the importance of thorough assessments of local conditions and capacities to fully leverage AI's potential.

Since 2023, under the "smart healthcare" policy, advanced Chinese cities like Hangzhou, Shanghai, and Beijing have been piloting AI based diagnostic imaging systems.[15] These cities benefit from high-quality digital infrastructure and fixed line broadband speeds often exceeding 220 Mbps, with internet penetration rates around 85 percent. In contrast, many rural areas, especially in western provinces such as Gansu or Yunnan, have average broadband speeds under 50 Mbps and penetration rates below 65 percent. With limited specialist staff they continue to rely on traditional diagnostic methods.[16]

The Indian Aadhaar national biometric system provides a unified digital identity for all citizens. This uses AI to verify identities, detect fraud, and ensure targeted disbursement of Direct Benefit Transfers. However, its rollout has highlighted risks around authentication failures. During the early years, this was particularly the case for vulnerable and remote communities, leading to delay or denials of benefits. This effect is termed the "automation of exclusion."

Gender inequality: algorithmic bias and institutional blind spots

While AI systems in public services may appear gender-neutral, the training data and institutional logic they rely on often embed gender biases. According to one survey in 2025 of ten countries, including Singapore and Australia, only 28 percent of people were aware of gender bias in AI, yet once informed, 51 percent expressed concern, and 66 percent believed governments should regulate AI to ensure gender fairness.Rural and low-income groups in particular are under-represented in digital records, leading algorithms to misclassify their eligibility for services.

India – AI systems used in public administration associate service access with the identity of the officially registered household head, who is frequently male – reinforcing existing gender hierarchies and reducing the visibility of women's needs. In India, many women lack independent accounts or official identification, making them reliant on male family members to access Aadhaar-linked benefits.

Indonesia – AI-powered health prediction systems often fail to identify women as service recipients due to lack of mobile phone skills or online records, weakening maternal health monitoring – especially in rural areas.[20]

Viet Nam – AI-based job matching systems tend to recommend technical roles to male users while guiding women toward traditional low-paid jobs, reflecting algorithmic reinforcement of gender roles and limiting women's access to public service and development opportunities.[21]

Moreover, design blind spots and the lack of women-centered features – such as prenatal healthcare, gender-based violence alerts, and employment support for women – lead to implicit discrimination in service provision

Elderly exclusion – the forgotten generation

Elderly populations are frequently 'technologically forgotten'. Older adults may encounter significant barriers due to a lack of devices, unfamiliar interfaces, limited digital skills, lack of digital confidence or cognitive decline. System designers often fail to ensure interface accessibility, navigation simplicity, and language comprehension for older users who may thus miss healthcare monitoring and appointments or find it difficult to make pension applications.

In Japan, for example, despite advanced AI-based eldercare robots and health systems, many elderly citizens, especially those living alone, resist using technology and miss online consultations and medicine delivery.[22] The Korean Government's AI-enabled public service app has a low adoption rate among elderly citizens, who face challenges registering online, leading to pension delays and failed welfare applications.[23] Singapore's GovTech promotes paperless and AI-verified services, but many seniors struggle with language and digital literacy, relying on family members for assistance, thus compromising service autonomy and privacy.[24]

Creating 'digital ornaments'

Adopting AI involves substantial financial investment and puts new demands or burdens on frontline personnel and on citizens.[25] Governments attracted by digitalization can fall into an 'administrative efficiency paradox,' where frontline workers are burdened with excessive digital documentation requirements – such as frequent photo submissions or redundant data entry. As a result, rather than boosting productivity AI systems can become ineffective 'digital ornaments'.[26] And the benefits of existing AI applications often remain limited and difficult to quantify.

China's digital government initiative provides a cautionary example. A 2017 inspection report by the General Office of the State Council revealed that 20 percent of government service platforms suffered from search function failures, and that some platforms that were misaligned with real-world needs were ultimately abandoned.[27] One province invested in AI-powered government service centers, but this only involved the addition of superficial AI interfaces, leaving the core administrative processes and governance mechanisms largely unchanged. Large AI models can become mere expensive showcases that fail to deliver meaningful improvements in public service efficiency.[28]

Social welfare crises due to AI decision-making errors

Beyond increasing administrative burdens and reducing governance efficiency, AI deployment in public services can result in decision-making failures that jeopardize social welfare.

In 2016, due to flawed algorithmic modelling an automated debt recovery system in Australia erroneously assessed the incomes of nearly 500,000 welfare recipients. The resulting mass debt recovery campaign triggered public outrage and legal disputes.[29] A Royal Commission later described this as a "catastrophic failure of public administration".[30] In 2021, the Ethics Committee, the leading professional association for the technology community, concluded that Robodebt illustrates how an algorithmically correct calculation can nevertheless be "unfair and illegal if it is applied without due consideration of errors that can arise and without appropriate human intervention."[31] Such design flaws which cause significant harm to social welfare can require expensive corrective measures and erode public trust.

Privacy violations

Another risk in AI-driven public services is that of data privacy breaches. Facial recognition- systems, while enhancing efficiency and reducing the need for manual verification, have sparked public controversy over biometric data collection.[32] The extensive collection of sensitive data without due attention to security and legitimacy can lead to public outrage, posing significant reputational and governance risks.

In October 2019, a lawsuit was filed in China against a wildlife park in Hangzhou (Zhejiang Province) for mandating facial recognition authentication for entry. This marked China's first legal challenge against facial-recognition technology.[33]

In 2021, the Government of the Republic of Korea transferred approximately 170 million facial images of citizens and foreigners to a private company for AI-based immigration screening. This move prompted constitutional litigation by civil rights groups, alleging violations of fundamental rights.[34]

System breaches threaten national security

Beyond privacy concerns, the concentration of vast amounts of public data within government platforms can present risks to national security. Centralized data storage and open-source codebases significantly increase the risk of unauthorized access by foreign malicious actors, raising serious data and national security concerns.[35] It has been estimated that by 2027, over 40 percent of AI-related data breaches will stem from the cross-border misuse of generative AI.[36] Without robust safeguards, the use of AI systems in public services heightens exposure to cyberattacks, placing both private and public data at substantial risk.

Policy options and frameworks

While some regions and individuals may experience economic growth and better public services as a result of AI, others may face job displacement, heightened surveillance, or unequal treatment by automated systems. To address these challenges, governments will need targeted policies – investing in the necessary digital infrastructure, enhancing digital literacy, and implementing safeguards against algorithmic bias.

Public officials and staff will need to be aware of these dangers – and equipped to recognize potential biases and errors. They should be able to intervene appropriately and be able to develop standards for interpreting AI -driven decisions, present clear explanations of algorithmic processes, and enable independent audits. AI systems thus need to be designed carefully to enable clear oversight, and ethical governance and sustain fairness, inclusivity and public trust. Governments should protect citizens against unintended harms, uphold ethical standards, and ensure that AI-driven public services remain fair, accountable, and trustworthy.

Ensuring that AI -driven public services operate inclusively and sustainably requires a structured, multi-layered approach. This section presents six interconnected policy recommendations that form a progressive pathway for action – from the foundational level of digital infrastructure to the broader horizon of international cooperation (Table 1)

Table 1 – Framework for inclusive public service transformation

Pillar	Focus	Policy Action
1. Foundational	Infrastructure	Digital access for marginalized groups
2. Data	Governance	Data security and privacy mechanisms
3. Algorithm	Ethics	Pre-, mid-, and post- ethical review mechanisms
4. Application	Optimization	Service efficiency through tech and organizational integration
5. Digital literacy	Empowerment	Targeted training for women, the elderly, and low-income groups
6. International cooperation	Regional collaboration	Mutual assistance and collective governance

1. Digital access for marginalized groups

Digital access strategies should focus on underserved and marginalized groups. Some countries have integrated digital equity goals into national development frameworks, recognizing connectivity as a key enabler of social and economic inclusion.[37]

- *Extend core digital infrastructure to underdeveloped or remote areas* – Australia's National Broadband Network (NBN) and its Mobile Black Spot program, for example, aim to extend high-speed internet and mobile coverage to underserved communities.[38] Similarly, India's BharatNet initiative is building optical fiber networks in over 250,000 rural villages.[39]

- *Identify digitally vulnerable groups* – Census and social data can be used to identify digitally excluded groups. In the Republic of Korea, for example, the digital inclusion policy includes targeted diagnostics and surveys to assess the needs of the elderly, for example, people with disabilities, and low-income populations. This enables tailored interventions and the efficient allocation of digital support resources.[40]

- *Promote community-based digital access* – In Singapore, the Digital Access Program provides low-income families with subsidized broadband and devices, while also offering in-home digital literacy support through community partners.[41] Similarly, Australia's Be Connected initiative targets seniors with free digital skills training via libraries and community centers.[42] Inspired by these models, we propose establishing free-access "digital corners" in public venues such as libraries, community centers, or rural service hubs.

- *Establishing evaluation and monitoring mechanisms* – In the Republic of Korea, for example, the Digital Divide Index offers annual, data-driven assessments of regional and group-level disparities in digital access and capabilities.[43]

2. Data security and privacy mechanisms

Systems for data security privacy should be tiered, transparent, and controllable and address the unique vulnerabilities of at-risk populations, including rural women, children, and marginalized communities.

- *Building a risk-based system* – Data should be classified and protected according to type, usage scenarios, and level of sensitivity. Data collection should adhere to principles of legality, necessity, and minimization, with explicit approval required for third-party sharing after national security review and citizen authorization. Unnecessary data should be removed using a mechanism for dynamic deletion. Stricter collection, transmission, and storage standards must be applied for high-risk data such as biometrics.[44]
- *Developing a citizen data management platform* – People and organizations should be informed when the government holds data on them and be in a position to verify this.[45] In Singapore, for example, the MyInfo platform clearly displays the requester and users of data and triggers anomaly alerts for unauthorized or abnormal data activities.[46]

3. Ethical review mechanisms

This process should take place in three stages:

- *Pre-application* – assessing social impact and ethical risks – The potential social impact must be carefully designed with attention to fairness, safety, transparency, and controllability and taking into account the differentiated impacts on vulnerable groups.[47]
- *Mid-application – strengthening dynamic monitoring and human intervention* – Detect and respond to unintended outcomes or deviations from policy objectives.[48] Public service personnel must oversee automated decisions, intervene where necessary, and support citizens in understanding and contesting decisions that affect them.
- *Post-application* – improving dispute resolution and clarifying accountability – Accessible and transparent grievance mechanisms should address concerns or complaints. Clear lines of responsibility must be defined to ensure corrective action, and lessons learned.

4. Building integrated systems

Public service efficiency should be enhanced through technology adaptation, organizational coordination, and service optimization.

- *Integrate resources and technologies* – Governments should integrate services and clarify departmental responsibilities to ensure transparent, traceable operations.[49] This can include unified citizen information platforms for secure data sharing that reduce the demand for repetitive data submissions.
- *Remove systemic challenges* – Based on grassroots research and public consultations, government should identify key administrative 'systemic challenges', or problem parts of the process, and deploy technologies that reduce burdens on public servants and citizens. A real-time feedback system should monitor the performance of technologies and prevent deviation from intended goals.
- *Build human-centered services* – To lower barriers for diverse groups and improve the overall user experience, digital service interfaces should be based on user-centric design principles. These include larger font sizes, simplified operational flows, dialect-based voice recognition, and visual process guidance

5. Digital literacy

Inclusive empowerment through AI capacity training

- *Training courses for citizen groups* – For the elderly, courses can cover, for example, mobile payments, online healthcare, and fraud prevention. For women, they can address career upskilling on e-commerce, remote work, and AI-assisted tools. And for low-income groups and digital public services can offer online job platforms and access to social protection. Beyond basic digital literacy, courses should cover AI-specific awareness – on how the technology works, and limitations and bias, misuse, and privacy risks – as well as on how it can be used in everyday life – to support writing, translation, or education.

- *Capacity building for public officers* – Such programs should be institutionalized, scaled, and tailored to different levels of decision-making – policy, technical, and implementation. In Singapore, for example, the Smart Nation Scholarship and Digital Academy is training over 20,000 officers in areas including algorithmic thinking and AI ethics.[50] Similar efforts are emerging in India and the Republic of Korea, often supported by partnerships with universities or international organizations.[51]

- *Community-based training* – Grassroots organizations, NGOs, universities, and volunteers should be mobilized to deliver multi-tiered training programs through public libraries, digital learning centers, and mobile teaching units. These can include digital mutual aid networks – local peer support schemes – such as India's internet Saathi program, where trained rural women volunteers teach digital skills to others in their communities.[52] Similarly, Kerala's Akshaya grassroots centers provide computer literacy training to villagers.[53] Learning can be extended and personalized using AI-driven tools such as chatbots or virtual tutors.

- *Incentive mechanisms* – Uptake among marginalized populations can be boosted by digital learning incentives, certificates linked to employment databases, and subsidized access to devices and data plans. In India's PMGDISHA initiative, for example, digital training for rural citizens is coupled with certification and job facilitation support.[54]

- *Clear institutional frameworks* – In collaboration with local authorities, academia, and civil society, central governments should design national frameworks for digital and AI literacy – with learning objectives for each group – citizens, frontline workers, and managers– and cover delivery methods, assessment systems, and institutional responsibilities along with monitoring measures for learning impact.

6. Stronger international cooperation

Enhancing regional cooperation mechanisms for public service transformation.

- *AI for public services* – Asia-Pacific countries should build on existing mechanisms such as the ASEAN Digital Masterplan 2025, the APEC Digital Economy Roadmap, and trilateral dialogues among Japan, Republic of Korea, and China, by establishing a dedicated AI for Public Services stream. This should focus on concrete service domains – such as healthcare triage, digital identity, disaster response, and social protection - and culminate in toolkits and pilot projects. These collaborations, led by rotating digital governance agencies, should include biannual exchanges, repository development, and coordinated outputs such as an annual Regional AI-Governance Report.[55]

- *A civil servant twinning program* – To address governance capacity disparities, a public sector AI twinning program should be established, pairing civil servants from developing countries with counterparts in advanced digital governments such as Australia, Japan, and Republic of Korea. Each cohort would codevelop and deploy simple, functional AI tools – such as eligibility screening algorithms or chatbot based grievance systems. Fellows would also complete practical training modules on AI ethics, risk mitigation, and evaluation. These would sustain a use case driven and peer supported model of skill development.[56]

- *Regional financing of digital Infrastructure* – The Asian Development Bank (ADB) and the Asian Infrastructure Investment Bank should create channels for financing AI-ready digital public infrastructure. This should prioritize interoperability, accessible application processing interfaces, and algorithmic transparency – in health data registries, for example, education databases, and social service portals. Financing should require measurable public service outcomes and offer co-financing incentives to ensure national ownership. One useful model is the 2023 ADB loan to support Indonesia's digital transformation.[57]

- *Regional observatory for AI risks in public services* – An observatory should be created under APEC or UNESCAP to collect anonymized data on AI-related public service risks such as algorithmic exclusion, systemic bias, and data misuse. Based on national submissions, the observatory would issue annual guidance, maintain a shared mitigation library, and support institutional audits. One example that covers pre-deployment impact reviews and post-deployment accountability protocols is South Australia's AI strategy.[58]
- *Aligning with global governance frameworks* – To ensure mutual learning and inclusive rule-making, Asia-Pacific initiatives should be coordinated through APEC or ASEAN and aligned with global efforts such as UNESCO's AI Ethics Recommendation and the UN Global Digital Compact.[59]

AI policy stands at a crossroads: one path leads to unchecked inequality and destabilization, the other to inclusive prosperity. By integrating reskilling, ethical governance, global solidarity, and green innovation, policymakers can harness AI's potential while safeguarding societal well-being. The challenge is not merely technical but also profoundly political – requiring a reimagining of cooperation in a polarized world.[60]

END NOTES

1. (van Noordt and Misuraca, 2022; Madan and Ashok, 2023)
2. (Maragno et al., 2023)
3. (Meijer, Lorenz and Wessels, 2021)
4. (Busuioc, 2021)
5. (Wang, Xiao and Liang, 2024)
6. (Weber, 1968)
7. Algorithmic authority refers to legitimate power of algorithms, as AI tools play a significant role in decision-making.
8. (Singapore Government, 2023)
9. (AI Thailand, 2023)
10. (Vatamanu and Tofan, 2025)
11. (Stacey, 2023)
12. (Fang et al., 2022; Gong and Ghazali, 2023)
13. (UNICEF East Asia & Pacific, 2023)
14. (Infocomm DataInsighTopia, 2025)
15. (Yuan et al., 2025)
16. (China Internet Network Information Center, 2024)
17. (Jakhar, 2024)
18. (HeForSHE, 2025)
19. (Times of India, 2025)
20. (Adidharma et al., 2024)
21. (Sutassanamarlee, 2024)

22. (Tokuhisa and Morimoto, 2025)
23. (Hwang, Byun and Yi, 2025)
24. (Pakianathan and Perrault, 2020; Infocomm Media Development Authority, 2023)
25. (Madsen, Lindgren and Melin, 2022; Griffiths, 2024)
26. (Xiaojuan, 2024)
27. (Xinhua News Agency, 2017)
28. (Changqi, Li and Mi, 2025)
29. (Francis Mao, 2023)
30. (Government of Australia, 2023)
31. (ACS, 2021)
32. (People's Court Daily, 2022)
33. (People's Court Daily, 2022)
34. (Ins-eon, 2022)
35. (Ghaffar, 2020)
36. (Gartner, 2025)
37. (Infocomm Media Development Authority, 2023; Australia Government, 2024)
38. (Infocomm Media Development Authority, 2023; Australia Government, 2024)
39. (India Government, 2024)
40. (Republic of Korea Government, 2022)
41. (Infocomm Media Development Authority, 2023)
42. (Australia Government, 2025)
43. (Republic of Korea Government, 2022)
44. (Janssen et al., 2017)
45. (Janssen et al., 2017)
46. (Singapore Government, 2025)
47. (Taeihagh, 2025)
48. (Janssen et al., 2020)
49. (Janssen et al., 2020; Taeihagh, 2025)
50. (Singapore Government, 2025)
51. (OECD, 2021)
52. (Google & Tata Trusts, 2023)
53. (Kerala State IT Mission, 2023)
54. (India Government, 2024)(India Government, 2024)
55. (ASEAN, 2021; APEC Digital Economy Steering Group, 2022)
56. (Australia Government, 2024)(Australia Government, 2024)
57. (ADB, 2023)
58. (South Australia Government, 2024)
59. (UNESCO, 2021; Secretary-General (EOSG), 2023)
60. (UNDP, 2024a)

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