Telecom Advisory Services

ECONOMIC IMPACT OF ARTIFICIAL INTELLIGENCE AND CLOUD COMPUTING DEVELOPMENT IN ASIA AND THE PACIFIC

THE IMPORTANCE OF PUBLIC POLICIES TO PROMOTE DEVELOPMENT OF CLOUD AND ARTIFICIAL INTELLIGENCE AND ACHIEVE ECONOMIC GROWTH

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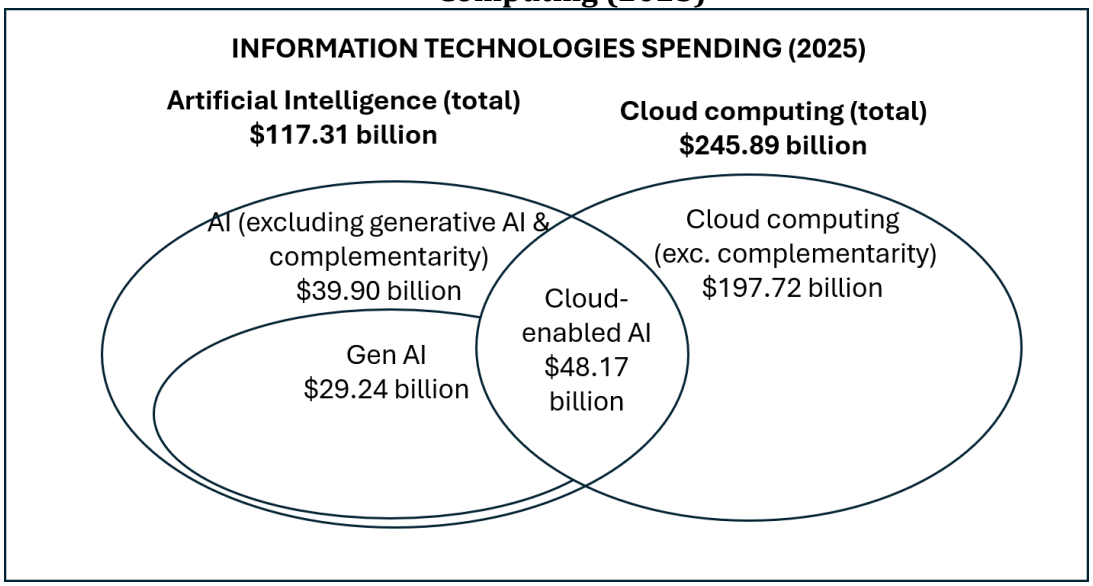
EXECUTIVE SUMMARY

The purpose of this study is to assess the economic contribution of artificial intelligence (AI) and cloud computing in selected countries of the Asia-Pacific region and identify the policies that will accelerate their impact while controlling for potential social inequalities derived from technology diffusion.

The 2025 Asia-Pacific AI and cloud computing markets in Australia, India, Indonesia, Japan, Republic of Korea, Malaysia, New Zealand, the Philippines, the PRC, Singapore, Thailand, and Viet Nam, are developing at a fast pace, having reached US$ 117.31 billion (0.35% of the regional GDP)[1] and US$ 245.89 billion (0.73% of the regional GDP)[2] respectively in 2025 (Figure A).

Figure A. Asia-Pacific: Spending on Artificial Intelligence and Cloud Computing (2025)



Note 1: Information Technology spending includes 16 technologies: Hardware (IaaS, server, and storage), software (AI applications [content workflow and management applications, CRM applications, ERM applications], AI application development and deployment, AI platforms [AI life-cycle software, computer vision AI tools, conversational AI tools, intelligent knowledge discovery software], AI system infrastructure software), and services (business services and IT services).
Note 2: these calculations include spending by Australia, India, Indonesia, Japan, Republic of Korea, Malaysia, New Zealand, Philippines, Singapore, the People's Republic of China, Thailand, and Viet Nam.
Sources: IDC (2026). IDC Worldwide AI and Generative AI Spending Guide - Forecast 2026 | Mar (V1 2026); IDC (2024). IDC Worldwide Software and Public Cloud Services (2024) July (V2 2024)

In particular, spending by Asia-Pacific public and private sector organizations in purchasing AI technology from cloud service providers, and in platforms bought from AI companies but run on cloud platforms amounts to US$ 48.17 billion (or 41.1% of the AI market). This highlights the economic relevance of the complementarity between AI and cloud computing. While private enterprises

[1] Source: *IDC (2026). IDC Worldwide AI and Generative AI Spending Guide - Forecast 2026 | Mar (V1 2026)*
[2] Source: *IDC (2024). IDC Worldwide Software and Public Cloud Services (2024) July (V2 2024)*

represent the dominant source of spending, the public sector has a significant share in four countries: Australia, New Zealand, the PRC and Singapore (see table B).

Table B. Sector source of spending (2025)

Country	Current spending (in US$ million)		Percent of public sector	
	AI	Cloud	AI (%)	Cloud (%)
Australia	$ 8,371.6	$ 26,198.6	15.7%	18.5%
India	$ 6,347.8	$ 20,540.1	8.2%	9.4%
Indonesia	$ 1,182.4	$ 2,959.8	8.9%	11.5%
Japan	$ 15,662.5	$ 56,503.0	4.4%	9.6%
Republic of Korea	$ 5,276.2	$ 10,777.1	9.9%	13.7%
Malaysia	$ 1,535.7	$ 3,697.5	8.9%	13.7%
New Zealand	$ 2,016.3	$ 4,773.2	8.9%	18.8%
Philippines	$ 957.4	$ 2,356.2	8.9%	11.6%
PRC	$ 63,166.4	$ 91,584.4	8.8%	15.7%
Singapore	$ 6,693.2	$ 10,670.4	7.3%	20.6%
Thailand	$ 1,547.8	$ 3,649.4	8.9%	10.3%
Viet Nam	$ 666.8	$ 1,642.6	8.9%	13.5%

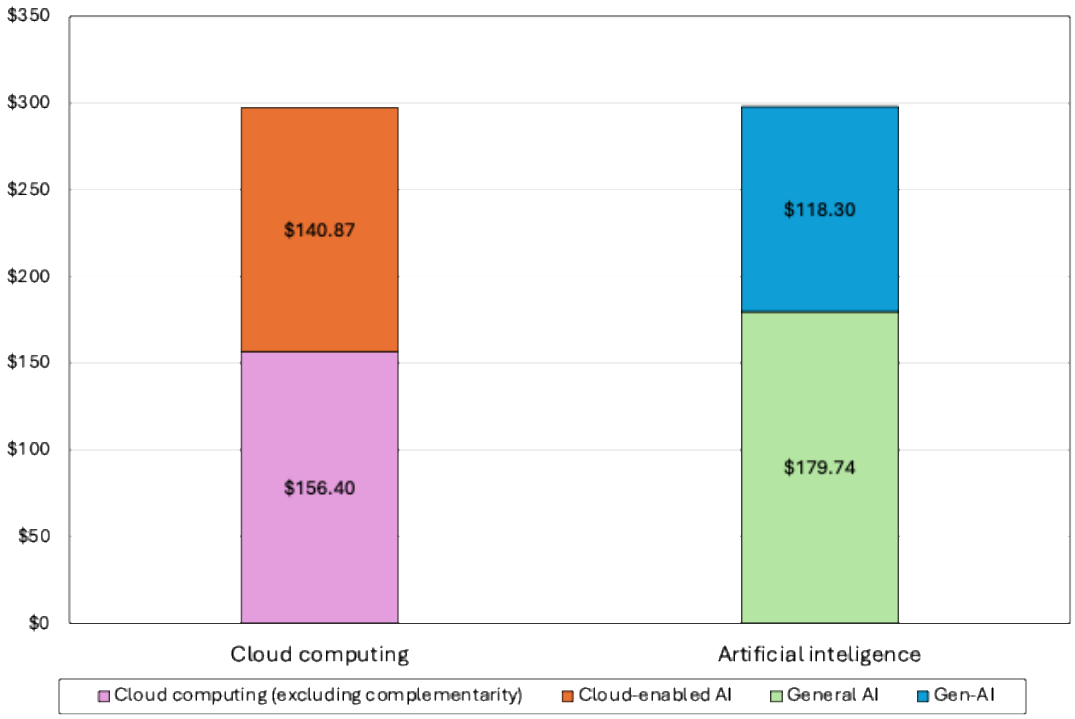
Note: The values of AI spending for Indonesia, Malaysia, New Zealand, the Philippines, Thailand, and Viet Nam were calculated by prorating the spending for "Rest of Asia Pacific" based on the respective weight of cloud spending for each country.
Sources: IDC (2026). IDC Worldwide AI and Generative AI Spending Guide - Forecast 2026 | Mar (V1 2026); IDC (2024). IDC Worldwide Software and Public Cloud Services (2024) July (V2 2024); Telecom Advisory Services analysis

Beyond the direct spending on both technologies, their most important economic effect resides in their impact on productivity and economic growth, labeled spillovers.[3] These have been estimated through econometric models that establish that the increase in AI (including generative AI) and cloud spending is associated with enhanced productivity of skilled workers and aggregate economic growth.

Once economic spillovers from spending are considered, the total economic impact of AI in the countries under study increases significantly. As depicted in figure C below, the total contribution of AI for 2025 increases almost nine times, reaching US$ 438.91 billion (equivalent to 2.72% of the GDP of all countries considered). The large increase in economic impact relative to spending levels is associated with the massive annual growth that this technology is experiencing, as it is in the initial phase of deployment.[4] In turn, the total impact of cloud computing for 2025 is US$ 297.27 billion (equivalent to 1.84% of the GDP of the countries considered) (see Figure C). In contrast to AI, the cloud computing market and its economic impact, indicates a more mature technology, with spending reaching moderate growth levels.

[3] An economic spillover generated from technology adoption is an indirect benefit where the use of a new tool or process by the productive sector raises its productivity and efficiency, including that of other non-adopting firms, supply chains, due to economic linkages.
[4] Between 2023 and 2024 alone, the spending in AI in the Asia-Pacific countries under study increased 70.3%.

Figure C. Asia-Pacific: Total economic impact (spending and spillover) of Artificial Intelligence and Cloud Computing (2025)



Note: these calculations include Australia, India, Indonesia, Japan, the Republic of Korea, Malaysia, New Zealand, the Philippines, Singapore, Thailand, and Viet Nam. The PRC was not included in the overall impact results because its scale would distort the aggregate.
Sources: IDC (2026). IDC Worldwide AI and Generative AI Spending Guide - Forecast 2026 | Mar (V1 2026); IDC (2024). IDC Worldwide Software and Public Cloud Services (2024) July (V2 2024); Telecom Advisory Services analysis

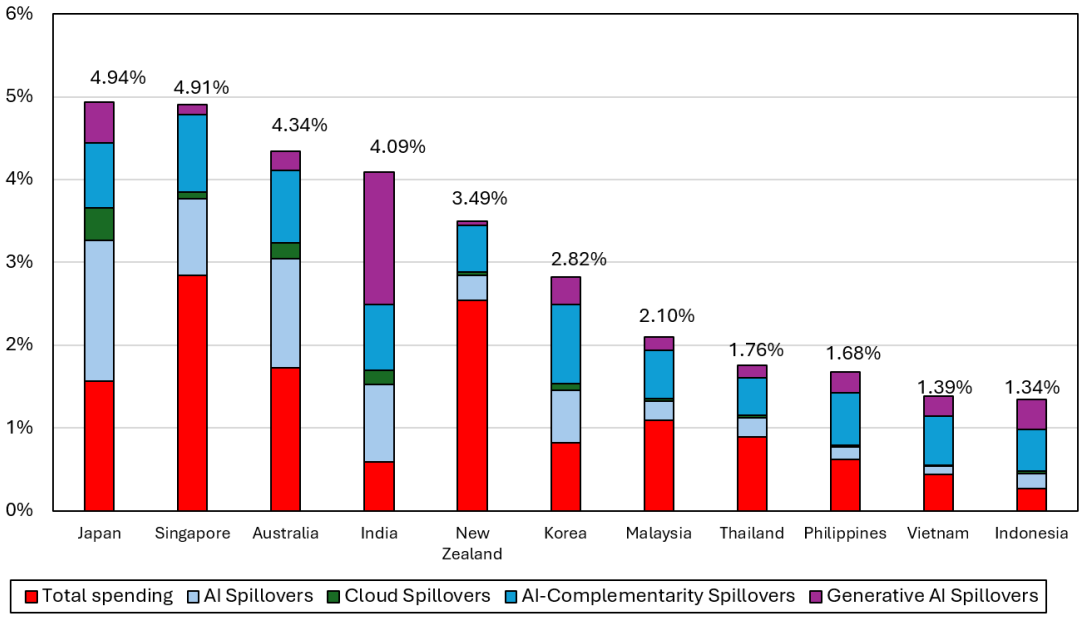
The total contribution of both technologies can be disaggregated into key components. For example, the total contribution of generative AI, a subset of AI including applications such as chatbots[5] and agentic AI applications,[6] reaches US$ 118.30 billion (equivalent to 0.73% of the GDP of the countries under analysis). Furthermore, the complementarity between cloud technology and AI is an important source of economic value since the capability of cloud computing is a critical enabler of AI use cases. This effect amounts to US$ 140.87 billion in 2025 (or 0.87% of the region's GDP). As also indicated in figure C, the total economic impact of each technology should be considered in terms of the overlapping effects. For example, in 2025 AI standalone (without including Generative AI or the complementarity with cloud) contributed US$ 179.74 billion to the region's Gross

[5] Type of artificial intelligence that can simulate conversation with human users. These programs are designed to engage in conversations, answer questions, and even perform tasks, often mimicking human-like interaction. They can be used in various applications, including customer service, information gathering, and even entertainment.
[6] Agentic is often used in the context of artificial intelligence, referring to AI agents that can make decisions, take actions, and learn autonomously to achieve specific functional goals. Generative AI creates content you review, while agentic AI takes policy-bounded actions to complete tasks; most enterprises benefit from using both, where each fits best.

Domestic Product (GDP) (equivalent to 1.11% of the region's GDP). In turn, cloud computing (excluding its enablement of AI) contributed US$ 156.40 billion to the annual GDP (equivalent to 0.97% of the region's GDP). Counting the shared cloud-enabled AI component once, the combined 2025 economic contribution is US$ 595.3 billion, equivalent to 3.68% of GDP in the 11 economies analyzed.

When examined on a country basis, total spending and spillovers are significant ranging from 1.34% of GDP for Indonesia to 4.94% for Japan (see graphic D).

Graphic D. Asia Pacific countries: AI and Cloud total spending and economic spillovers (as percent of GDP) (2025)



Sources: Telecom Advisory Services analysis

On the basis of the coefficients driving spillovers, the differential economic impact by country was calculated, leading to the following conclusions:

- **Countries that increase AI and Cloud spending are associated with economic gains.** The models developed for this study suggest that a 1% increase in AI spending in Australia, India, Indonesia, Japan, the Republic of Korea, Malaysia, New Zealand, the Philippines, Singapore, Thailand, and Viet Nam is associated with an increase of 0.031% of the GDP, while a 1% increase in cloud spending is associated with an increase of 0.011% of the GDP.[7]

- **Economic spillovers that depend on the complementarity of cloud and AI exhibit larger economic effect.** A 1% increase in the share of spending on cloud service providers (CSP) destined to AI platforms is associated with an increase in GDP of 0.034%. The higher coefficient of impact of

[7] For comparison purposes, in a recent study, the authors estimated that, on a worldwide basis, 1% increase in fixed broadband adoption would yield 0.159% increase in GDP (see Katz and Callorda, 2025).

> complementary AI and cloud than each technology on a stand-alone basis, underscores the potential for integrating both technologies to enhance organizational performance, emphasizing the need for skill development, security measures, and the strategic utilization of organizational resources to fully exploit the benefits of this integration.[8]

Based on these coefficients, two economic impact scenarios based on IDC spending forecast for both technologies over the next five-years (2026-30) were developed.[9] The first scenario assumes that spending will evolve as stated by the IDC forecast, while the second one, more moderate, is based on a spending growth rate of half of the future growth rate. According to the IDC forecast of spending growth rate, the economic impact of AI and cloud as standalone technologies in Australia, India, Indonesia, Japan, Republic of Korea, Malaysia, New Zealand, the Philippines, Singapore, Thailand, and Viet Nam will be significant, reaching respectively US$ 3,049 billion and US$ 3,978 billion (or 3.00% and 3.91% of the forecast cumulative GDP for the same period). The complementarity between both technologies will add an additional US$ 2,920 billion to the economy (2.87% of the region's GDP). Generative AI, in turn, will add a further US$ 385 billion (0.38% of the region's GDP). The sum of all sources of value accounts for $ 10,331.8 billion (10.15% of the region's GDP).

A more moderate estimation, based on half the growth rates of AI spending would suggest that the economic impact of AI and cloud as standalone technologies in Australia, India, Indonesia, Japan, the Republic of Korea, Malaysia, New Zealand, the Philippines, Singapore, Thailand, and Viet Nam will reach respectively US$ 1,594 billion and US$ 2,351 billion (or 1.57% and 2.31% of the forecast cumulative GDP for the same period). Under this scenario, the complementarity between both technologies will add an additional US$ 2,561 billion to the economy (2.52% of the region's GDP). Generative AI, in turn, will add a further US$ 280.6 billion (0.28% of the region's GDP). The sum of all sources of value accounts for $ 6,787 billion (6.67% of the region's GDP) under these moderate projections.

As the estimates indicate, it is important to underline the critical role of technology complementarity in the two forecast scenarios between cloud computing and AI in driving economic growth.

In order to achieve this forward-looking level of impact, countries in Asia Pacific need to implement important public policy interventions. The theory of change underlying this study posits that the positive externalities mentioned above are contingent upon a set of public policies promoting the development and adoption of artificial intelligence combined with the migration of government and private enterprise systems to cloud computing (see Figure E).

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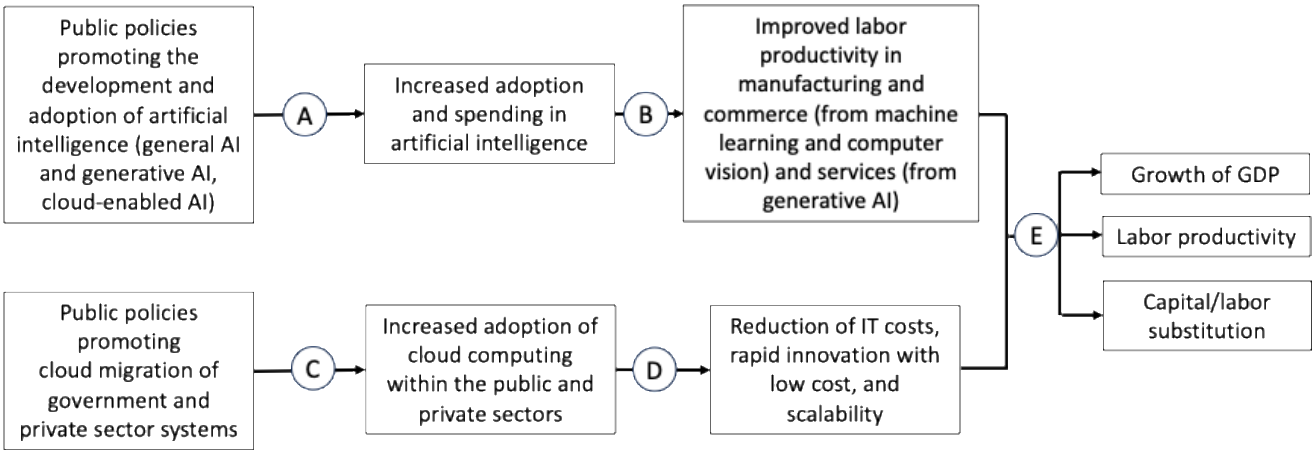
[8] This complementary effect was also proven by Katz and Jung (2024b) where, in a sample of firms in Israel, the combination of cloud computing and machine learning has a cumulative correlation coefficient of 0.233 compared with 0.143 for cloud computing alone.

[9] The two IDC spending reports cited in footnotes 1 and 2 provide spending forecasts through 2028. For purposes of this analysis the rate of growth was extrapolated through 2030.

Figure E: Theory of change linking AI and cloud policies to economic growth



Source: Telecom Advisory Services

The development and adoption of AI in its multiple versions (general, generative, and cloud-enabled) in a given country is influenced by a set of specific public policies:

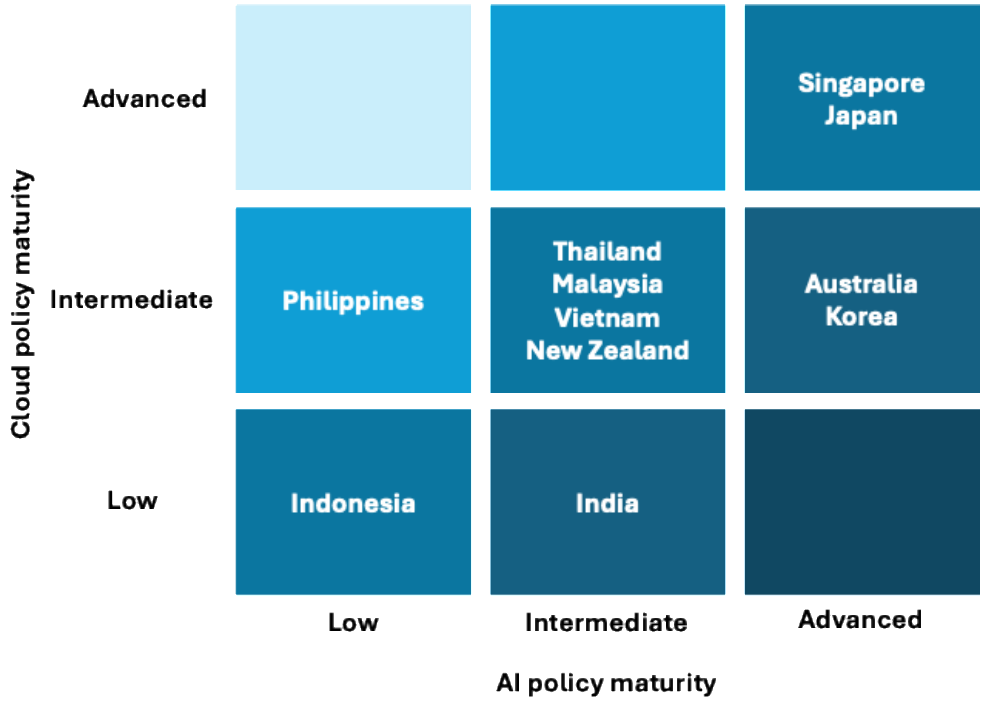
- Promotion of in-country R&D (public and private) and advancement of academic strength in the field with an AI focus
- Development of AI start-ups and deployment of required infrastructure for training AI models (e.g. large-scale data centers, supercomputers)
- Deployment of general infrastructure (e.g. high-speed broadband) and advanced cybersecurity rules
- Implementation of policies and governance conducive for adoption of AI (national AI strategy, AI legislation to protect consumer data, etc.) AI regulation should be flexible and risk-based, reflect different risk levels and roles across the value chain, and avoid unnecessary barriers to adoption.
- Skills development in terms of training of AI development workforce and labor reskilling

In addition, six policies have been identified as being critical for stimulating the migration of public and private sector systems to the cloud:

- Relax data localization requirements to preserve customers' choice and access to competitive cloud and AI services.
- Stimulate cloud enterprise adoption in regulated industries by promoting standardized, risk-based cloud migration approval processes.
- Remove barriers and discriminatory practices towards foreign CSPs.
- Modernize public procurement for consumption-based cloud services, reflecting on-demand, pay-as-you-go purchasing rather than up-front hardware acquisition.
- Invest in cloud and AI upskilling and partner with cloud service providers in developing local talent.
- Improve Cybersecurity levels in terms of legal framework, regulatory accountability and technical capacity.

These policies will have an impact on technology spending and, consequently, on spillovers. However, a wide variance in terms of policy maturity across countries in the region exists (see table F).

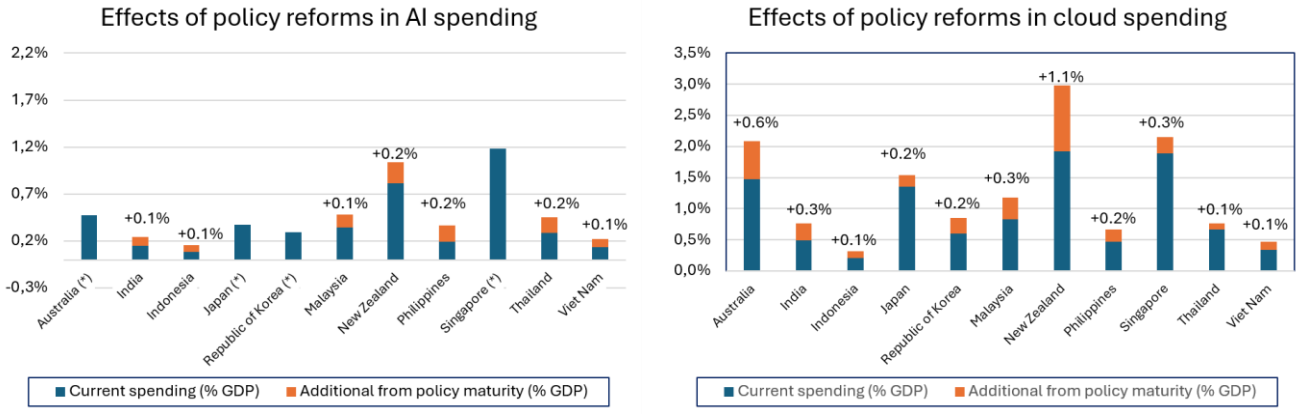
Figure F. AI and Cloud policy maturity



Source: Telecom Advisory Services analysis (see appendices D and E)

Applying a hypothetical increase in policy maturity for each country, the impact on AI and cloud spending is estimated (see Graphic G).

Graphic G. Effects of increase in policy on AI and Cloud spending



(*) Country has already achieved the hypothetical increase in policy maturity
Source: Telecom Advisory Services analysis

These results demonstrate the importance of AI, cloud computing and cloud enabled AI for the economic development of the region, and the relevance of creating a policy and regulatory environment aimed at maximizing their impact. Asia Pacific

countries have the opportunity of accelerating their technological development in cloud computing and AI. In order to do so, the region should rethink their digital policies to identify cloud and AI impediments to the fulfillment of development objectives.

On a final note, beyond the contribution to GDP, both technologies, especially AI, represent a critical input to improving labor productivity. The econometric model developed for this study indicates that the average annual incremental productivity derived from spending on AI and cloud computing in the countries under analysis is equivalent to an additional US$ 544.37 per worker (from a current amount of US$ 14,776).

However, the study models also indicate that labor productivity enhancement will materialize primarily in the skilled workforce (i.e. workers with a tertiary educational level) combined with a process of substitution of unskilled workers. To explain the variation in the level of skilled and unskilled employment, regression models were estimated in which these variables were introduced as the dependent ones, while regressors include the level of spending on AI and other controls.[10] According to our econometric analysis, 1% increase in AI spending will increase the demand for skilled workers by 0.21% to 0.22% but will also decrease the demand for unskilled workers by 0.15% to 0.17% (in both cases, the exact magnitude will depend on the empirical model considered). Despite the use of fixed effects and a simultaneous equation framework, the results should be interpreted with caution, as several sources of endogeneity may still affect the estimated coefficients. First, reverse causality is a concern: countries or firms with a larger or more skilled workforce may be better positioned to adopt and invest in AI, so that the observed positive association between AI spending and skilled employment could partly reflect the effect of skilled labor on AI adoption rather than the reverse. Second, omitted variable bias may persist even after including country and year fixed effects, since time-varying factors that are correlated with both AI spending and labor market composition may not be fully captured by the controls.

With these caveats in mind, if the number of skilled workers were equal to the number of unskilled workers in a given country, both effects would largely offset each other, and the net result would be close to zero. This is why, according to our models and assumptions, job creation in the Republic of Korea, Japan, New Zealand, and Singapore as a consequence of AI adoption more than compensates for the losses. On the other hand, in emerging economies, which tend to have a greater number of unskilled workers net job losses could be higher.

Furthermore, if demand for skilled jobs increases, so will their salaries. As firms compete to hire the best talent, wages should increase. On the other hand, if demand for low skilled workers reduces, so would their salaries. The net result, a potential excess supply of unskilled workers, could then drive firms to pay them less. This

[10] Estimates were made through the 3-stage least squares (3SLS) simultaneous equation system procedure, which is considered more efficient than the separate estimation of both employment demands, since both decisions are expected to be correlated.

means that, even in the eventuality of no overall effects on jobs, the change in the composition of employment, may augment the salary gap and increase inequality.

This detrimental effect should incentivize countries to implement policies focused on upskilling and reskilling the labor force that will be affected by the adoption of AI. Seven of them are critical:

- Establishing clear metrics for assessing AI-related skills.
- Incorporating training in AI-centric skills taxonomies in education.
- Promote national programs to improve skills and retraining to prevent unemployment of workers in areas highly exposed to AI and promote their retraining in sectors complementary to AI
- Incorporate criteria of equity, gender and territory in all AI adoption policies in order to reduce the deepening of structural gaps

Assessing/auditing the quality of existing "AI-readiness" training programs.

- Incentivizing employers and employees to participate in upskilling programs.
- Develop systems for monitoring and evaluating the impact of AI on employment by sector and occupational profile in order to adjust public policies based on evidence

1. INTRODUCTION AND STUDY OBJECTIVES

The purpose of this study is to assess the economic contribution of artificial intelligence (AI) and cloud computing in selected countries of the Asia-Pacific region (Australia, India, Indonesia, Japan, Korea, Malaysia, New Zealand, Philippines, Singapore, Thailand, and Vietnam) and identify the policies that will accelerate its impact while controlling for potential social inequalities derived from technology diffusion. **The study's fundamental premise is that accelerated spending of cloud computing and AI has potentially wide-ranging macroeconomic benefits for each country.** The study also aims to measure the impact of sector spending on cloud and AI. Finally, it considers the importance of public policies for controlling any potential social disruptions resulting from the growing adoption of AI.

The study is structured as follows. Chapter 2 reviews the current state of spending of AI and cloud computing in selected countries of Asia-Pacific, highlighting in a descriptive fashion the correlation between both technologies and economic development.[11] On this basis, recognizing that cloud and AI use is already "naturally" growing driven by intrinsic demand features, Chapter 3 presents a theory of change linking public policies to stimulate AI and cloud spending by the public sector, an accelerated transition by private sector enterprises (both large and small/medium-sized enterprises) and the consequent contribution to economic growth. Based on the theory of change, we introduce theoretical models that are used to estimate the economic impact of AI and cloud. In chapter 4, we specify the econometric models and estimations regarding the economic impact of AI, cloud and cloud-enabled AI by Asia-Pacific country and test the hypotheses that the enhancement of AI and cloud policies can accelerate their development and consequently their economic contribution. In Chapter 5 econometric modelling estimates the boost to AI and cloud computing spending and therefore to the economies in Asia Pacific by putting in place selected policies oriented to stimulate their development. Chapter 6 quantifies the potential impact of AI adoption on employment. Chapter 7 presents the policy implications aimed at driving adoption of AI, migrating IT infrastructure to the cloud, addressing any potential social disruptions. It is complemented by a case study of Singapore AI policies, a country that is outperforming its peers in terms of AI and cloud development. Chapter 8 draws the final study conclusions.

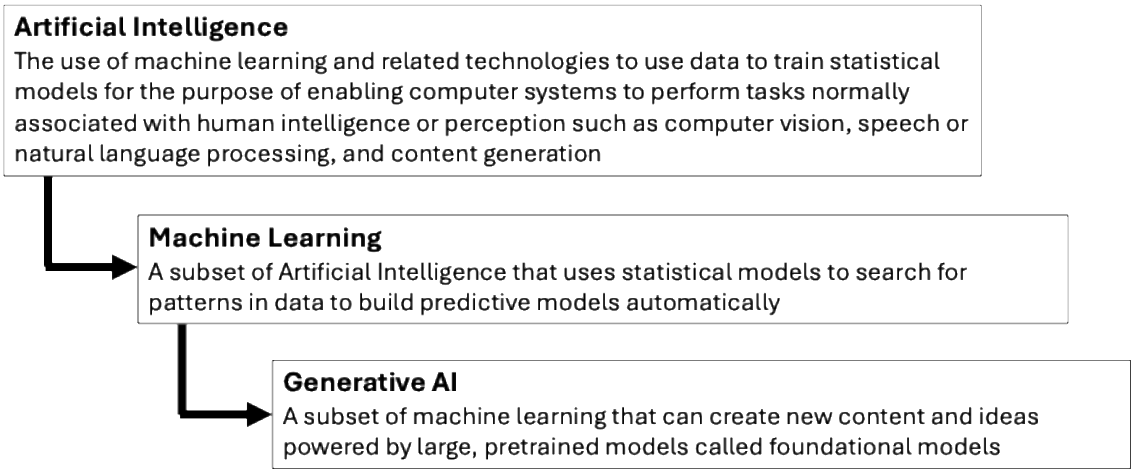
[11] The study focuses on Australia, India, Indonesia, Japan, the Republic of Korea, Malaysia, New Zealand, Philippines, Singapore, Thailand, and Viet Nam. We also include some descriptive figures for the PRC.

2. THE STATE OF DEVELOPMENT OF ARTIFICIAL INTELLIGENCE AND CLOUD COMPUTING IN ASIA-PACIFIC

2.1. Context and definitions

AI can be defined as the use of machine learning and related technologies that use data to train statistical models for the purpose of enabling computer systems to perform tasks normally associated with human intelligence or perception, such as computer vision, speech or natural language processing, and content generation. AI relies on data and other inputs to capture large volumes of information, perform analyses, and formulate customized outputs. With its more recent advances, AI has emerged as a transformative technology with the potential to reshape the economy, revolutionizing the way we work. AI is becoming a driving force behind automation and innovation in various industries, offering immense opportunities. Research on the economic impact of AI has been developing over the past decade, although the original contributions focused on robotics and machine learning and only recently have shifted to areas such as computer vision and generative AI (see Figure 2-1).

Figure 2-1. Definitions of Artificial Intelligence



AI requires an inordinate amount of computing resources to operate. In response to this requirement, cloud computing represents a powerful enabler. Furthermore, large datasets are expected to contribute to accelerating the use of *Machine Learning*, by providing useful information for AI-related decision-making processes. Under the premise of technological complementarity, it is reasonable to consider that AI adoption would be higher for enterprises that have adopted cloud, yielding in turn higher business performance. Consequently, we argue that countries with high adoption of AI and cloud computing will create high economic value, as measured by GDP contribution. Thus, cloud computing and AI represent a classic case of technological complementarity.

In general terms, cloud Computing represents a critical contribution to digital transformation of an organization through several internal effects. Supported by cloud computing, the provision of IT-based services has experienced a significant transformation. The ability to share and access computing resources such as servers,

storage areas, and network service applications remotely with high reliability and scalability is one of cloud computing's primary advantages. Moreover, these computational resources can be accessed online at a minimal additional cost thanks to cloud technology. This means that businesses will not have to spend significant resources developing their own infrastructure.[12] As a result, firms that use cloud services can gain from advantages like cost savings, flexibility, and scalability. Businesses can also automatically scale software and storage in response to load by utilizing cloud infrastructure, which helps them save resources. Spending less on resources improves a company's margins and, as a result, its monetary value, which is, in turn, translated into an economic contribution. Moreover, SaaS cloud services can have a potential impact on firm-driven ICT-enabled innovation (e.g., product development). Lastly, the economic impact of cloud services on software development is expected to be significant. Software development work is made easier when cloud vendors implement technologies that allow them to create products "higher up the stack" and provide services with higher abstractions. This is because companies can now concentrate solely on writing code and deploying it, which reduces development costs. This ultimately results in increased margins and possibly higher sales.

This section presents a general overview of the spending and adoption levels of both AI and cloud computing in the Asia-Pacific region. Following IDC's implicit definition of spending on AI and cloud computing, this study relies on the amount of resources in constant US$ used for the acquisition of hardware, software and services to deliver the functionality of technology use cases. Thus, spending is used as a metric of technology adoption to conduct the econometric analyses that will be presented in chapter 3 and 4. In that sense, data on adoption is provided for illustrative purposes only, measuring the percent of public and private organizations having implemented AI or cloud technology. Its purpose is to set the stage for the analysis of their economic contribution if spending (and consequently adoption) in these technologies were to be accelerated.

The assessment is structured around four components of the Information Technologies universe (see figure 2-2).

[12] In the past, businesses had to build their own data centers, acquire the necessary hardware and software, and hire skilled personnel to manage them when cloud computing was not commercially available. This limited the benefits of this technology primarily to large companies.

Figure 2-2. Components and definitions

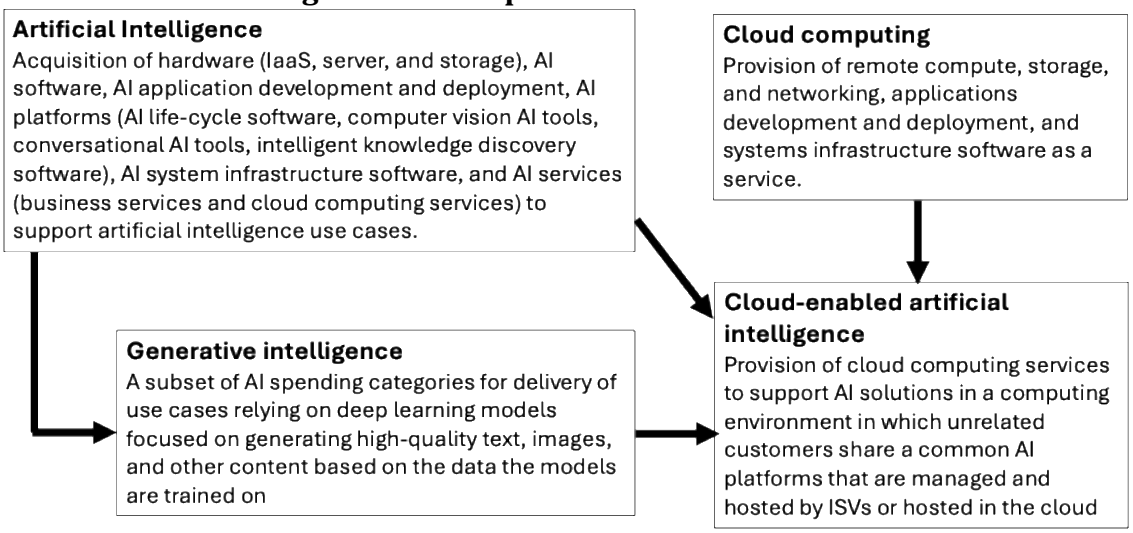
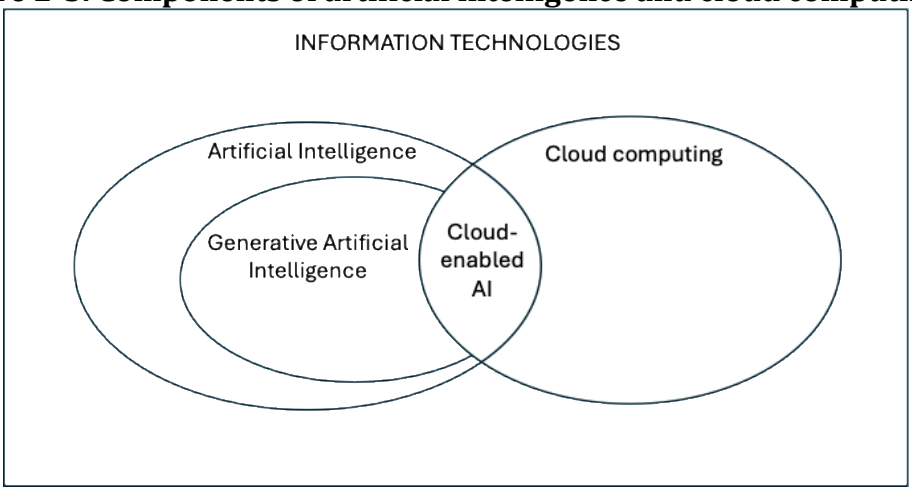


Figure 2-3 depicts the conceptual interaction of spending between all four components.

Figure 2-3. Components of artificial intelligence and cloud computing



Source: Telecom Advisory Services

Each component is assessed in terms of region and country spending, and public and private sector spending and adoption.

2.2. Artificial Intelligence as an engine of economic growth

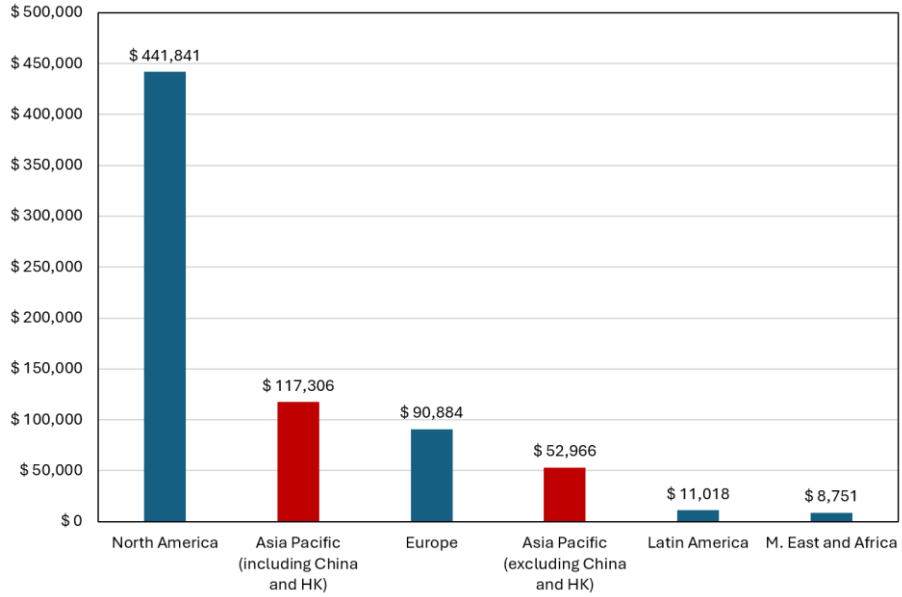
2.2.1. Artificial Intelligence spending and adoption by Asia Pacific country

AI spending in all countries of the Asia-Pacific is evolving fast when compared to advanced economies. AI spending, which comprises hardware and software acquisition, fees paid to cloud service providers, and systems integration consulting, for selected countries in the region[13], amounts to US$ 117.31 billion (or 17.51% of

[13] This amount includes spending in Australia, PRC, Hong-Kong, China, India, Indonesia, Japan, the Republic of Korea, Malaysia, New Zealand, the Philippines, Singapore, Thailand, and Viet Nam.

the global market) in 2025. Even if the PRC and Hong Kong, China, are excluded from this statistic, the region still ranks second in the world, with spending at US$ 52.97 billion (see Graphic 2-1).

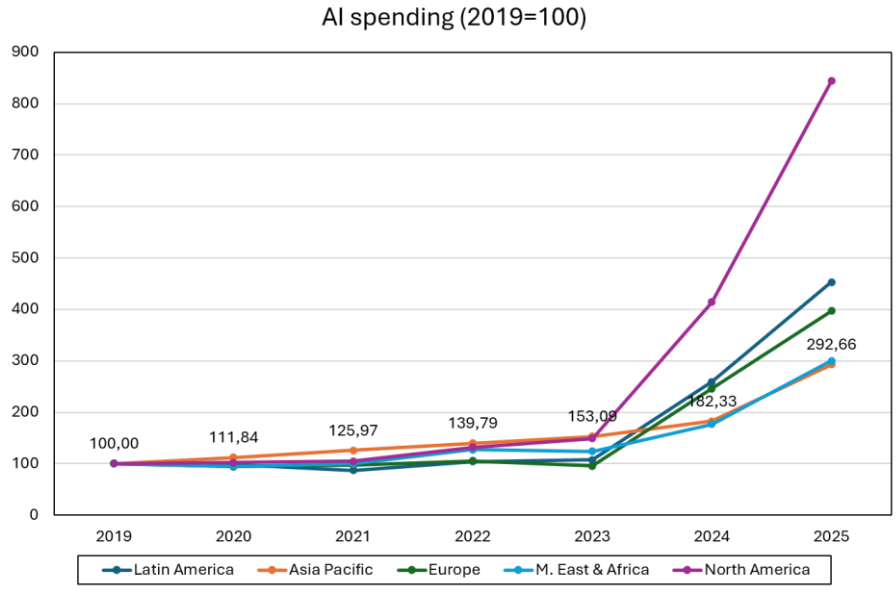
Graphic 2-1. World: Artificial Intelligence spending (in US$ million) (2025)



Source: IDC (2026). IDC Worldwide AI and Generative AI Spending Guide - Forecast 2026 | Mar (V1 2026)

As indicated in Graphic 2-1, the region stands only below North America in terms of AI spending, and well above Europe, Middle East and Africa as well as Latin America and the Caribbean. In addition, AI spending levels are also growing fast in the region, although below the levels of the rest of the regions (see Graphic 2-2).

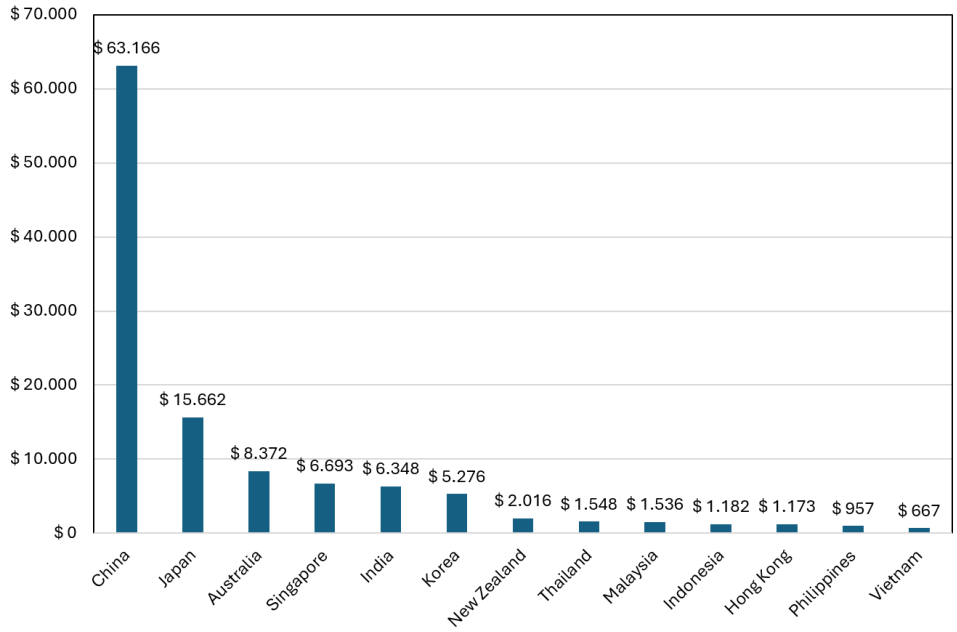
Graphic 2-2. World: Evolution of AI spending since 2019



Sources: IDC (2026). IDC Worldwide AI and Generative AI Spending Guide - Forecast 2026 | Mar (V1 2026); IDC Semiannual Artificial Intelligence Infrastructure Tracker - Final Historical 2024; Telecom Advisory Services analysis

When disaggregating the spending level by country, it is apparent that the position of the region on a global scale is largely fueled by the PRC, with AI spending amounting to US$ 63.17 billion in 2025. The remaining countries never surpass US$ 20 billion in AI spending: Japan (US$ 15.66 billion), Australia (US$ 8.37 billion) and Singapore (US$ 6.69 billion) (see Graphic 2-3).

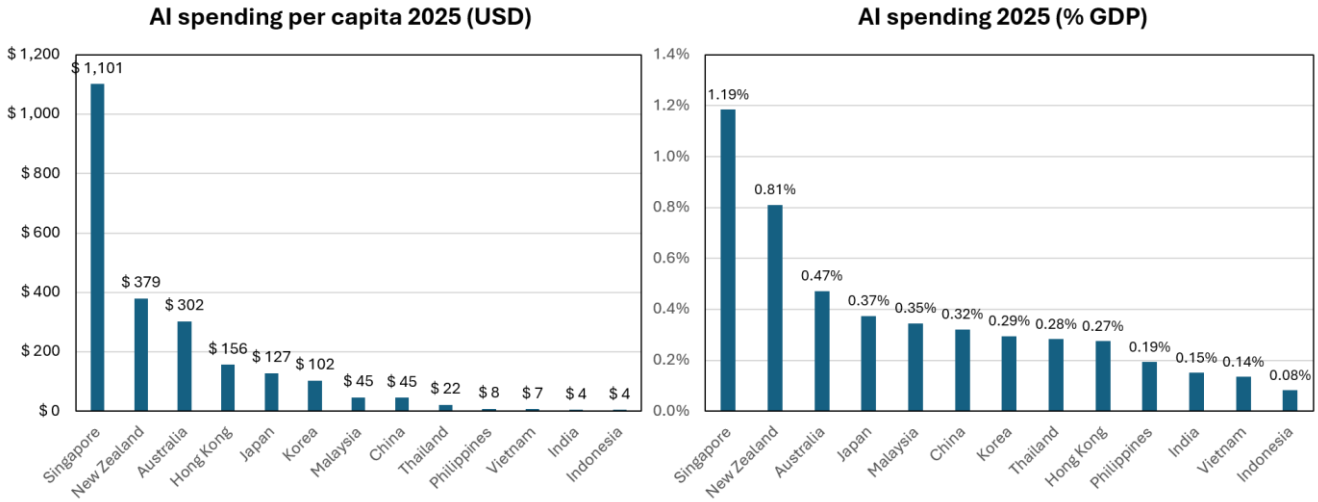
Graphic 2-3. Asia-Pacific: AI spending by country (in US$ million) (2025)



Note: values for Indonesia, Thailand, Viet Nam, Malaysia, the Philippines and New Zealand are prorated from the category "rest of Asia-Pacific" based on the respective weight of each country on cloud spending.
Source: IDC (2026). IDC Worldwide AI and Generative AI Spending Guide - Forecast 2026 | Mar (V1 2026) Telecom Advisory Services analysis

Considering that the distribution by absolute spending in Graphic 2-3 is largely distorted due to differences in country scale, AI spending is normalized by population (in the left graphic) and by GDP (right graphic) (see Graphic 2-4).

Graphic 2-4. Asia-Pacific: AI spending per capita and as a share of GDP by country (2025)

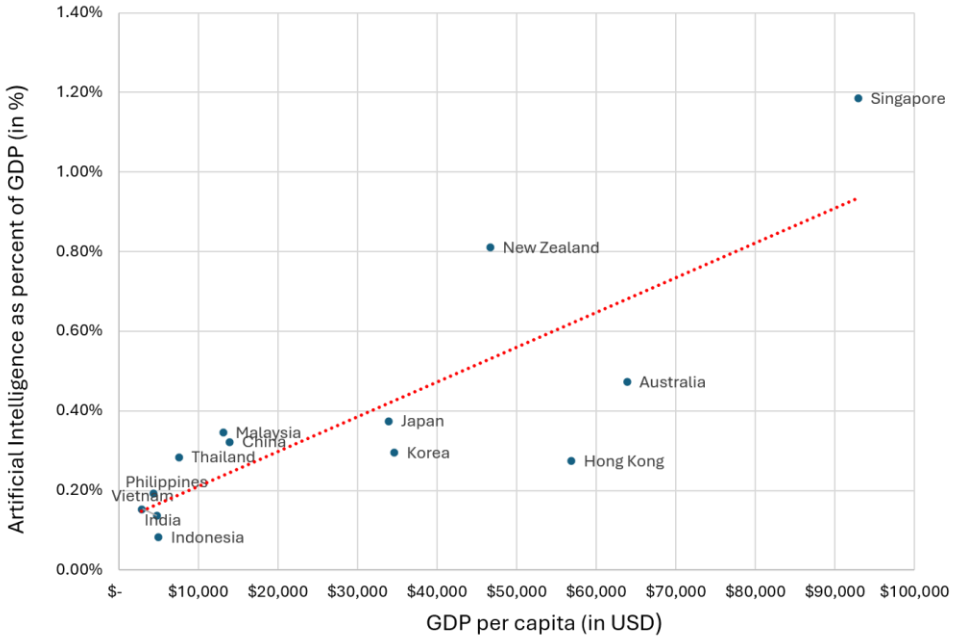


Note: spending values for Indonesia, Thailand, Viet Nam, Malaysia, the Philippines and New Zealand are prorated from the reported category "rest of Asia-Pacific" according to the cloud weight of each country.
Source: IDC (2026). IDC Worldwide AI and Generative AI Spending Guide - Forecast 2026 | Mar (V1 2026); Telecom Advisory Services analysis

When data is normalized by scale, it is apparent that the region's leader is Singapore, with a spending level equivalent to $1,101 per person (or 1.19% of its GDP). China presents low spending per capita ($ 45), although when measured in terms of GDP it is in sixth position (0.32%). New Zealand, Australia, Hong-Kong, the Republic of Korea, and Japan are the remaining region leaders. At the other end, the lowest levels are detected in Indonesia.

As might be expected, the level of AI spending (measured as percent of GDP) is correlated with a country's economic development (see Graphic 2-5).

Graphic 2-5. Asia Pacific: GDP per capita vs. AI Spending as % of GDP (2025)



Source: IDC (2026). IDC Worldwide AI and Generative AI Spending Guide - Forecast 2026 | Mar (V1 2026); International Monetary Fund. World Economic Outlook, October 2024; Telecom Advisory Services analysis

That being said, as depicted in Graphic 2-5, Singapore appears to be in a position that is much higher than the one predicted by the correlation line, which could reflect a boost in spending driven by particular policy initiatives (this particular point will be addressed in chapter 5).

In this case, data has been compiled from different sources and is not necessarily based on homogeneous definitions, time periods, and sampling. This means that the comparison across countries should be done with caution. With this caveat in mind, the evidence suggests that Singapore again leads in terms of adoption (60% of organizations), followed by India, and New Zealand. On the other hand, lower adoption levels are registered in Thailand and Malaysia (Table 2-1).

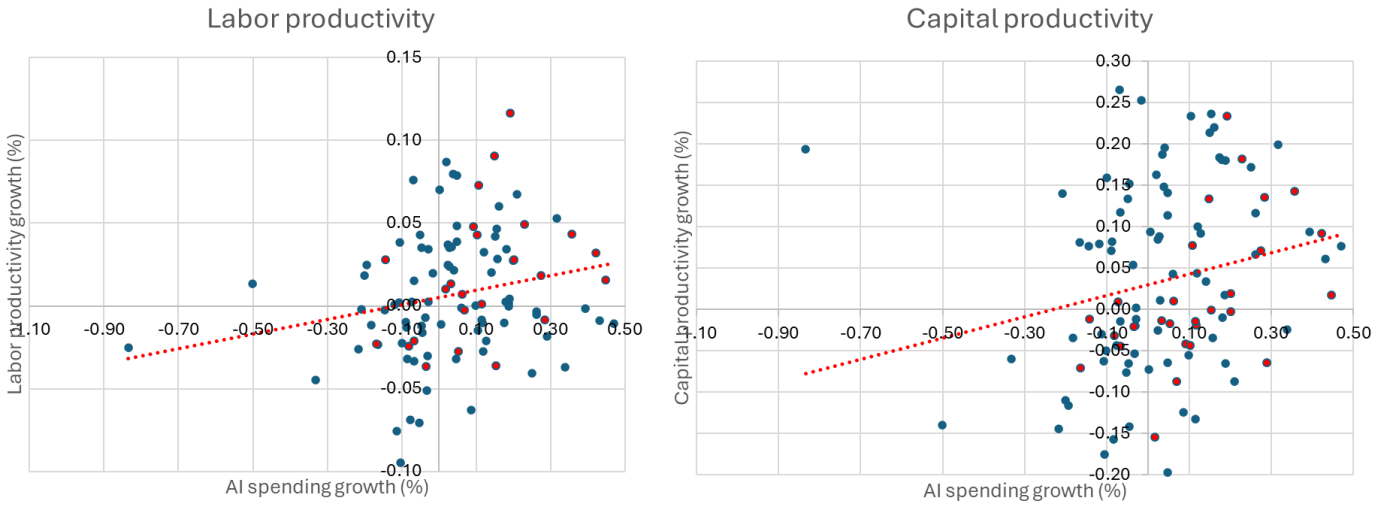
Table 2-1. Asia-Pacific: AI adoption by country (last data available)

Country	Share of firms adopting AI	Year	Source
Singapore	60%	2024	https://www.allaboutai.com/resources/ai-statistics/global-ai-adoption/
India	57%	2024	https://www.allaboutai.com/resources/ai-statistics/global-ai-adoption/
New Zealand	48%	2023	https://datacom.com/nz/en/solutions/experience/insights/ai-attitudes-research-report
Repblic of Korea	33%	2024	OECD Stat (https://data-explorer.oecd.org/)
Australia	25%	2024	https://www.allaboutai.com/resources/ai-statistics/global-ai-adoption/
Japan	24%	2024	https://www.reuters.com/technology/artificial-intelligence/more-than-40-japanese-companies-have-no-plan-make-use-ai-2024-07-17/
Thailand	18%	2024	https://www.bangkokpost.com/business/general/2877427/survey-says-strong-appetite-to-adopt-ai-among-thai-firms
Malaysia	18%	2024	https://ai.gov.my/media/thought-leadership/Reports-06-EN-Economic-Impact-of-Generative-AI-MY-1.pdf

Source: OECD *Stat (retrieved in: https://data-explorer.oecd.org/), Reuters, Bangkok Post, Datacom, Malaysia Centre for the Fourth Industrial Revolution, allaboutai.com*

Beyond the association between AI spending and GDP highlighted in Graphic 2-5, the descriptive evidence also suggests that the growth in AI spending is associated with increases in both labor and capital productivity (Graphic 2-6).

Graphic 2-6. AI spending and productivity growth



Note: Asia Pacific countries marked in red.
Sources: IDC (2025). Worldwide AI and Generative AI Spending Guide. Feb (V1 2025). Released on 2025-03-25, International Monetary Fund. World Economic Outlook, October 2024; The Conference Board; World Bank; Telecom Advisory Services analysis

Graphics 2-5 and 2-6 provide preliminary evidence supporting the hypothesis that AI is a potential enabler of economic growth and productivity increase for both labor and capital. This point will be tested in the following chapters.

2.2.2. Artificial Intelligence spending and adoption by sector

In terms of AI spending by economic sector in Asia Pacific, data is available only for Australia, India, Japan, the Republic of Korea and Singapore (Table 2-2).

Table 2-2. Asia-Pacific: AI spending by sector (2025) (in US$ million)

Industry	Australia	India	Japan	Republic of Korea	Singapore	Rest of Asia Pacific
Financial services	$ 1,760.9	$ 1,067.9	$ 1,459.4	$ 618.4	$ 838.1	$ 1,603.7
Health care	$ 694.5	$ 319.1	$ 355.6	$ 269.9	$ 222.3	$ 512.0
Telecommunications	$ 345.9	$ 631.2	$ 1,045.4	$ 307.8	$ 221.3	$ 845.4
Energy	$ 377.3	$ 282.3	$ 284.6	$ 202.1	$ 150.3	$ 467.8
Manufacturing and resources	$ 734.3	$ 954.0	$ 2,728.4	$ 970.1	$ 508.8	$ 1,696.1
Retail and services	$ 3,148.0	$ 2,573.1	$ 9,093.1	$ 2,385.7	$ 4,265.5	$ 4,544.5
Public Sector	$ 1,310.7	$ 520.3	$ 695.9	$ 522.2	$ 486.9	$ 945.4
TOTAL	$ 8,371.6	$ 6,347.8	$ 15,662.5	$ 5,276.2	$ 6,693.2	$ 10,614.9

Note: the category "Rest of Asia-Pacific" includes all the remaining countries of the region except for China and Hong-Kong.
Source: IDC (2026). IDC Worldwide AI and Generative AI Spending Guide - Forecast 2026 | Mar (V1 2026)

As indicated in table 2-2, the sector that invests the most in AI in all countries is Retail and Services, reflecting the wide availability of use cases in consumer distribution (for example, customer care and logistics). This position is followed by Financial Services in Australia, India and Singapore, while in Japan and the Republic of Korea the second highest investing sector is manufacturing and resources. In most cases, the sectors that invest the least are Health care and Energy, which highlights the opportunity for increasing adoption in sectors with wide social benefits.

In terms of adoption by organizations, sectoral data is only available through OECD statistics for Australia (2022), the Republic of Korea (2024), New Zealand (2022) and Japan (2023). As the data sources and year of reference are different from those reported in Table 2-1 (except for the Republic of Korea), this means that these penetration statistics may reflect some inconsistencies with the national averages presented above. Having said that, the relevant information that arises in this case is the relative position of the different sectors within each country. In this case, the ICT sector is the one in which AI adoption is the highest in all countries, except in the Republic of Korea, where Finance reaches the highest values (Table 2-3).

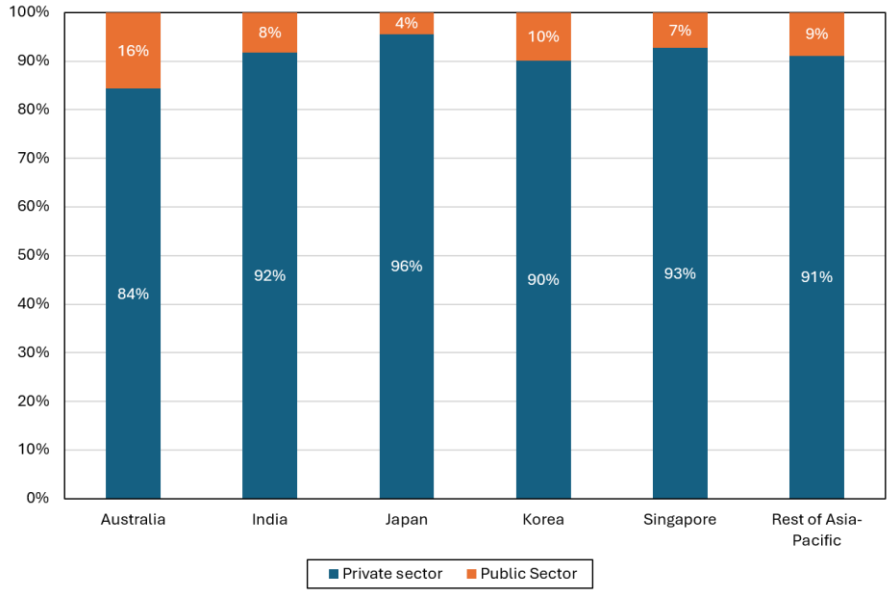
Table 2-3. Asia-Pacific: AI adoption by sector (last data available)

Industry	Australia (2022)	Japan (2023)	Republic of Korea (2024)	New Zealand (2022)
Manufacturing	5.1%	9.7%	36.4%	7.8%
Construction	0.1%	2.6%	15.9%	4.6%
Wholesale trade	2.7%	7.9%	41.1%	9.5%
Retail trade	6.8%	- - -	- - -	7.8%
Transportation and storage	0.6%	2.0%	25.1%	9.5%
Accommodation and food	1.0%	7.4%	30.4%	5.7%
ICT	19.2%	43.4%	56.0%	20.3%
Finance	2.0%	25.2%	63.1%	18.7%
Real estate	10.8%	11.4%	16.1%	16.2%
Professional, scientific and technical	1.3%	20.6%	29.6%	19.2%
Administration and support	2.0%	9.1%	20.8%	9.4%

Source: OECD Stat. Retrieved in: https://data-explorer.oecd.org/

In terms of breakdown between public and private sectors, most AI spending originates from private enterprises, although private enterprises represent the dominant source of spending, the public sector has a significant share in four countries: Australia, Republic of Korea, India and Singapore (Graphic 2-7).[14]

Graphic 2-7. Asia-Pacific: composition of AI spending by public / private sectors (2025)



Note: the category "Rest of Asia-Pacific" includes all the remaining countries of the region except for China and Hong-Kong.
Source: IDC (2026). IDC Worldwide AI and Generative AI Spending Guide - Forecast 2026 | Mar (V1 2026)

Disaggregating AI spending by public sector segment indicates that the central government is the main focus of spending in all countries, except for Japan where most of the spending occurs in public education (see table 2-4).

Table 2-4. Asia Pacific: Spending by public sector organizations (2025) (in US$ million)

Industry	Australia	India	Japan	Republic of Korea	Singapore	Rest of Asia Pacific
Education	$ 304.96	$ 170.54	$ 313.07	$ 86.71	$ 111.25	$ 194.47
Central government	$ 521.51	$ 263.33	$ 206.79	$ 257.51	$ 375.64	$ 532.39
State government	$ 484.25	$ 86.38	$ 176.06	$ 178.02		$ 218.49
Total	**$ 1,310.73**	**$ 520.26**	**$ 695.92**	**$ 522.24**	**$ 486.89**	**$ 945.35**

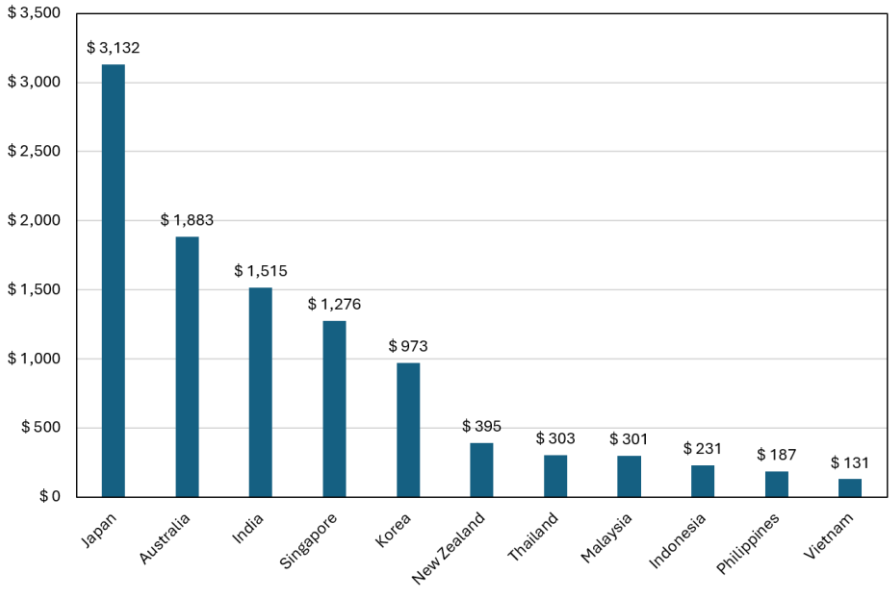
Note: the category "Rest of Asia-Pacific" includes all the remaining countries of the region except for China and Hong-Kong.
Source: IDC (2026). IDC Worldwide AI and Generative AI Spending Guide - Forecast 2026 | Mar (V1 2026)

[14] Although not the focus of this study, it is worth considering that public and private sectors may generate synergies among them in the spending and adoption of these technologies. While the private sector clearly leads, governments are important demanders of both cloud and AI, potentially generating crowding-in or anchor-demand effects that justify a deeper analysis.

2.3. Generative AI as a productivity lever

As stated above, generative AI is a subset of artificial intelligence, focused on generating high-quality text, images, and other content based on the data that large language models are trained on. Regarding the use of generative AI in the Asia Pacific countries under analysis, spending is led by Japan, with an amount of US$ 3.1 billion in 2025, followed by Australia, India and Singapore (Graphic 2-8).

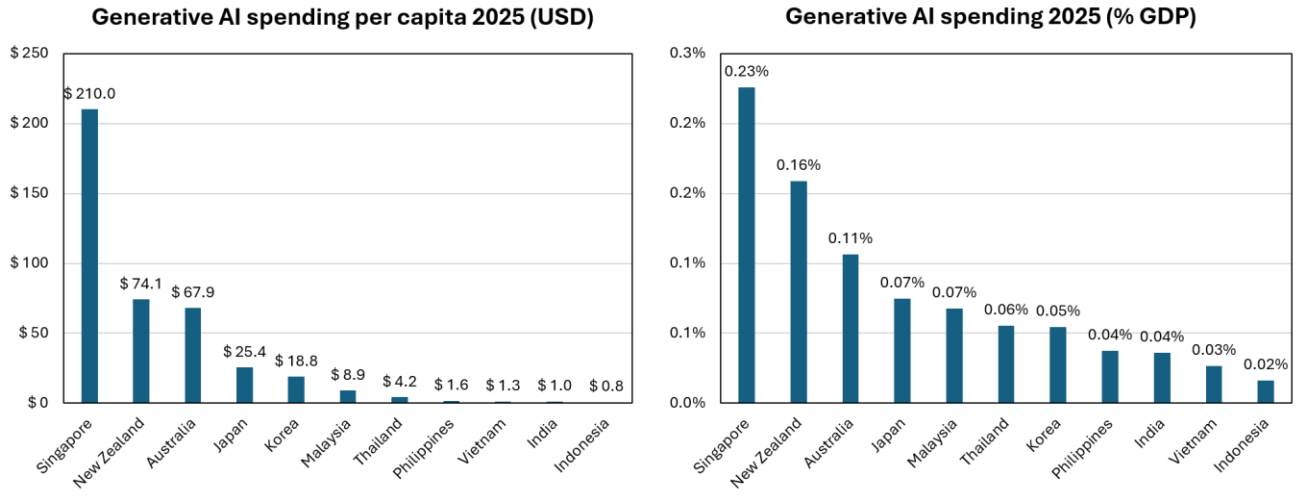
Graphic 2-8. Asia-Pacific: Generative AI spending by country (in US$ million) (2025)



Note: values for New Zealand, Thailand, Malaysia, Indonesia, Philippines and Vietnam are prorated from the category "Rest of Asia-Pacific", according to their respective weight in AI spending.
Source: IDC (2026). IDC Worldwide AI and Generative AI Spending Guide - Forecast 2026 | Mar (V1 2026)

The leadership of Singapore emerges when adjusting for scale differentials. The country is by far the region's most spending-intensive, reaching US$ 210 per person, an equivalent of 0.23% of its GDP (Graphic 2-9).

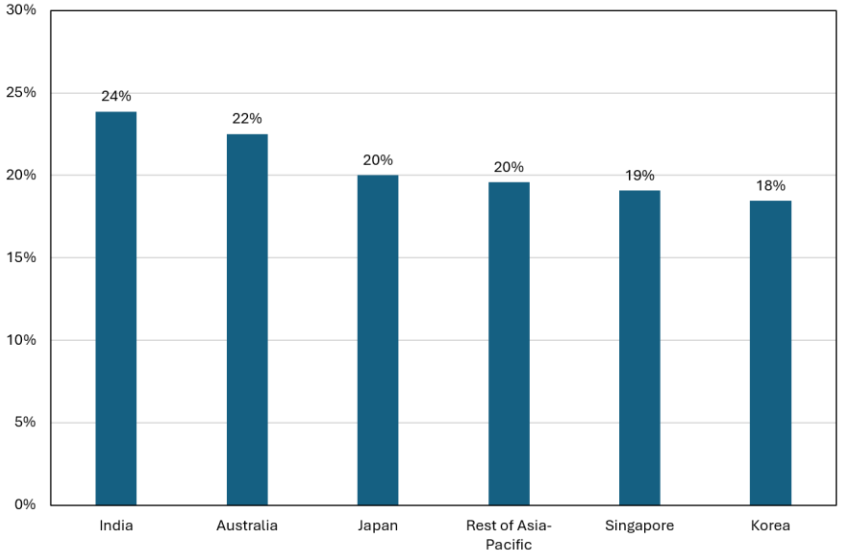
Graphic 2-9. Asia-Pacific: Generative AI spending per capita and as a share of GDP by country (2025)



Note: values for New Zealand, Thailand, Malaysia, Indonesia, the Philippines and Viet Nam are prorated from the category "Rest of Asia-Pacific", according to their respective weight in AI spending.
Source: IDC (2026). IDC Worldwide AI and Generative AI Spending Guide - Forecast 2026 | Mar (V1 2026); International Monetary Fund. World Economic Outlook, April 2026; Telecom Advisory Services analysis

In addition, India is the highest country in the region in terms of the share of generative AI of total AI spending (24%), surpassing Australia (22%) (see Graphic 2-10).

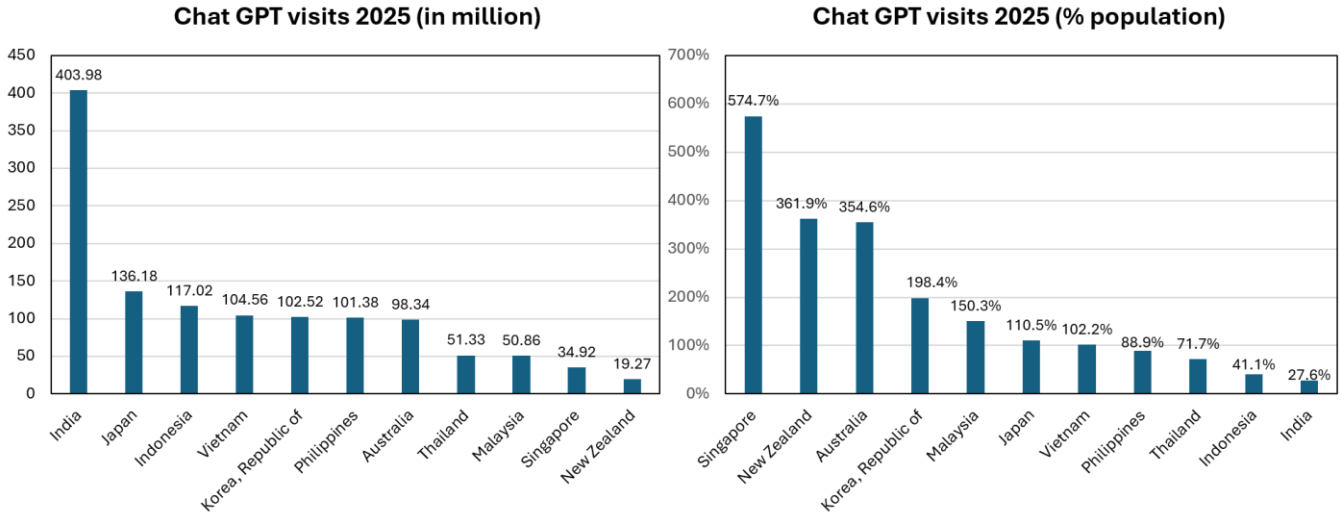
Graphic 2-10. Asia-Pacific: Generative AI spending as a share of AI spending by country (2025)



Note: the category "Rest of Asia-Pacific" includes all the remaining countries of the region except for the PRC and Hong-Kong.
Source: IDC (2026). IDC Worldwide AI and Generative AI Spending Guide - Forecast 2026 | Mar (V1 2026); Telecom Advisory Services analysis.

To further analyze generative AI usage intensity across countries in Asia Pacific, we calculated the monthly average visits and the number of unique users of ChatGPT[15], by relying on the country metrics in Semrush, a platform that tracks website traffic. Regarding traffic for the ChatGPT website, India tops the region with respect to visits, having reached 404 million in 2025, followed by Japan, Indonesia, and Vietnam. Adjusting the number of visits by population, Singapore emerges as the leader again, with a number of visits to ChatGPT that is equivalent to 575% of its population (Graphic 2-11).

Graphic 2-11. Asia-Pacific: ChatGPT visits (2025)

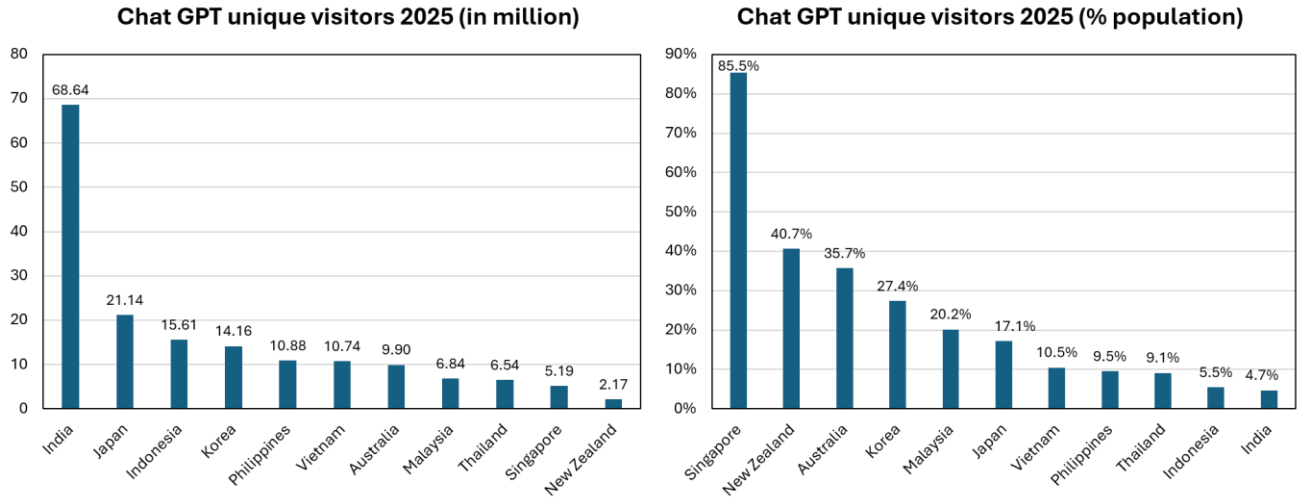


Source: Semrush

Since the value in the previous graphics can be affected by the fact that a single person can make several visits, these statistics were analyzed in terms of unique visitors. In this case, India leads again, although Singapore tops the list when weighted by population. In particular, 85.5% of Singapore's population has visited ChatGPT during 2025, a remarkable figure that positions this country well above their followers in intensity of generative AI use (Graphic 2-12).

[15] ChatGPT is a large language model chatbot developed by OpenAI that can engage in natural language conversations. It is trained on a massive dataset and uses algorithms to generate human-like text responses to various prompts and questions.

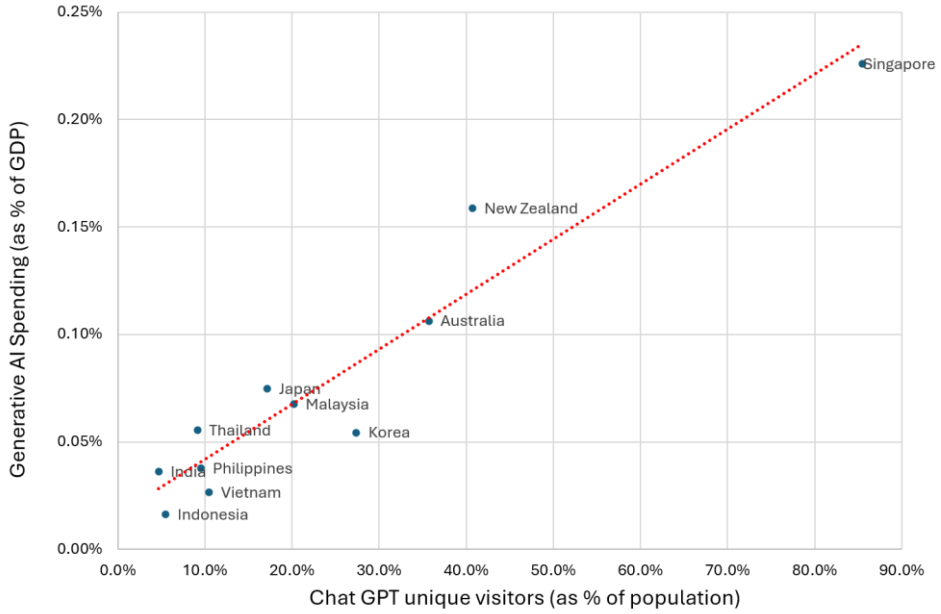
Graphic 2-12. Asia-Pacific: ChatGPT unique visitors (2025)



Sources: Semrush; Telecom Advisory Services analysis

Generative AI usage intensity, when measured by ChatGPT, is associated with spending on the technology as indicated in graphic 2-13.

Graphic 2-13. Asia Pacific: ChatGPT Use vs. Generative AI Spending (2025)



Sources: Semrush; IDC (2026). IDC Worldwide AI and Generative AI Spending Guide - Forecast 2026 | Mar (V1 2026); Telecom Advisory Services analysis.

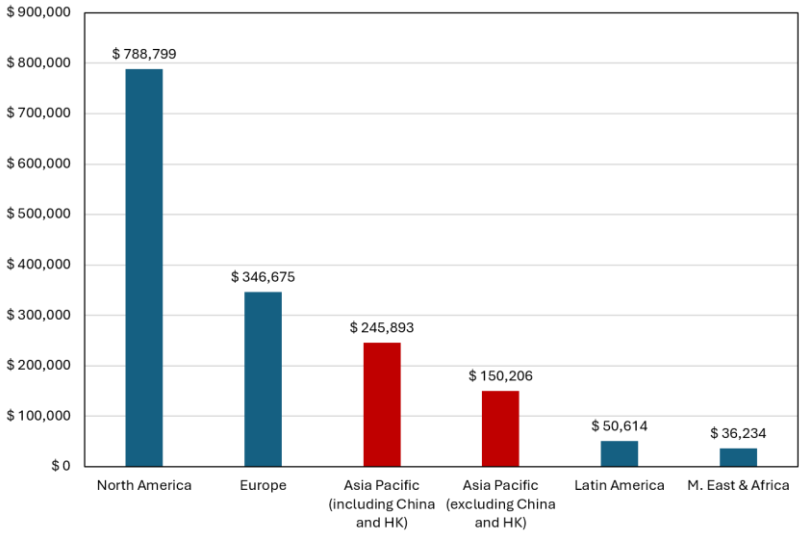
This would indicate that enterprise adoption of generative AI (when measured by spending) is associated with the intensity of consumer adoption of the technology.

2.4. Cloud computing as enabling infrastructure

2.4.1. Cloud computing spending and adoption by Asia Pacific country

The Asia-Pacific cloud computing market, while still under development, is growing at a fast rate, although in this case it remains below North America and Europe. As of 2025, cloud spending in Asia-Pacific accounts for US$ 245.89 billion (US$ 150.21 if the PRC and Hong Kong, China are excluded), representing 16.75% of the global market (see graphic 2-14).

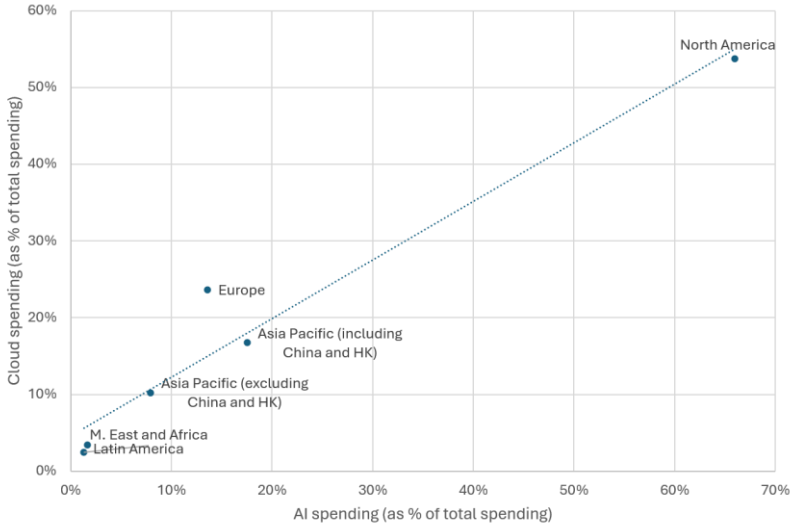
Graphic 2-14. Cloud spending (in US$ million) (2025)



Source: IDC (2024). Worldwide Software and Public Cloud services Spending Guide July (V2 2024) Forecast

This suggests that the region seems to be relatively more advanced in AI than in cloud, as it now reaches a position below both North America and Europe (see Graphic 2-15).

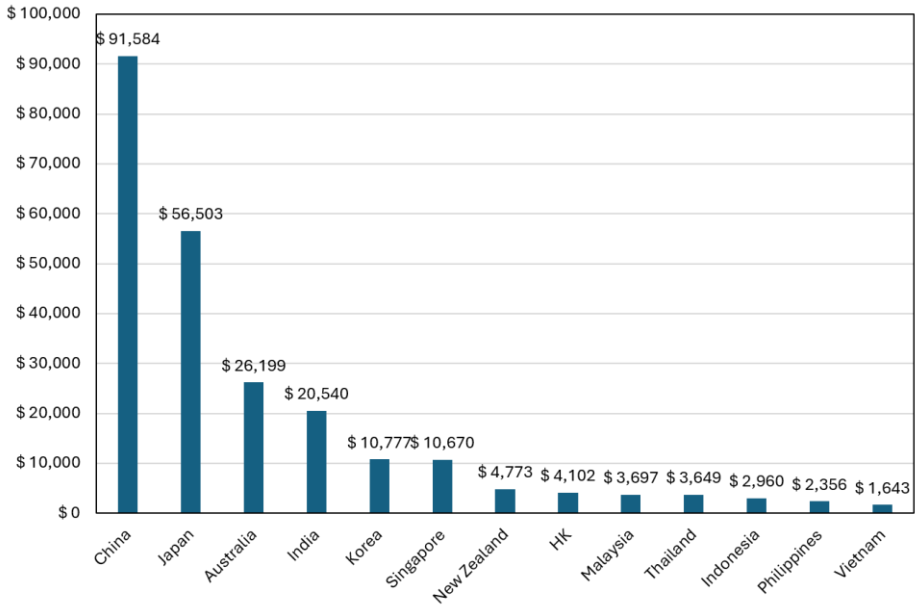
Graphic 2-15. Regional percent of global spending (2025)



Sources: IDC (2026). IDC Worldwide AI and Generative AI Spending Guide - Forecast 2026 | Mar (V1 2026). Worldwide Software and Public Cloud services Spending Guide July (V2 2024) Forecast; Telecom Advisory Services analysis

Within Asia Pacific, the PRC is again in a leader position, with a cloud spending of US$ 91.58 billion. Beyond China, the largest markets are Japan, Australia and India (see Graphic 2-16).

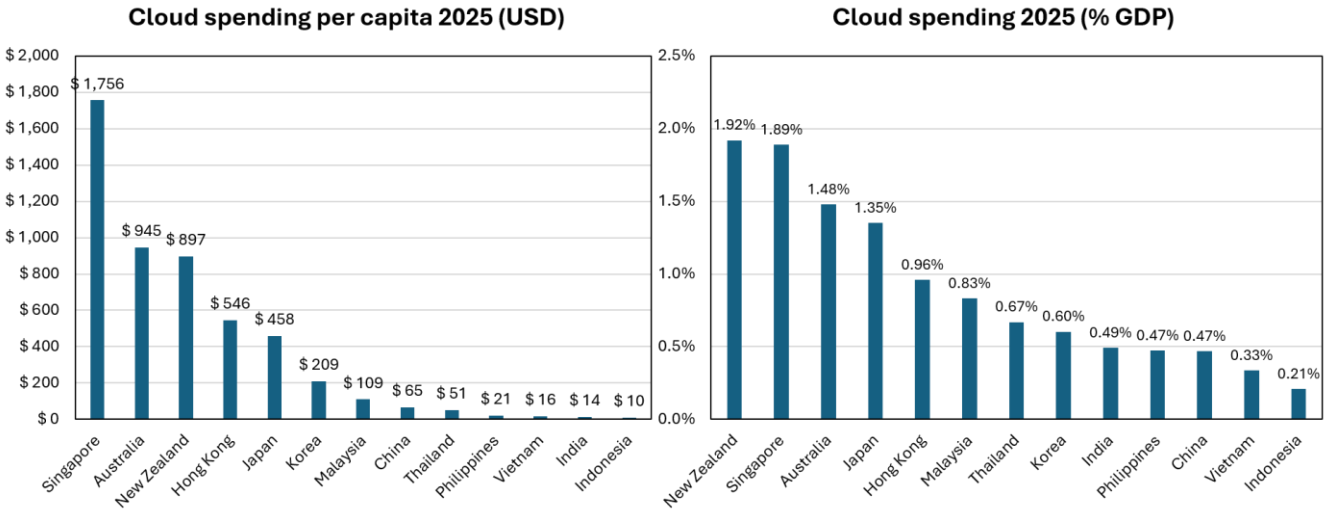
Graphic 2-16. Asia-Pacific: Cloud spending by country (in US$ million) (2025)



Source: IDC (2024). Worldwide Software and Public Cloud services Spending Guide July (V2 2024) Forecast

When adjusted by scale, the region's leader is again Singapore, with a spending level equivalent to $1,756 per person (or 1.89% of the GDP). The PRC presents low spending in both per capita ($ 65) and when measured in terms of GDP (0.47%). Australia, New Zealand, Hong-Kong, China and Japan come next. At the other end, the lowest levels are registered in Indonesia, both in per capita terms and as a share of GDP.

Graphic 2-17. Asia-Pacific: Cloud spending per capita and as a share of GDP by country (2025)



Sources: IDC (2024). Worldwide Software and Public Cloud services Spending Guide July (V2 2024) Forecast; International Monetary Fund. World Economic Outlook, April 2026; Telecom Advisory Services analysis

In terms of adoption, the same caveats raised for AI adoption regarding data consistency apply for cloud computing. That being said, it would appear that cloud adoption is particularly high across Japanese (87%), the Philippines (85%) and Singaporean (80%) organizations, while lower values are being registered in Malaysia (Table 2-5).

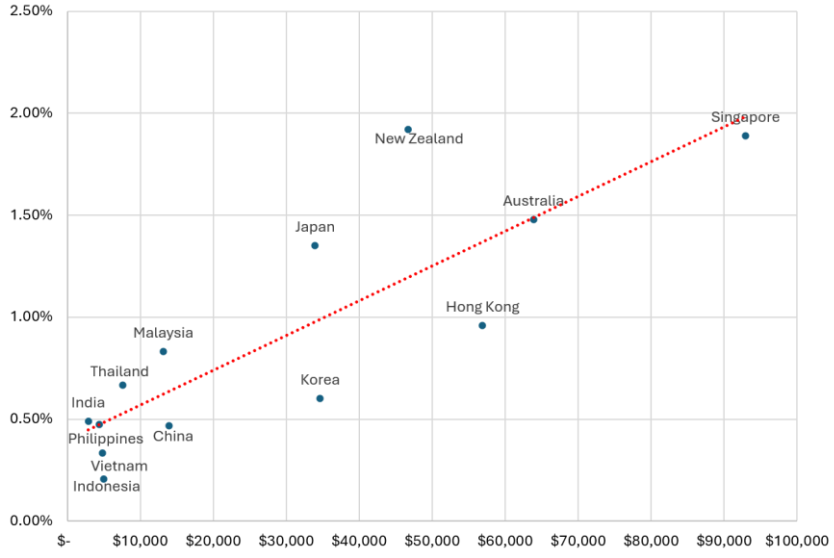
Table 2-5. Asia-Pacific: cloud adoption by country (last data available)

Country	Share of firms adopting cloud	Year	Source
Japan	87%	2023	https://aster.cloud/2023/12/18/cloud-computing-leads-emerging-technology-uptake-in-asia-pacific-according-to-latest-findings-by-economist-impact-and-red-hat/?utm_source=chatgpt.com
Philippines	85%	2025	https://www.datacuberesearch.com/philippines-cloud-computing-market
Singapore	80%	2025	https://www.applify.com.sg/technology-trend/cloud-adoption-trends
Indonesia	77%	2021	https://www.alibabacloud.com/en/press-room/indonesia-adopts-cloud-based-technology-during-pandemic?_p_lc=1
Australia	72%	2022	OECD Stat (https://data-explorer.oecd.org/)
Republic of Korea	78%	2024	OECD Stat (https://data-explorer.oecd.org/)
Thailand	60%	2023	https://www.nationthailand.com/business/tech/40030846
Vietnam	56%	2023	https://www.techsciresearch.com/report/vietnam-cloud-computing-market/14512.html
N. Zealand	56%	2022	OECD Stat (https://data-explorer.oecd.org/)
Malaysia	40%	2022	https://www.atlantis-press.com/article/126009213.pdf

Sources: OECD Stat (retrieved in: https://data-explorer.oecd.org/), Alibaba, Nation Thailand, Atlantis Press, Data Cube Research, Applify, Aster, TechSciResearch.

As in the case of AI, the level of cloud spending (measured as percent of GDP) is correlated with a country's economic development (see Graphic 2-18).

Graphic 2-18. GDP per capita vs. Cloud Spending as % of GDP (2025)



Sources: IDC (2024). Worldwide Software and Public Cloud services Spending Guide July (V2 2024) Forecast; International Monetary Fund. World Economic Outlook, April 2026; Telecom Advisory Services analysis

2.4.2. Cloud computing spending and adoption by sector

When assessed spending by sector to determine use intensity, Finance represents the highest cloud user in the Republic of Korea (90.5%), while professional, scientific and technical activities lead in Australia (90.7%) and New Zealand (79.4%), and ICT is the leader in Japan (66.4%), as depicted in Table 2-6.

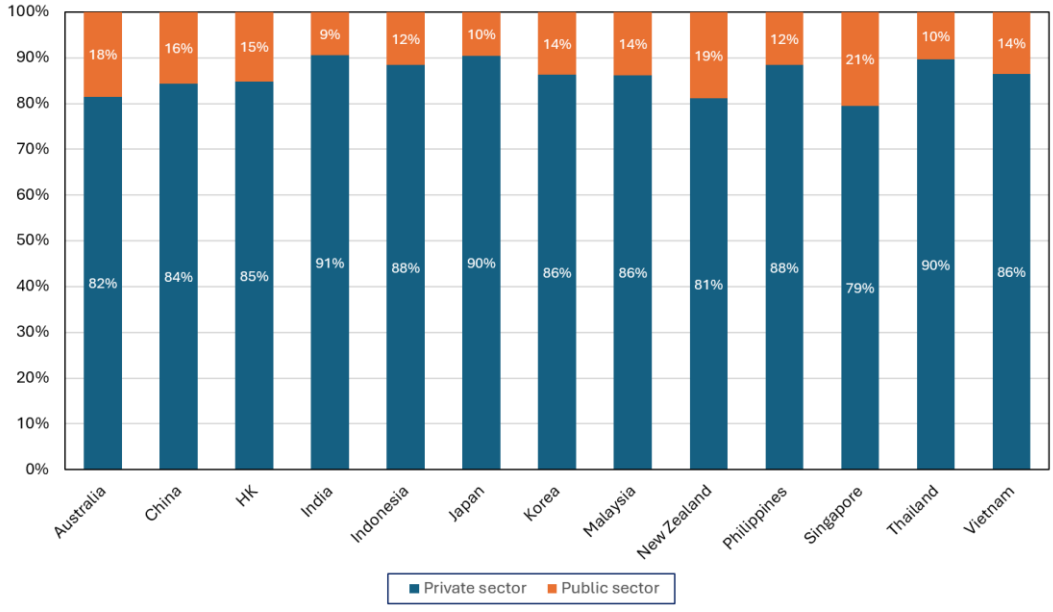
Table 2-6. Asia-Pacific: cloud adoption by sector (last data available)

Industry	Australia (2022)	Japan (2023)	Republic of Korea (2024)	New Zealand (2022)
Manufacturing	67.8%	28.2%	85.1%	59.8%
Construction	73.9%	21.2%	70.2%	58.2%
Wholesale trade	73.4%	28.5%	84.1%	54.7%
Retail trade	78.2%			47.2%
Transportation and storage	71.7%	23.1%	75.2%	64.8%
Accommodation and food	53.8%	21.1%	57.4%	39.5%
ICT	86.4%	66.4%	85.6%	77.4%
Finance	88.7%	51.5%	90.5%	73.9%
Real estate	87.9%	31.8%	61.2%	71.0%
Professional, scientific and technical	90.7%	53.2%	75.7%	79.4%
Administration and support	74.1%	32.5%	63.2%	56.8%

Source: OECD Stat. Retrieved in: https://data-explorer.oecd.org/

In terms of the breakdown between the public and private sectors, most cloud computing spending originates from private enterprises, although in Singapore and New Zealand the spending of the public sector is highly relevant, representing 21% and 19%, respectively, of the total (Graphic 2-19).

Graphic 2-19. Asia-Pacific: composition of cloud spending by public / private sectors (2025)



Source: IDC (2024). Worldwide Software and Public Cloud services Spending Guide July (V2 2024) Forecast

Disaggregating cloud spending by public sector segments indicates that the central government is always the main source of spending, except for Japan where spending for public education prevails (see table 2-7).

Table 2-7. Asia Pacific: Cloud computing spending by public sector organizations (2025) (in US$ million)

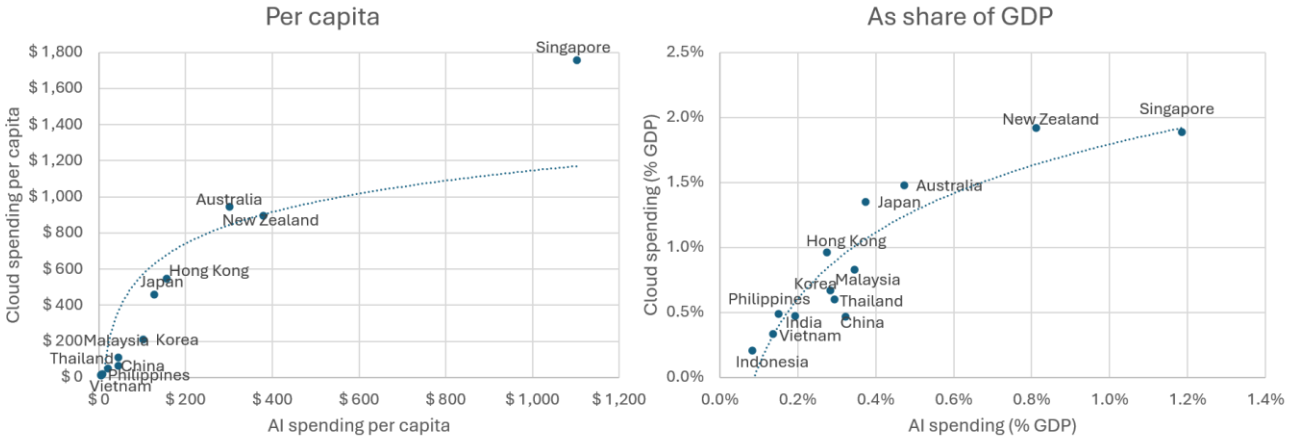
	Australia	India	Indonesia	Japan	Republic of Korea	Singapore	New Zealand	Malaysia	Thailand	Philippines	Viet Nam
Education	$ 1,327.2	$ 746.6	$ 83.4	$ 2,565.2	$ 428.5	$ 408.3	$ 260.0	$ 90.3	$ 114.7	$ 79.8	$ 46.4
Central government	$ 2,353.4	$ 1,008.1	$ 202.0	$ 1,683.5	$ 573.9	$ 1,786.4	$ 521.5	$ 323.4	$ 205.1	$ 155.0	$ 140.2
State government	$ 1,155.7	$ 176.3	$ 55.9	$ 1,161.3	$ 477.2		$ 116.9	$ 94.7	$ 57.1	$ 37.7	$ 35.4
Total	$ 4,836.3	$ 1,931.0	$ 341.2	$ 5,410.1	$ 1,479.6	$ 2,194.7	$ 898.4	$ 508.4	$ 376.9	$ 272.5	$ 221.9

Source: IDC (2024). IDC Worldwide Software and Public Cloud Services (2024) July (V2 2024)

2.5. Cloud-enabled AI as a critical complementary technology

As defined in the introduction, technological complementarity reflects the interaction of technologies that work together to enhance or improve their respective overall performance or functionality. A very preliminary indication of the complementarity between cloud computing and AI is the correlation in spending of both technologies when measured for the countries in Asia-Pacific (see graphic 2-20).

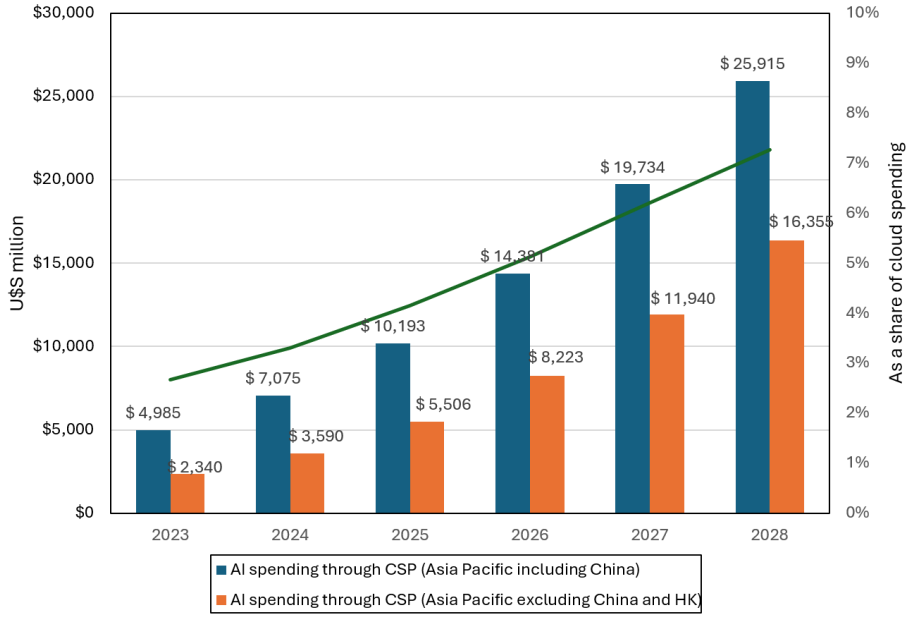
Graphic 2-20. Cloud and AI spending per capita and as a share of GDP (2025)



Sources: IDC (2026). IDC Worldwide AI and Generative AI Spending Guide - Forecast 2026 | Mar (V1 2026); IDC (2024). Worldwide Software and Public Cloud services Spending Guide July (V2 2024) Forecast; International Monetary Fund. World Economic Outlook, October 2024; Telecom Advisory Services analysis

Underlying the complementarity of both technologies, cloud computing service providers are extremely active in the provision of AI platforms. Enterprise spending on AI platforms purchased from cloud providers in Asia-Pacific in 2025 amounts to US$ 10,193 million (8.7% of the regional AI market) and is expected to grow fast over the next five years (Graphic 2-21).

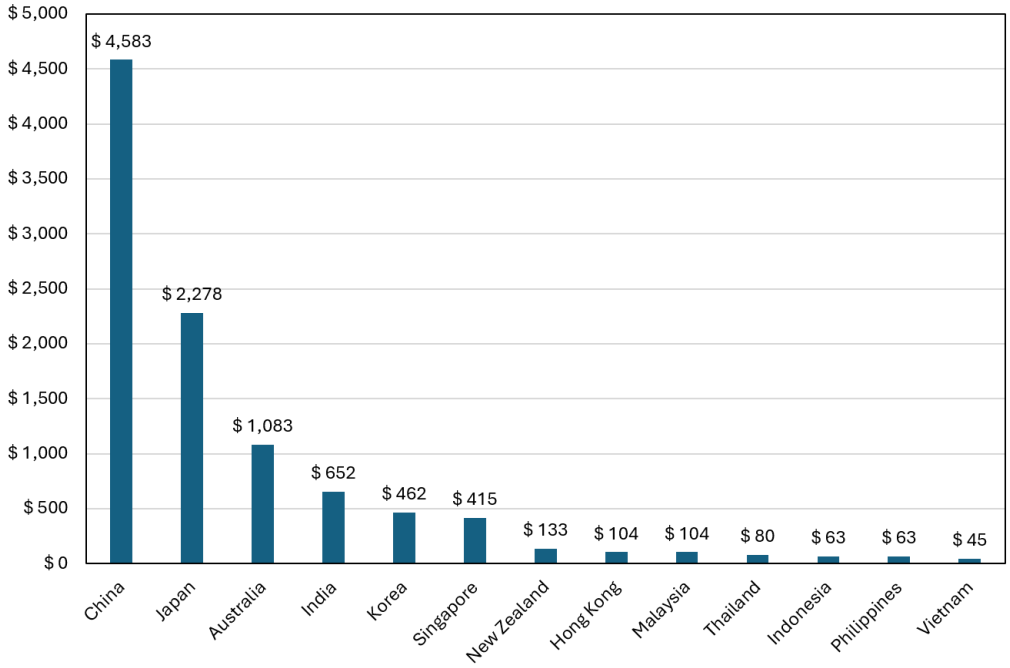
Graphic 2-21. Asia-Pacific: AI platforms delivered by CSP (2023-2028)



Sources: IDC (2024). Worldwide Software and Public Cloud services Spending Guide July (V2 2024) Forecast; Telecom Advisory Services analysis

As indicated in Graphic 2-21, cloud computing service providers generate approximately 4% of their revenue in the provision of AI platforms in Asia-Pacific. This percentage will reach 7.3% by 2028. When broken down by country, China is, as expected, the lead country in the region (see Graphic 2-22).

Graphic 2-22. Asia-Pacific: AI platforms delivered by CSPs (2025)



Source: IDC (2024). Worldwide Software and Public Cloud services Spending Guide July (V2 2024) Forecast; Telecom Advisory Services analysis

2.6. Conclusion

A review of the descriptive evidence of spending and adoption of AI, generative AI, cloud computing and the complementarity space among technologies in Asia Pacific presented in this chapter indicates a highly dynamic ecosystem, probably the most important segment of the information technology sector. All statistics point to a clear direct economic impact of countries in the region:

- AI technology reached a spending level of US$ 117.31 billion in the region in 2025, being the second region in the world only behind North America. While recognizing that China is the clear leader in Asia-Pacific, if this country is omitted from the analysis the rest of the region remains very dynamic, with spending levels representing US$ 52.97 billion (or 0.31% of the regional GDP).

- Cloud computing reached a spending level of US$ 245.9 billion in the region in 2025, being the third region in the world behind North America and Europe. When the PRC and Hong Kong, China are excluded, the region reaches US$ 150.2 billion (0.78% of the regional GDP).

- The comparison of the AI and Cloud market sizes with those of the rest of the world suggests that Asia-Pacific is relatively more advanced in AI than in cloud, something that is confirmed even when omitting China from the analysis.

- When disaggregated by country, the data regarding spending and adoption allow us to conclude that Singapore appears to be the most dynamic economy in the region regarding AI, which could be the result of sound policies being implemented locally (this will be addressed in subsequent chapters).

- The complementarity between AI and cloud computing in Asia-Pacific is growing fast, with US$ 10.2 billion of AI revenues generated through CSPs, which in turn are expected to increase up to US$ 25.9 billion by 2028. This is part of the US$ 48.17 billion shared component (Figure A).

In addition, the country statistics indicate the potential for additional externalities:

- The level of AI spending (measured as percent of GDP) is correlated with a country's economic development
- The growth in AI spending is associated with increases in labor productivity
- The level of cloud computing spending is associated with economic growth

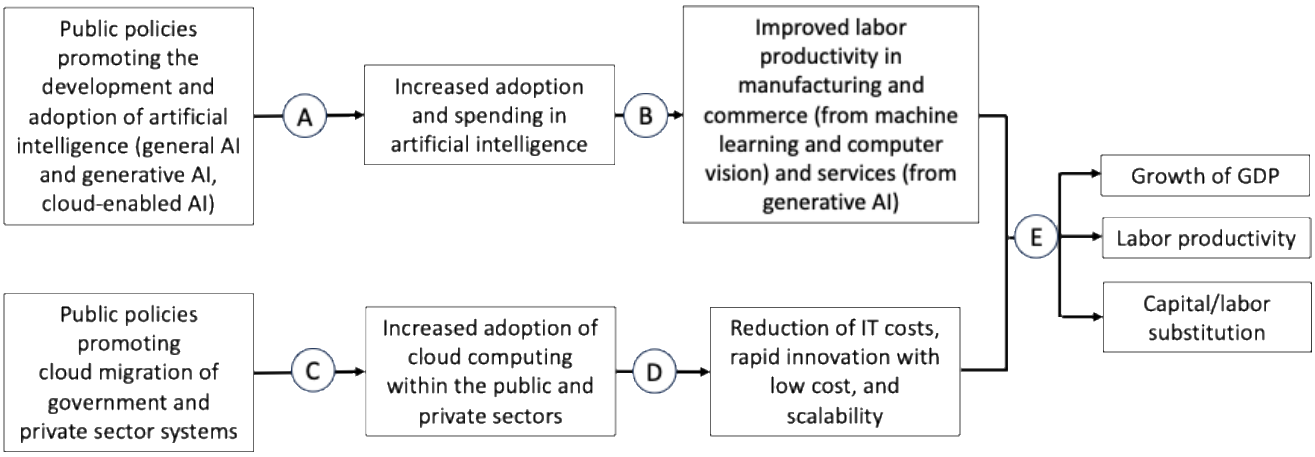
All these three effects need to be tested through a review of the research literature generated to date and supported by the empirical strategy implemented in this study, to be presented in the next chapter.

3. GENERAL ECONOMETRIC MODELS

3.1. A theory of change linking artificial intelligence and cloud computing to economic development and the importance of public policies

The theory of change underlying this study posits that public policies promoting the development and adoption of artificial intelligence combined with the migration of government and private enterprise systems to cloud computing can generate positive externalities, measured in productivity growth and GDP contribution. In addition, it is assumed that the impact of these technologies on factors of production (such as capital, skilled and unskilled labor) might result in some social disruptions that need to be mitigated by specific government policies (see figure 3-1).

Figure 3-1: Theory of change linking AI and cloud policies to economic growth



Source: Telecom Advisory Services

According to the causal link A in figure 3-1, the development and adoption of AI in its multiple versions (general, generative, and cloud-enabled) in a given country is influenced by a set of specific public policies, which can be categorized as follows:

- Promotion of in-country R&D (public and private) and advancement of academic strength with an AI focus
- Development of AI start-ups and deployment of required infrastructure for training AI models (e.g. supercomputers)
- Deployment of general infrastructure (e.g. high-speed broadband) and advanced cybersecurity rules
- Implementation of policies and governance conducive for adoption of AI (national AI strategy, AI legislation to protect consumer data, etc.) AI regulation should be flexible and risk-based, account for different risk levels and roles across the AI value chain, and avoid unnecessary barriers to adoption.
- Skills development in terms of training of AI development workforce and labor reskilling

In turn, the adoption and spending in AI, highlighted in the causal link B, indicate the existence of a set of productivity effects:

- Given the characterization of AI as a general-purpose technology, it has the potential to become a major source of productivity gains, generating several economic effects that go beyond those of regular capital goods.

- In particular, Damioli et al. (2021), Bassetti et al. (2022), and Brynjolfsson et al. (2018) argue that AI has the potential to disrupt almost every industry due to its numerous areas of application. In this sense, Brynjolfsson et al. (2018) present some examples of possible gains in productivity in functions such as customer service centers, autonomous vehicles or a more efficient use of energy.

- Similarly, Hang and Chen (2022) argue that AI can increase revenue by improving employee productivity and understanding of consumer behavior, setting more competitive prices, and creating non-imitable skills and resources. A microeconomic study by Brynjolfsson et al. (2023) proved significant productivity gains from the use of generative AI assisting workers in a customer service firm in the United States.

- As an explanation of labor productivity effect, research also indicates this to be the result of substitution of low cognitive routine occupations by jobs requiring interactive, highly analytical skills (Webb, 2020; Huang, 2024; Acemoglou et al., 2022b).

- AI productivity effects materialize in occupations such as software development, technical researchers, and customer service agents. recent work focused on generative AI appears to conclude that technology would contribute to the substitution of partially skilled labor in sectors such as data science (Felten et al, 2023; Frank et al., 2023), finance (Autor, 2022; Acemoglu & Restrepo, 2022a; Felten et al, 2023, Zarifhonarvar, 2023), and the legal profession. According to these views, AI's impact on the workforce can be simplified as follows: this technology is expected to be a substitute for unskilled work and complementary to skilled work (Maswana, 2024). This explains how AI can affect different countries or sectors very differently, favoring both economic growth and employment in those environments where the workforce is highly qualified.

As highlighted in causal link C, three types of policies have been identified as being critical for stimulating the migration of public and private sector systems to the cloud:

- ***Policies for government cloud service provisioning***: when governments adopt policies to stimulate the migration of public sector IT to the cloud (a policy known as “Cloud First”), they face three policy options for structuring the local supply side: (i) cloud services are provided by either multinational hyperscalers or local private operators within a competitive market with no protectionist restrictions; (ii) a state-owned cloud enterprise becomes the

de-facto private cloud service provider; (iii) local cloud providers comprise both the government-owned entity and private commercial enterprises (a "hybrid" model). As expected, not all three options are equally effective in driving cloud adoption. First and foremost, competition among cloud service providers remains a critical factor driving industry performance. Customers need to benefit from accelerated innovation, falling prices, and state-ot-the-art quality of service (in particular, the latest version of cybersecurity technology). In contrast to a moderately competitive environment, an industry configuration composed of a single provider – the private (government) option - does not guarantee an adequate level of competition, thereby restricting choice, and limiting capital spending. Second, a hybrid configuration, particularly one that combines the presence of a public providers with private sector operators naturally restricts fair competition and potentially distorts market behavior. Benchmark data and case studies compiled in this study indicate that option (i) is the most efficient one to meet government cloud needs.

- ***Data management and processing principles***: in determining government data residency or data localization requirements, governments face three options: (i) government data storage and processing have to be conducted **only** locally, thereby prohibiting data transfers beyond the national boundaries, (ii) government data can be stored and processed locally or abroad depending on its nature (using a risk-based data classification scheme), (iii) while government data has to be stored locally, processing can take place beyond the national boundaries. In terms of incentives for development of the cloud industry, the more restrictive level (local processing and storage) is detrimental to serving government needs in terms of scale economics and access to state-of the-art technology. In terms of incentives for development of the cloud industry, the more restrictive level (local processing and storage) is detrimental to the development of the industry. Considering the level of capital spending required for developing adequate cloud infrastructure, remote processing and/or storage (option (ii) would be more conducive for fulfilling economies of scale in support of lower pricing and product innovation.

- ***Level of cybersecurity***: the attacks on the data processing infrastructure have become more prominent over the years (increased ransomware, incidents or breached affecting core industries such as financial services or energy, privacy concerns, general outages). Higher levels of cybersecurity provide the necessary incentives for migrating in-house IT to the cloud. The maturity of cybersecurity policy is typically conceptualized across five components (ITU, 2024): (i) enactment of laws and regulations on cybercrime and cybersecurity, (ii) existence of technical capabilities in national agencies, (iii) presence of agencies measuring fulfillment and organizational implementation of cybersecurity, (iv) capacity development in cybersecurity domain, and (v) cooperation between government agencies and between the private and public sectors. The level of cybersecurity of a given country across these five components provide stimulate the migration to the cloud.

Public policies promoting the migration of government and private sector systems to cloud computing, highlighted in causal link D of figure 3-1 above have a dual impact: (i) the transition of government operations and systems to cloud infrastructure, with consequent impact on GDP, and (ii) the accelerated adoption of cloud among private enterprises with a similar effect.

Public policies are not the only driver of this dual effect; they are complemented by other initiatives, such as the development of broadband as a technology enabler[16] and of human capital needed to support such migration. While the objective of certain pro-cloud policies, such as Cloud First is to accelerate the migration of government systems to the cloud, the policy impact on the private sector is a frequently unintended positive spillover. Case study data gathered in this study indicates that this effect occurs at several levels. First, pro-cloud policies lead to investment and deployment of hyperscalers, which in turn provide the infrastructure needed to accommodate private sector systems.[17] Second, the migration to government cloud systems triggers the development of a domestic source of human capital, such as systems integrators with expertise in the digital transformation linked to cloud implementation, which serve not only public organizations but also private enterprises.[18] Third, in defining the government cloud model, which includes hosting arrangements, data classification and regulations, pro-cloud policies partly reduce the implementation risk incurred by private enterprises in migrating to the cloud. In sum, the enactment and implementation of pro-cloud public policies has a derivative positive effect on cloud adoption by private enterprises.[19].

As expected, beyond the spillover effect on the private sector of pro-cloud policies, there are other initiatives that have a direct impact on the adoption of cloud among private businesses. More prominently, the development of broadband as an enabler of cloud access is a critical initiative. As such, policies promoting the deployment of broadband infrastructure in terms of coverage and speed of access, as a result of increased capital spending of telecommunications operators (e.g., network sharing, reduction of tax burden) are critical. Similarly, training of human resources capable of supporting the migration of enterprise IT to the cloud is also an initiative yielding increased adoption in the private sector. Third, government support in the form of

[16] The economic impact of cloud computing is linked to the adoption of complementary technologies such as broadband. *Complementary technology* refers to technologies that are designed to work together to enhance or improve their overall performance or functionality.

[17] In New Zealand, the Digital Public Service (DPS), at the Department of Internal Affairs, collaborates with global CSPs with the development of New Zealand-based cloud centers for handling government and private sector data. In particular, agreements have signed with AWS and Microsoft focus on accelerating digital transformation, supporting government initiatives, and fostering innovation across various sectors (see Digital.govt.nz)

[18] Partly stimulated by the government initiatives, most large private enterprises in Singapore have begun to use some form of cloud storage or computing and are starting to tap into more advanced use cases such as artificial intelligence and machine learning.

[19] For example, the Cloud First policy enacted in 2013 and refined in 2017 in Australia served as an adoption incentive by the private sector, signaling that data is secure enough within public cloud platforms to receive government accreditation. In fact, the private sector is well aware of the security and compliance standards set by the government and has reacted accordingly.

subsidies to small and medium enterprises to migrate their systems to the public cloud also represents a key policy lever impacting the private sector.

Finally, as explained in the theory of change, the migration to the cloud of public and private organizations triggers a series of microeconomic benefits, which in turn drive a contribution to economic growth, when measured by GDP. However, the nature of the economic impact varies by sector. Public cloud adoption by governments contributes to increased efficiency of government services, reducing transaction costs (for interaction with government) for the private sector and creating further growth externalities. Cloud adoption by enterprises drives productivity enhancements, cost efficiencies, and innovation dynamics, all contributing to GDP growth.

The theory of change depicted in figure 3-1 will be tested in two models as presented below.

3.2. Theoretical model to estimate the economic impact of AI, generative AI, and cloud computing

In this section we develop a theoretical model to estimate the impact of AI and cloud on the economy (addressed in links B and D presented in the theory of change depicted in figure 3-1 above). The starting assumption is that the economic impact of AI and cloud computing is driven by different factors of production that may be complementary or substitutive among them. To allow for different elasticity of substitution between any two factors, we use a two-level CES production function.

As its name implies, the CES (Constant Elasticity of Substitution) production function represents a general framework that allows estimating how the different factors of production are linked. In this sense, it is worth mentioning that the production functions of fixed proportions that denote perfect complementarity (Leontief), the linear function that denotes perfectly substitutive factors, and the Cobb-Douglas are all particular cases of the CES production function.

In the theoretical model, the factors of production are the stock of physical capital (K), skilled labor (S), and unskilled labor (N), whose basic specification can be modeled as follows:

$$Y_{it} = A_{it}\left[\alpha[\beta K_{it}^{\theta} + (1-\beta)A_{it}^{S}S_{it}^{\theta}]^{\frac{\rho}{\theta}} + (1-\alpha)N_{it}^{\rho}\right]^{\frac{1}{\rho}}$$

In the equation, Y represents the gross domestic product (GDP), and the subscripts i and t indicate country and year, respectively. The term A_{it} represents Total Factor Productivity (TFP). On the other hand, α and β are parameters that take values between zero and one, reflecting the relative importance of the different factors of production. A key element of the proposed production function is the interpretation of the parameters θ and ρ, which, depending on the value they take, will allow us to evaluate to what extent the different factors of production are complementary or substitutive.[20]

[20] Following the conventional specification of CES functions, it is assumed that $\theta \leq 1$ and $\rho \leq 1$.

Starting with θ, this parameter will allow us to identify the relationship between skilled labor and physical capital. The elasticity of substitution between physical capital and skilled labor can be approximated as $\sigma_{K-S} = \frac{1}{1-\theta}$, so it can be stated that:

$$\sigma_{K-S} = \begin{cases} 0 \ \ if \ \theta \to -\infty \\ 1 \ \ if \ \ \theta = 0 \\ \infty \ if \ \theta = 1 \end{cases}$$

From this approximation, it can be deduced that physical capital and skilled labor will be:

$$\begin{cases} \text{perfect complementary,} & if \ \theta \to -\infty \\ \text{gross complementary,} & if \ \theta < 0 \\ \text{independent,} & if \ \ \theta = 0 \\ \text{gross substitutes,} & if \ 0 < \theta < 1 \\ \text{perfect substitutes,} & if \ \theta = 1 \end{cases}$$

Therefore, a positive value of θ would indicate a substitutability relationship, while a negative one would indicate complementarity. On the other hand, if such a parameter were zero, both factors of production would be independent (as reflected, for example, in the Cobb-Douglas production functions). Considering previous evidence from the literature, we expect the link between physical capital and skilled labor to be complementary, i.e., $\theta < 0$.

On the other hand, we assume that physical capital and skilled labor act as a composite factor in their relationship with unskilled labor. In this way, the link between the two is interpreted from the parameter ρ. Therefore, the elasticity of substitution between the compound factor and unskilled labour is represented as $\sigma_{KS-N} = \frac{1}{1-\rho}$, so it can be stated that:

$$\sigma_{KS-N} = \begin{cases} 0 \ \ if \ \rho \to -\infty \\ 1 \ \ if \ \ \rho = 0 \\ \infty \ if \ \rho = 1 \end{cases}$$

From which it can be deduced that the compound factor and unskilled labor will be:

$$\begin{cases} \text{perfect complementary,} & if \ \rho \to -\infty \\ \text{gross complementary,} & if \ \rho < 0 \\ \text{independent,} & if \ \rho = 0 \\ \text{gross substitutes,} & if \ 0 < \rho < 1 \\ \text{perfect substitutes,} & if \ \rho = 1 \end{cases}$$

Thus, ρ will take a positive value in the case of substitutability and a negative value in the case of complementarity (and zero in the case of the composite factor and the unskilled work being independent of each other). Naturally, in this case we expect

capital and skilled labor to act as substitutes for unskilled labor, so we hypothesize that $\rho > 0$.

A relevant aspect in the analysis will depend on the treatment to be given to A_{it}^{S}, that is, the productivity term associated with skilled labor. Given that the objective of this work is to analyze the role of AI and cloud in this matter, we model this term as follows:

$$A_{it}^{S} = e^{\delta_{AI} AI_{it} + \delta_{CL} CL_{it} + \delta_{AI\&CL}(AI_{it}\&CL_{it}) + \delta_{Chat\ GPT} Chat\ GPT_{it}}$$

In other words, the idea is to verify to what extent spending on AI, cloud, and its complementarity contributes to increasing the productivity of skilled labor. We also introduce a term associated with ChatGPT traffic, in order to account for generative AI use. Substituting the term associated with the productivity of skilled labor in the production function, we obtain:

$$Y_{it} = A_{it}\left[\alpha[\beta(K_{it})^{\theta} + (1-\beta)(e^{\delta_{AI} AI_{it} + \delta_{CL} CL_{it} + \delta_{AI\&CL}(AI_{it}\&CL_{it}) + \delta_{Chat\ GPT} Chat\ GPT_{it}} S_{it})^{\theta}]^{\frac{\rho}{\theta}} + (1-\alpha)N_{it}^{\rho}\right]^{\frac{1}{\rho}}$$

Applying logs to the production function, the following expression is obtained:

$$\ln Y_{it} = \ln A_{it} + \frac{1}{\rho}\ln\left[\alpha[\beta(K_{it})^{\theta} + (1-\beta)(e^{\delta_{AI} AI_{it} + \delta_{CL} CL_{it} + \delta_{AI\&CL}(AI_{it}\&CL_{it}) + \delta_{Chat\ GPT} Chat\ GPT_{it}} S_{it})^{\theta}]^{\frac{\rho}{\theta}} + (1-\alpha)N_{it}^{\rho}\right]$$

Where it is appreciated that important nonlinearities persist, coming from the nature of the CES function. This implies that the econometric analysis cannot be performed through Ordinary Least Squares (OLS), but through Non-linear Least Squares (NLS).

3.3. Theoretical model to estimate the impact of public policy on AI and cloud computing development

To analyze how policies affect AI and cloud computing diffusion (links A and C in the theory of change outlined in Figure 3-1), we propose running the two following regressions:

$$\ln AI_{it} = v_i^{AI} + \Omega^{AI} AI\ policy_{it} + \phi^{AI} X_{it}$$

$$\ln Cloud_{it} = v_i^{CL} + \Omega^{CL} Cloud\ policy_{it} + \phi^{CL} X_{it}$$

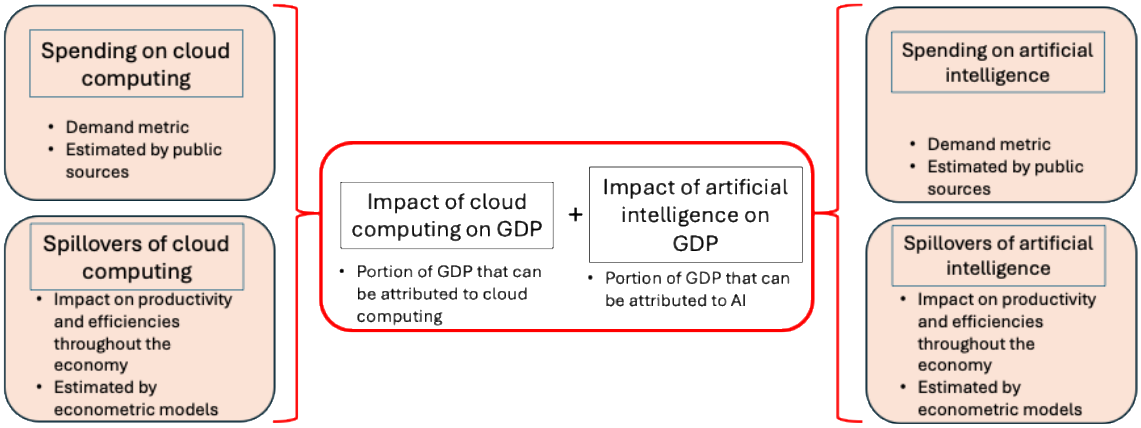
In the proposed models, the dependent variables are respectively AI and cloud spending, while on the right-hand side we include country fixed effects, the AI/Cloud policy variable, and further controls (X), which will include skilled labor and GDP (in lags). Naturally, we expect $\Omega^{AI} > 0$ and $\Omega^{CL} > 0$, something that should verify that sound policy frameworks are relevant to stimulate the spending on both technologies.

These fixed effects estimates are done simultaneously with the output equation presented in chapter 3.2 (which results in a unique econometric routine to estimate the three models).

4. ESTIMATION OF ECONOMIC IMPACT OF ARTIFICIAL INTELLIGENCE AND CLOUD COMPUTING IN ASIA PACIFIC

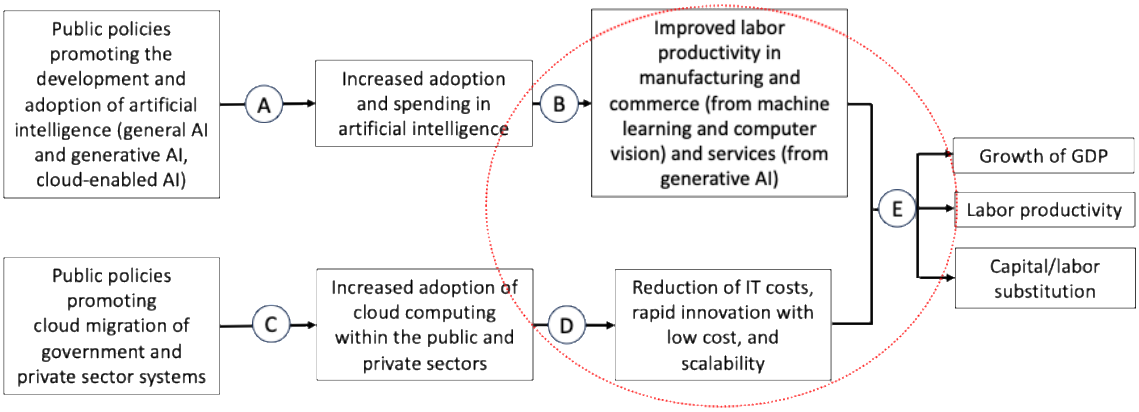
Beyond spending in AI and cloud, the technology impact is measured in spillovers from productivity and economic growth (see figure 4-1).

Figure 4-1. Economic contribution of cloud and artificial intelligence



Following the theory of change outlined in figure 3-1, economic impact of AI and cloud was estimated for causal links B and D (see figure 4-2).

Figure 4-2. Modelling of economic impact



Source: Telecom Advisory Services

4.1. Data set

The econometric estimation is done for a panel of 26 countries covering the period 2020-2024 (see countries included in Appendix B). This panel includes the main economies of the Asia-Pacific region. The variables to be used in the empirical estimation of the model are detailed in Table 4-1.

Table 4-1. Variables to be used in econometric regressions

Variable	Description	Mean	Standard Deviation	Source
Y	Real Gross Domestic Product (2021 billion dollars in PPP).	4,591.210	6,997.408	IMF
K	Real physical capital stock (2021 billion dollars in PPP).	19,009.680	28,411.700	PWT / IMF
S	Skilled labor (workers with tertiary education, in thousands)	20,0068.010	30,783.540	TCB / WB
N	Unskilled work (workers without tertiary education, in thousands)	60,121.080	139,475.100	TCB / WB
AI	AI spending (million dollars)	5,688.429	139,475.100	IDC
Cloud	Cloud spending (million dollars)	32,368.370	96,544.120	IDC
AI & Cloud	Spending of AI done through CSP (as % of CSP revenue)	1.839	0.879	IDC
ChatGPT users	Number of unique users who have visited the ChatGPT domain (monthly averages, in millions)	3.814	10.040	Semrush

Source: Telecom Advisory Services analysis

The dependent variable is the gross domestic product (GDP), compiled from the International Monetary Fund (IMF) database. For capital stock, the 2019 value reported in the Penn World Tables (PWT) (last year available) is projected up to 2024 by taking the annual investment according to the IMF and the capital depreciation rate per country according to PWT. Both GDP and capital stock are deflated and converted to purchasing power parity (PPP), in 2021 dollars.

The level of employment is obtained from The Conference Board (TCB), and the number of workers is categorized as skilled or unskilled depending on the attainment of a tertiary degree. To do this, the percentage of the population over 25 years of age with tertiary education according to the World Bank is taken as a reference, which is then multiplied by the number of workers to make the distinction between skilled and unskilled.[21]

With respect to AI and cloud, the variable of spending on these technologies, as reported by IDC, is taken as a reference.[22] In order to measure the cloud-AI complementarity we take as reference the spending on AI platforms when delivered through CSP (as a share of its total revenue). Finally, to begin analyzing the role of generative-AI, we calculated the number of unique users of the ChatGPT site, from the metrics in Semrush, a platform that tracks website traffic.[23] Values for ChatGPT use are presented in Appendix C.

[21] For missing values in the World Bank reported data of percentage of the population over 25 years of age with tertiary education, we make an imputation based on the remaining years and existing variation rate on such ratio by country.

[22] The accurate mechanism for economic impact should be technological spending → technological adoption → productivity growth. However, given that adoption variables are not available for most of the countries in the sample, we introduce in the model the direct link from technological spending to productivity growth. In this sense, spending proxies' adoption in the econometric model, capturing the rises in productivity and efficiency associated with technological spillovers.

[23] The use of generative AI usage statistic rather than spending is based on the fact that we lack data for all 26 countries in the panel.

4.2. Model results of economic impact for Asia-Pacific countries

Table 4-2 presents the estimates made by the non-linear least squares method. All econometric estimates incorporate fixed effects by country and by year. Country fixed effects absorb unobservable aspects that can make some countries more productive than others because of industrial organization, cultural, idiosyncratic, or institutional reasons, as long as they are invariant over time. The addition of fixed effects per year, on the other hand, allows us to contemplate exogenous technological growth, as well as absorb any cyclical shock that affects all economies (for example, the effects of COVID-19 in 2020). Both AI and cloud variables are standardized to facilitate the convergence process of the model.

Table 4-2. Non-linear Least Squares estimates

	(i)	(ii)	(iii)	(iv)
Constant	-1.8270***	-2.6043***	-2.7974***	-1.9820***
	[0.1219]	[0.0284]	[0.0749]	[0.1628]
α	0.5331***	0.5467***	0.5315***	0.5425***
	[0.0215]	[0.0246]	[0.0217]	[0.0237]
β	0.1053**	0.1317**	0.1041**	0.1303**
	[0.0523]	[0.0607]	[0.0520]	[0.0585]
ρ	0.5321***	0.2839	0.5264***	0.3159*
	[0.1715]	[0.1823]	[0.1745]	[0.1719]
θ	-1.9599***	-1.8776***	-1.8697***	-1.7226***
	[0.5149]	[0.6803]	[0.4871]	[0.5900]
δ_{AI}	0.4045***		0.3811***	
	[0.1102]		[0.1222]	
δ_{CL}		0.3128**	0.0525	
		[0.1325]	[0.1113]	
δ_{AI+CL}				0.3735**
				[0.1485]
$\delta_{AI \& CL}$	0.0471**	0.0676***	0.0474**	0.0653***
	[0.0183]	[0.0231]	[0.0183]	[0.0219]
δChatGPT	0.0050***	0.0030	0.0047**	0.0029*
	[0.0019]	[0.0018]	[0.0019]	[0.0017]
Country FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
R-squared	0.9996	0.9996	0.9996	0.9996
Obs	130	130	130	130
Method	NLS	NLS	NLS	NLS

*Note: *** p<1%, ** p<5%, * p<10%. Robust standard errors in brackets.*
Source: Telecom Advisory Services analysis

We start by considering the AI spending to enhance the productivity of skilled workers in column (i), with δ_S proving to be positive and statistically significant, indicating that AI spending is associated with higher skilled-labor productivity. Also, the interaction term presents a positive and significant coefficient as well, verifying the joint role of cloud and AI technologies. Similarly, the generative AI variable also yields an increase in skilled labor productivity according to these results. In column (ii) we introduce cloud spending instead of AI, also presenting a positive and statistically significant coefficient, verifying that an increase of cloud spending is also associated with improved productivity of skilled labor. However, when all the

variables are introduced together, cloud spending loses significance as presented in column (iii), which can be explained by the collinearity between cloud and AI spending (as both variables are largely correlated). Therefore, in column (iv) we introduce as variable the sum of spending in AI and cloud, plus the interaction term and the chat GPT regressor, with all these variables proved to be statistically significant. In short, these results verify that both cloud and AI, separately and when they are complemented, are critical to enhance the productivity of skilled workers. Also, generative AI is also yielding productivity gains.

In addition, α takes values close to 0.55 across the different estimates, meaning that the composite factor accounts more than unskilled labor for the productive process. Similarly, β rounds 0.10-0.15, highlighting a larger role of skilled labor than of capital.

Another result to highlight in the model is that $\rho > 0$, which suggests substitution between the composite factor (capital and skilled labor, also influenced by AI and cloud) and unskilled labor. Furthermore, AI's contribution to skilled labor productivity could confirm its substitutability with unskilled labor, as only when this variable is omitted (in column (ii) results) is when ρ loses significance. This can be suggesting that AI accelerates the substitutivity of unskilled labor. In addition, we find evidence on $\theta < 0$, suggesting complementarity between physical capital and skilled labor, as expected.

The quantification of the estimated effects is detailed in Table 4-3, by relying on the average coefficients of the estimations presented in columns (i) to (iii) of Table 4-2 above.

Table 4-3. Quantification of the effects

Variable	Increase	GDP impact	Elasticity – effect after 1% increase
AI spending	1 million	0.0010%	0.031%
Cloud spending	1 million	0.0001%	0.011%
Spending of AI done through CSP (as % of CSP revenue)	1 percentage point	1.95%	0.034%
ChatGPT unique visitors	1 million	0.12%	0.002%

Note: elasticity measures calculated as an increase with respect to the mean-median averages
Source: Telecom Advisory Services analysis

According to the model results, a million dollar increase in AI (cloud) spending is associated with a GDP increase of 0.0010% (0.0001%), something that when expressed in elasticity terms can be summarized as follows: a 1% increase in AI (cloud) spending is associated with a GDP increase of 0.031% (0.011%). Similarly, a 1% increase in the share of Cloud Service Providers revenue that is destined to AI platforms is associated with a GDP increase of 0.034%, highlighting the relevance of the complementarity between both technologies. Finally, a 1% increase in ChatGPT unique visitors is associated with a 0.002% increase in GDP. In all cases, these effects materialize through an improvement of the productivity of skilled workers. As defined in table 4-1, a skilled worker in our model is defined as an individual of over

25 years of age with tertiary education according to the World Bank.[24] It is assumed that workers with these characteristics have a skill level that will benefit from artificial intelligence use. Table 4-4 provides a breakdown between skilled and unskilled workforce in the Asia Pacific countries under study.

Table 4-4. Asia Pacific: Skilled vs. unskilled workforce (2024)

Country	Persons employed	Skilled	Unskilled
Australia	14134.29	49.73%	50.27%
India	562860.46	14.58%	85.42%
Japan	68760.5	58.55%	41.45%
Republic of Korea	28298.62	55.13%	44.87%
Singapore	3976.08	54.72%	45.28%
Indonesia	142518.56	13.06%	86.94%
Malaysia	16484.29	23.34%	76.66%
New Zealand	2908.1	41.55%	58.45%
Philippines	46863.4	24.84%	75.16%
Thailand	39659.69	17.06%	82.94%
Viet Nam	55859.34	14.69%	85.31%

Source: World Bank

In conclusion, the model suggests several key findings regarding the economic impact of AI and cloud computing:

- AI and cloud spending are associated with increased productivity of skilled workers
- Generative AI use also yields an increase in skilled labor productivity
- Cloud and AI, when they are complemented, are critical to enhance the productivity of skilled workers, verifying the joint role of cloud and AI technologies
- The complementarity of skilled labor and physical capital as drivers of substitution of unskilled labor appears to be accelerated by generative AI.

While AI has indeed contributed to increasing the productivity of skilled labor, there is no evidence that it has done the same, for the moment, with the productivity of capital. The productivity of capital inputs reflects the efficiency with which equipment, machines, structures and vehicles are managed. While it is difficult to better understand the reasons behind the lack of AI contribution to the management of the capital base, we can hypothesize that the initial case studies underlying the returns of AI are focused on labor intensive operations such as customer service, telemarketing and administrative work. This can also be explained by the fact that AI is more likely to be applied first to increase labor productivity than the efficiency with which firms use their fixed assets.

4.3. Estimation of economic impact of AI and cloud computing in selected Asia-Pacific countries

[24] For reference, according to research from the Georgetown University Center on Education and the Workforce, 65% of job openings in private education and 58% in public education require a university degree. In health care, the percentage is 43% (see Job projections through 2013 by industry. Retrieved in: https://cew.georgetown.edu/cew-reports/projections2031/)

The calculation of economic impact in Asia-Pacific countries is based on the coefficients presented above. The estimation was done for Australia, India, Indonesia, Japan, Republic of Korea, Malaysia, New Zealand, Philippines, Singapore, Thailand, and Viet Nam. The results are calculated first for each country, and then they are summed up to form the region's overall figures. The analysis adds the annual spending (using 2025 values) as direct impact, while spillovers are calculated using average annual spending and usage changes between 2020 and 2025, with the model estimated on the 2020–2024 panel.[25] Aggregated results are presented in Table 4-5.

Table 4-5. Asia Pacific: economic impact (2025) (US$ million)

	Spending	Spillovers	Total
AI (excl. Gen AI and complementarity)	$ 22,656.4	$ 157,083.8	$ 179,740
AI - Cloud complementarity	$ 17,273.5	$ 123,595.8	$ 140,869
Generative AI	$ 10,327.8	$ 107,975.5	$ 118,303
Total AI	**$ 50,257.7**	**$ 388,655.1**	**$ 438,913**
Cloud total (excluding complementarity)	$ 126,494.5	$ 29,906.4	$ 156,401
AI - Cloud complementarity	$ 17,273.5	$ 123,595.8	$ 140,869
Total Cloud	**$ 143,768.0**	**$ 153,502.2**	**$ 297,270**
Total impact	**$ 176,752.2**	**$ 418,561.5**	**$ 595,314**
As % of GDP	1.09%	2.59%	3.68%

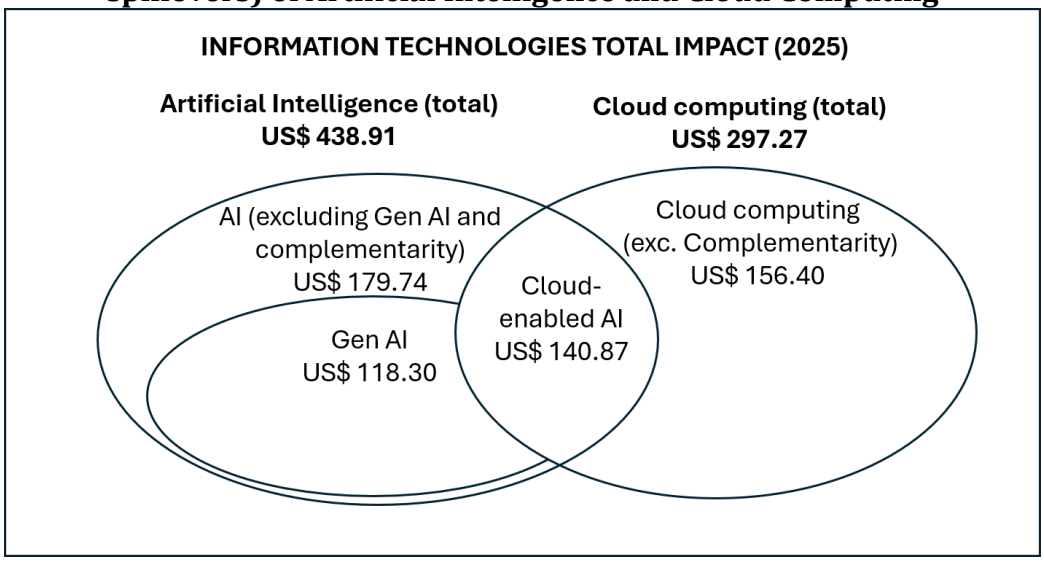
Note: these calculations do not include China or Hong Kong
Source: Telecom Advisory Services analysis

The annual impact for the selected countries in Asia Pacific, once both spending and spillovers are considered, amounts to US$ 595 billion, which represents 3.68% of the total GDP. This is the sum of both spending and spillovers associated with all the sources of economic value: impact due to AI standalone (excluding Gen AI and cloud-enabled AI) (US$ 179.7 billion), cloud standalone (US$ 156.4 billion), AI-cloud complementarity (US$ 140.9 billion), and Generative AI (US$ 118.3 billion). In percentage terms, AI economic impact is the largest source of value, accounting for 30.2%, followed by the cloud standalone (26.3%) and the complementarity (23.7%).

As presented in Graphic 4-1, total AI impact accounts for US$ 438.9 billion, including US$ 140.9 billion from cloud–AI complementarity. This highlights the crucial role that cloud plays for AI. The economic impact of AI that is not associated with cloud and neither linked to Generative AI accounts for 179.7 billion, while generative AI value amounts US$ 118.3 billion. On the other hand, the overall economic impact of cloud accounts for US$ 297.3 billion, of which US$ 140.9 billion is associated with the complementarity with AI.

[25] Except for the AI-cloud complementarity, for which spillovers are annual averages based on the period 2018-2024.

Graphic 4-1. Asia Pacific: distribution of total economic impact (spending and spillovers) of Artificial Intelligence and Cloud Computing



Note 1: Information Technology spending includes 16 technologies: Hardware (IaaS, server, and storage), software (AI applications [content workflow and management applications, CRM applications, ERM applications], AI application development and deployment, AI platforms [AI life-cycle software, computer vision AI tools, conversational AI tools, intelligent knowledge discovery software], AI system infrastructure software), and services (business services and IT services).
Note 2: these calculations do not include the PRC or Hong Kong, China because, given the country's overall size of the cloud (39%) and AI (56%) markets, the estimates would be somewhat distorted.
Sources: IDC (2026). IDC Worldwide AI and Generative AI Spending Guide - Forecast 2026 | Mar (V1 2026); IDC (2024). IDC Worldwide Software and Public Cloud Services (2024) July (V2 2024); Telecom Advisory Services analysis

The total contribution of both technologies can be disaggregated into key components. For example, the total contribution of generative AI, a subset of AI including applications such as Chatbots and agentics, reaches US$ 118.30 billion (equivalent to 0.73% of the GDP of the countries under analysis). Furthermore, the complementarity between cloud technology and AI is an important source of economic value since the capability of cloud computing is a critical enabler of AI use cases. This effect amounts to US$ 140.87 billion in 2025 (or 0.87% of the region's GDP). As also indicated in figure C, the total economic impact of each technology should be considered in terms of the overlapping effects. For example, in 2025 AI standalone (without including Generative AI or the complementarity with cloud) contributed US$ 179.74 billion to the region's Gross Domestic Product (GDP) (equivalent to 1.11% of the region's GDP). In turn, cloud computing (excluding its enablement of AI) contributed US$ 156.40 billion to the annual GDP (equivalent to 0.97% of the region's GDP).

When examined on a country basis, total spending and spillovers are significant ranging from 4.9% of GDP for Singapore to 1.3% for Indonesia (see table 4-6).

Table 4-6. Asia Pacific: economic impact by country (2025) (values in US$ million)

Source	Description	Australia	India	Indonesia	Japan	Republic of Korea	Malaysia	New Zealand	Philippines	Singapore	Thailand	Viet Nam
AI	AI spending 2020	$ 1,432.12	$ 1,437.62	$ 249.30	$ 6,700.86	$ 1,953.40	$ 323.77	$ 425.11	$ 201.85	$ 1,846.26	$ 326.32	$ 140.58
	AI spending 2025	$ 8,371.58	$ 6,347.80	$ 1,182.44	$ 15,662.48	$ 5,276.20	$ 1,535.66	$ 2,016.31	$ 957.39	$ 6,693.23	$ 1,547.77	$ 666.79
	Average annual increase	$ 1,387.89	$ 982.04	$ 186.63	$ 1,792.32	$ 664.56	$ 242.38	$ 318.24	$ 151.11	$ 969.39	$ 244.29	$ 105.24
	Annual impact on GDP (%)	1.319%	0.933%	0.177%	1.704%	0.632%	0.230%	0.303%	0.144%	0.921%	0.232%	0.100%
	GDP (2025)	$ 1,771,681	$ 4,187,017	$ 1,429,743	$ 4,186,431	$ 1,790,322	$ 444,984	$ 248,666	$ 497,495	$ 564,774	$ 546,224	$ 490,970
	Impact due to AI spillovers	$ 23,373.18	$ 39,084.89	$ 2,536.37	$ 71,324.19	$ 11,309.46	$ 1,025.22	$ 752.23	$ 714.59	$ 5,204.17	$ 1,268.39	$ 491.15
Cloud	Cloud spending 2020	$10,439.32	$6,705.78	$867.17	$25,069.46	$4,704.51	$1,282.69	$1,968.73	$766.75	$4,014.28	$1,350.57	$481.72
	Cloud spending 2025	$26,198.57	$20,540.12	$2,959.84	$56,503.00	$10,777.14	$3,697.45	$4,773.24	$2,356.22	$10,670.36	$3,649.40	$1,642.62
	Average annual increase	$ 3,151.85	$ 2,766.87	$ 418.53	$ 6,286.71	$ 1,214.53	$ 482.95	$ 560.90	$ 317.89	$ 1,331.22	$ 459.77	$ 232.18
	Annual impact on GDP (%)	0.197%	0.173%	0.026%	0.393%	0.076%	0.030%	0.035%	0.020%	0.083%	0.029%	0.014%
	Impact due to Cloud spillovers	$ 3,487.14	$ 7,234.54	$ 373.69	$ 16,435.58	$ 1,357.86	$ 134.20	$ 87.10	$ 98.76	$ 469.51	$ 156.83	$ 71.19
AI-Cloud complementarity	Spending in cloud through AI firms 2025	$ 2,985.68	$ 1,451.09	$ 192.75	$ 4,455.49	$ 836.01	$ 250.33	$ 328.68	$ 156.06	$ 880.77	$ 252.30	$ 108.69
	Spending in AI through Cloud firms 2025	$1,082.62	$651.99	$62.64	$2,277.53	$461.88	$103.94	$132.77	$62.51	$414.71	$80.01	$45.01
	Complementarity spending 2025	$ 4,068.30	$ 2,103.08	$ 255.39	$ 6,733.02	$ 1,297.89	$ 354.27	$ 461.45	$ 218.57	$ 1,295.48	$ 332.31	$ 153.70
	Share of Cloud spending on AI platforms 2018	1.01%	0.34%	0.32%	1.22%	0.84%	0.74%	0.77%	0.36%	0.53%	0.57%	0.65%
	Share of Cloud spending on AI platforms 2025	4.13%	3.17%	2.12%	4.03%	4.29%	2.81%	2.78%	2.65%	3.89%	2.19%	2.74%
	Average annual increase	0.45%	0.40%	0.26%	0.40%	0.49%	0.30%	0.29%	0.33%	0.48%	0.23%	0.30%
	Annual impact on GDP (%)	0.873%	0.790%	0.501%	0.786%	0.962%	0.578%	0.560%	0.640%	0.935%	0.452%	0.584%
	Impact due to AI-Cloud comp. spillovers	$ 15,459.74	$ 33,086.02	$ 7,167.38	$ 32,889.22	$ 17,219.79	$ 2,573.68	$ 1,393.77	$ 3,185.75	$ 5,282.62	$ 2,470.56	$ 2,867.30
Generative AI	Gen AI spending 2025	$ 1,882.86	$ 1,515.40	$ 231.43	$ 3,132.36	$ 973.33	$ 300.56	$ 394.63	$ 187.38	$ 1,276.47	$ 302.93	$ 130.50
	Chat GPT unique visitors 2020	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Chat GPT unique visitors 2025	9.900	68.642	15.615	21.144	14.160	6.836	2.167	10.884	5.194	6.544	10.739
	Average annual increase	1.98	13.73	3.12	4.23	2.83	1.37	0.43	2.18	1.04	1.31	2.15
	Annual impact on GDP (%)	0.231%	1.605%	0.365%	0.494%	0.331%	0.160%	0.051%	0.254%	0.121%	0.153%	0.251%
	Impact due to Gen AI spillovers	$ 4,099.84	$ 67,183.06	$ 5,218.62	$ 20,691.45	$ 5,926.06	$ 711.05	$ 125.96	$ 1,265.68	$ 685.66	$ 835.55	$ 1,232.54
Total direct impact		$ 30,501.85	$ 24,784.84	$ 3,886.89	$ 65,432.47	$ 14,755.45	$ 4,878.84	$ 6,328.10	$ 3,095.05	$ 16,068.10	$ 4,864.86	$ 2,155.71
Total impact due to spillovers		$ 46,419.90	$ 146,588.50	$ 15,296.05	$ 141,340.45	$ 35,813.17	$ 4,444.15	$ 2,359.05	$ 5,264.78	$ 11,641.95	$ 4,731.32	$ 4,662.18
Total impact		$ 76,921.75	$ 171,373.34	$ 19,182.95	$ 206,772.92	$ 50,568.62	$ 9,323.00	$ 8,687.15	$ 8,359.82	$ 27,710.06	$ 9,596.18	$ 6,817.88
Total impact per worker		$ 5,347.85	$ 256.99	$ 130.00	$ 3,001.29	$ 1,769.07	$ 548.34	$ 2,987.23	$ 176.68	$ 6,928.00	$ 242.68	$ 120.56
Total impact (% GDP)		4.34%	4.09%	1.34%	4.94%	2.82%	2.10%	3.49%	1.68%	4.91%	1.76%	1.39%

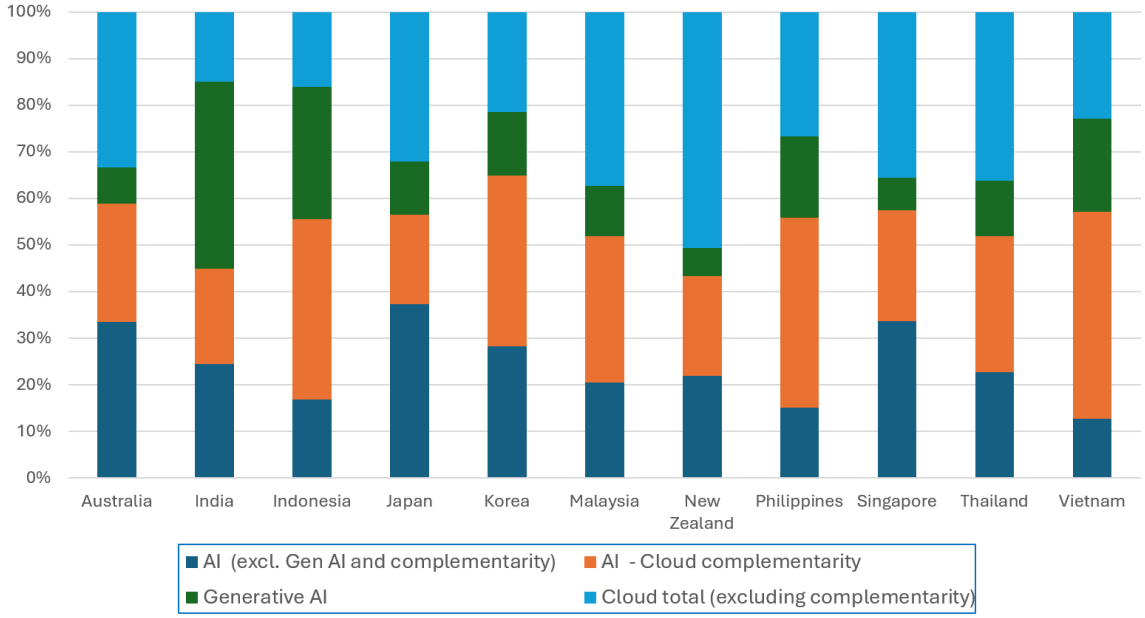
Source: Telecom Advisory Services analysis

The country where the annual economic impact was the largest is Japan (US$ 207 billion), followed by India (US$ 171 billion). In terms of percent of GDP, the economic impact is largest in Japan (4.94%), followed by Singapore (4.91%), Australia (4.34%) and India (4.09%).

In terms of labor productivity, the econometric model developed for this study indicates that the average annual incremental productivity derived from spending on AI and cloud computing in the countries under analysis is equivalent to an additional US$ 544.37 per worker (from a current amount of US$ 14,776), although there are important disparities between countries as highlighted in Table 4-5. The highest impact when measured in labor productivity terms is registered in Singapore and Australia, with annual gains equivalent to US$ 6,928 and US$ 5,348 per worker, respectively.

When analyzing the sources of impact for each country, important differences arise (Graphic 4-2).

Graphic 4-2. Asia Pacific: distribution of economic impact by country



Source: Telecom Advisory Services analysis

Cloud–AI complementarity and standalone cloud are major components of the economic impact in many countries. In addition, Generative AI seems to be very relevant for the case of India. In turn, AI as standalone technology generates a high impact on India and Indonesia.

Over the next 5-year timeframe, we calculated the economic impact according to the recent forecast presented by IDC for cloud and AI spending. The result, presented in Table 4-7, points to a massive economic impact in the region, accounting in total for US$ 10,331 billion (or 10.15% of the cumulated GDP according to IMF predictions).

Table 4-7. Asia Pacific: forecasted economic impact (2026-2030) (values in US$ billion)

	Spending	Spillovers	Total
AI (excl. Gen AI and complementarity)	$ 219.7	$ 2,828.9	$ 3,048.6
AI - Cloud complementarity	$ 229.6	$ 2,690.7	$ 2,920.3
Generative AI	$ 186.1	$ 199.1	$ 385.2
Total AI	**$ 635.4**	**$ 5,718.6**	**$ 6,354.1**
Cloud total (excluding complementarity)	$ 942.0	$ 3,035.8	$ 3,977.7
AI - Cloud complementarity	$ 229.6	$ 2,690.7	$ 2,920.3
Total Cloud	**$ 1,171.6**	**$ 5,726.4**	**$ 6,898.0**
Total impact	**$ 1,577.4**	**$ 8,754.4**	**$ 10,331.8**
As % of GDP	1.55%	8.60%	10.15%

Note: these calculations do not include China or Hong Kong
Source: Telecom Advisory Services analysis

During the next five years, the economic impact of AI and cloud as standalone technologies in Asia-Pacific will be significant, reaching respectively US$ 3,049 billion and US$ 3,978 billion (or 3.0% and 3.9% of the forecasted cumulative GDP for the same period). The complementarity between both technologies will add an additional US$ 2,920 billion to the economy (2.87% of the region's GDP). Generative AI, in turn, will add a further US$ 385 billion (0.38% of the region's GDP). The sum of all sources of value accounts for $ 10,331.8 billion (10.15% of the region's GDP).

However, this massive economic contribution is highly dependent on IDC forecasts, that project a huge increase in spending for the region (259% between 2025 and 2030). Therefore, we project an alternative scenario with more moderate growth ratios, taking as a reference the half of IDC projected growth rates (Table 4-8).

Table 4-8. Asia Pacific: forecasted economic impact (2026-2030) (values in US$ billion)

	Spending	Spillovers	Total
AI (excl. Gen AI and complementarity)	$ 179.9	$ 1,414.4	$ 1,594.4
AI - Cloud complementarity	$ 171.9	$ 2,388.6	$ 2,560.5
Generative AI	$ 86.7	$ 193.9	$ 280.6
Total AI	**$ 438.5**	**$ 3,997.0**	**$ 4,435.5**
Cloud total (excluding complementarity)	$ 833.3	$ 1,517.9	$ 2,351.2
AI - Cloud complementarity	$ 171.9	$ 2,388.6	$ 2,560.5
Total Cloud	**$ 1,005.2**	**$ 3,906.5**	**$ 4,911.8**
Total impact	**$ 1,271.9**	**$ 5,514.8**	**$ 6,786.7**
As % of GDP	1.25%	5.42%	6.67%

Note: these calculations do not include China or Hong Kong
Source: Telecom Advisory Services analysis

Under these moderate projections, during the next five years the economic impact of AI and cloud as standalone technologies in Asia-Pacific will reach respectively US$ 1,594 billion and US$ 2,351 billion (or 1.57% and 2.31% of the forecasted cumulative GDP for the same period). The complementarity between both technologies will add an additional US$ 2,561 billion to the economy (2.52% of the region's GDP). Generative AI, in turn, will add a further US$ 281 billion (0.28% of the region's GDP). The sum of all sources of value accounts for $ 6,787 billion (6.67% of the region's GDP).

On the basis of the coefficients driving spillovers, the differential economic impact by country was calculated, leading to the following conclusions:

- **Countries that increase AI and Cloud spending will generate important economic gains.** The models developed for this study suggest that a 1% increase in AI spending in Australia, India, Indonesia, Japan, the Republic of Korea, Malaysia, New Zealand, Philippines, Singapore, Thailand, and Viet Nam will yield an increase of 0.031% of the GDP, while a 1% increase in cloud spending will yield an increase of 0.011% of the GDP.[26]

- **Economic spillovers that depend on the complementarity of cloud and AI exhibit larger economic effect.** A 1% increase in the share of spending on cloud service providers (CSP) destined to AI platforms will increase GDP by 0.034%. The higher coefficient of impact of complementary AI and cloud than each technology on a stand-alone basis, underscores the potential for integrating both technologies to enhance organizational performance, emphasizing the need for skill development, security measures, and the strategic utilization of organizational resources to fully exploit the benefits of this integration.[27]

Based on these coefficients, two economic impact scenarios based on IDC spending forecast for both technologies over the next five-years (2026-30) were developed.[28] The first scenario assumes that spending will evolve as stated by the IDC forecast, while the second one, more moderate, is based on a spending growth rate of half of the future growth rate. According to the IDC forecast of spending growth rate, the economic impact of AI and cloud as standalone technologies in Australia, India, Indonesia, Japan, Republic of Korea, Malaysia, New Zealand, Philippines, Singapore, Thailand, and Viet Nam will be significant, reaching respectively US$ 3,049 billion and US$ 3,978 billion (or 3.00% and 3.91% of the forecast cumulative GDP for the same period). The complementarity between both technologies will add an additional US$ 2,920 billion to the economy (2.87% of the region's GDP). Generative

[26] For comparison purposes, in a recent study, the authors estimated that, on a worldwide basis, 1% increase in fixed broadband adoption would yield 0.159% increase in GDP (see Katz and Callorda, 2025).

[27] This complementary effect was also proven by Katz and Jung (2024b) where, in a sample of firms in Israel, the combination of cloud computing and machine learning has a cumulative correlation coefficient of 0.233 compared with 0.143 for cloud computing alone.

[28] The two IDC spending reports cited in footnotes 1 and 2 provide spending forecasts through 2028. For purposes of this analysis the rate of growth was extrapolated through 2030.

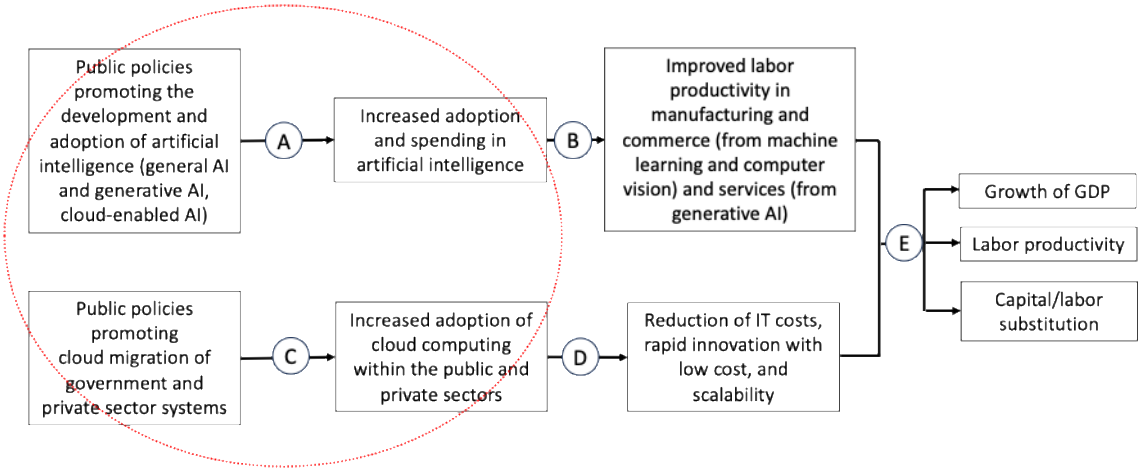
AI, in turn, will add a further US$ 385 billion (0.38% of the region's GDP). The sum of all sources of value accounts for $ 10,331.8 billion (10.15% of the region's GDP).

A more moderate estimation, based on half the growth rates of AI spending would suggest that the economic impact of AI and cloud as standalone technologies in Australia, India, Indonesia, Japan, the Republic of Korea, Malaysia, New Zealand, Philippines, Singapore, Thailand, and Viet Nam will reach respectively US$ 1,594 billion and US$ 2,351 billion (or 1.57% and 2.31% of the forecast cumulative GDP for the same period). Under this scenario, the complementarity between both technologies will add an additional US$ 2,561 billion to the economy (2.52% of the region's GDP). Generative AI, in turn, will add a further US$ 280.6 billion (0.28% of the region's GDP). The sum of all sources of value accounts for $ 6,787 billion (6.67% of the region's GDP) under these moderate projections.

5. THE IMPACT OF POLICY ON AI AND CLOUD DEPLOYMENT

In order to achieve this forward-looking level of policy impact, countries in Asia Pacific need to implement important public policy interventions. The theory of change underlying this study has proven that the positive externalities mentioned above are contingent upon a set of public policies promoting the development and adoption of artificial intelligence combined with the migration of government and private enterprise systems to cloud computing (see figure 5-1).

Figure 5-1. Modelling of policy impact



Source: Telecom Advisory Services

5.1. Data set

5.1.1. Cloud Policy Index

The cloud policies outlined in section 3.1. were used to create a country policy maturity level: basic, intermediate and advanced. Each maturity level is conceptualized in terms of progress along the three dimensions of cloud maturity (see table 5-1).

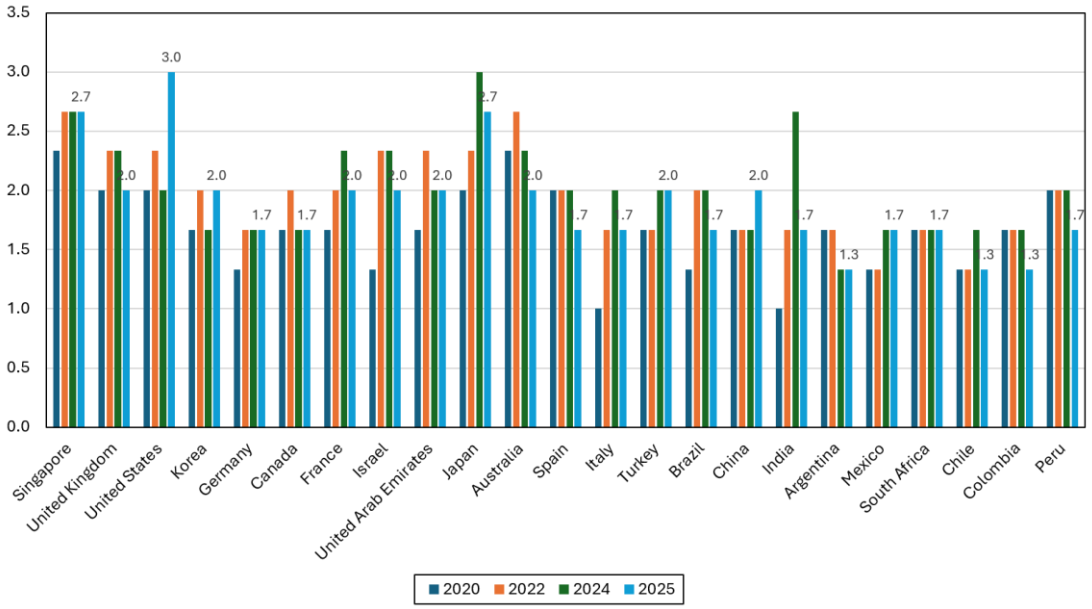
Table 5-1. Maturity of cloud policy maturity level

Level	Cloud policy for public sector (government)	Hosting policy for public sector data	Cybersecurity Level
Basic	• Private (State-owned)	• No policy • Keeping data inside the country	Low
Intermediate	• Hybrid (private state-owned and public commercial)	• Hybrid (keeping data inside and outside the country)	Medium
Advanced	• Public (commercial)	• Allow to process data outside the country	High

Source: Telecom Advisory Services

Originally developed in our 2022 study, the index was updated to reflect improvement in 2025. The results indicate the changes that have taken place since 2022 (see graphic 5-1).

Graphic 5-1. Cloud Policy Index (2020-2025)



Source: Telecom Advisory Services

5.1.2. AI Policy Index

While there is a lack of policy related indices regarding AI, recently the IMF developed the AI Preparedness Index (AIPI)[29], that can be considered a reference in the field. The AI Preparedness Index is the sum of four key dimensions: digital infrastructure, human capital, technological innovation, and legal frameworks. Each dimension is computed by normalizing and averaging a set of sub-indicators including, among others, the presence of relevant digital infrastructure, sustained human capital investment, STEM expertise, labor and capital mobility, a vibrant R&D ecosystem, and the adaptability of legal frameworks to digital business models.

Unfortunately, the AIPI cannot be used in a panel framework as the data is only available for a single year (2023). Therefore, we proceeded to develop an alternative index with data for all the years of the panel, following the structure detailed in Table 5-2.

[29] International Monetary Fund (2024). *AI Preparedness Index (AIPI).* Retrieved in: https://www.imf.org/external/datamapper/datasets/AIPI

Table 5-2. Structure of the AI Policy Index[30] (TAS)

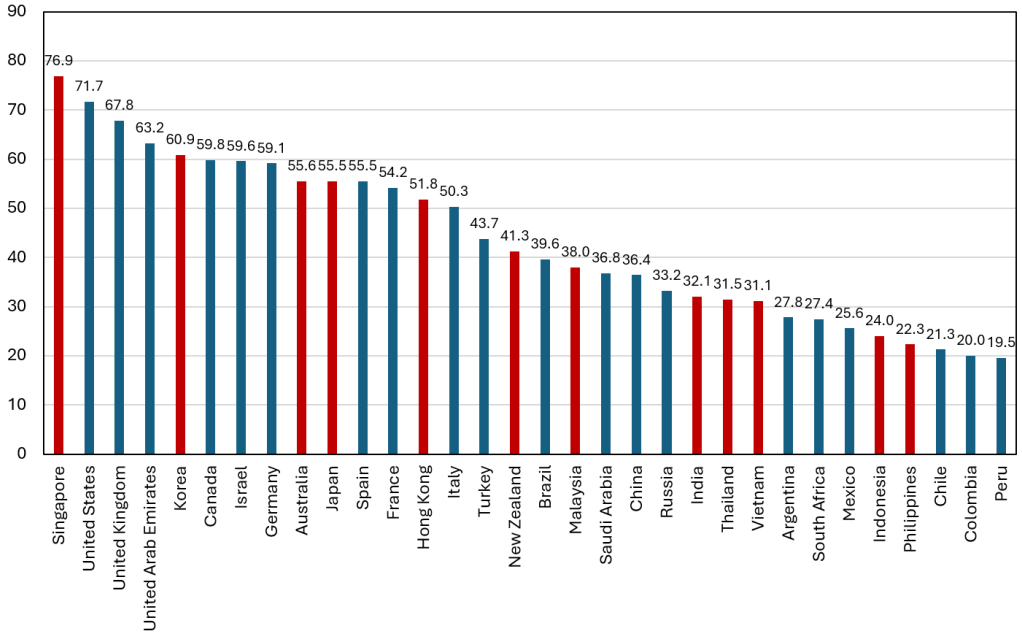
Pillar	Weight	Indicator	Weight	Source
R&D and Academic Strength	20.00%	Annual R&D expenditure as % of GDP	33.33%	UNESCO
		AI publications per capita	33.33%	OECD AI Observatory
		Number of Universities in Top 100 Computer Science Programs per million inhabitants	33.33%	CS Rankings
AI Industry & Advanced Tech Infrastructure	20.00%	Number of AI companies per million inhabitants	33.33%	Crunchbase
		AI talent concentration (professionals)	33.33%	OECD AI Observatory
		Top 500 supercomputers per million inhabitants	33.33%	https://www.top500.org/lists/top500/2024/06/
Digital Infrastructure & Security	20.00%	Global cybersecurity index	50.00%	ITU Global cybersecurity
		Fixed Broadband Adoption (% households)	50.00%	ITU Data Hub
AI Governance & Policy	20.00%	GDPR policies	20.00%	GDPR advisor (https://www.gdpradvisor.co.uk/gdpr-countries)
		AI Legislation Passed	20.00%	Stanford AI Index
		AI Strategy	20.00%	Oxford Insights
		AI Mentions in Legislative Proceedings	20.00%	Stanford AI Index
		Existence of digital nomad visas	20.00%	https://immigrantinvest.com/blog/countries-digital-nomad-visa-en/#colombia
AI Education & Skills	20.00%	AI courses in English per capita	50.00%	OECD AI Observatory
		AI skills penetration	50.00%	OECD AI Observatory

Source: Telecom Advisory Services analysis

As presented in Graphic 5-2, our AI Policy Index is led by Singapore (76.9), followed by the United States (71.7) and United Kingdom (67.8), as the countries with the more conducive environment for AI development (Asia-Pacific countries are denoted in red). The high score of Singapore in the policy index is aligned with the position of this country as the regional leader in terms of AI.

[30] See detail index results in Appendix A.

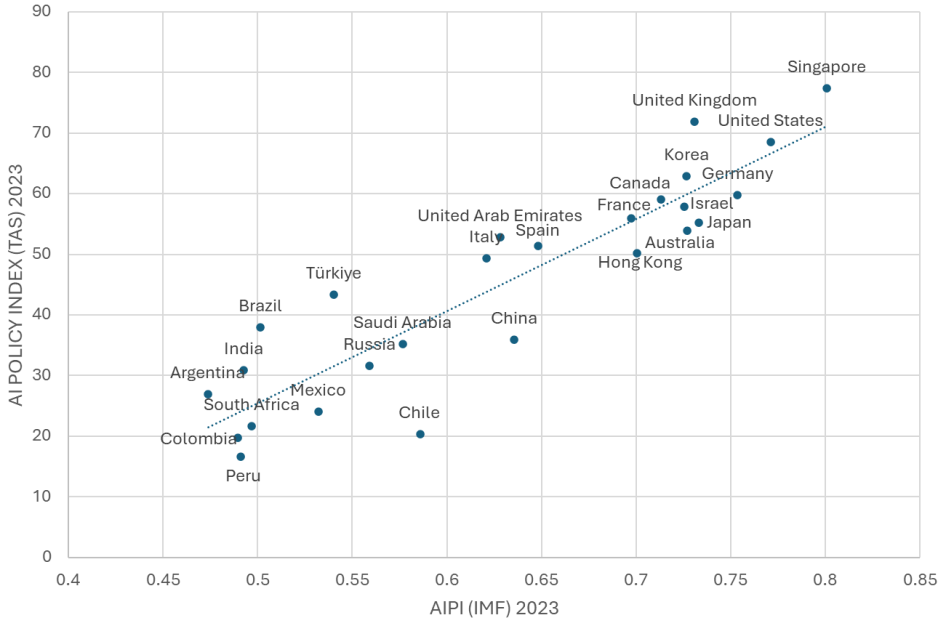
Graphic 5-2. AI Policy Index (TAS) 2025



Source: Telecom Advisory Services analysis

Since our development index is, as presented in Graphic 5-3, clearly correlated with the IMF's AIPI, we believe it is a reliable indicator to be used in our panel.

Graphic 5-3. Correlation between AIPI (IMF) - AI Policy Index (TAS) 2023



Source: IMF, Telecom Advisory Services analysis

5.2. Model results of Cloud computing and AI policy impact for Asia-Pacific countries

The models presented in chapter 3.3 are estimated with the results reported in Table 5-3. These estimates are done simultaneously with the output equation presented in chapter 4 (then being a unique econometric routine to estimate the three models).[31]

Table 5-3. Effects of policy on AI and Cloud spending

Dependent variable:	ln(AI)	ln(Cloud)
AI policy index	0.0325***	
	[0.0124]	
Cloud policy index		0.4139***
		[0.0724]
ln (Skilled labor)	1.6320***	1.2960***
	[0.4269]	[0.2705]
ln (Y) - lagged	-0.8620*	1.8179***
	[0.4576]	[0.3541]
Country FE	YES	YES
R-squared	0.9832	0.9852
Observations	130	130

*Note: *** p<1%, ** p<5%, * p<10%. Robust standard errors in brackets.*
Source: Telecom Advisory Services analysis

The results presented in Table 5-3 suggest that the role of policy is significant, as the coefficient associated with AI and cloud policy reach respectively 0.0325 and 0.4139, being in both cases significant at a 1% level.

5.3. Simulation of Cloud policy reforms

Once the coefficients associated with policy and spending were identified, in this section we simulate a potential improvement in local cloud policies for Asia Pacific countries. There are plenty of opportunities for pro-cloud policy reforms across the region, as reflected in Table 5-4, where each pillar of the policy index is classified as low, intermediate and advanced.

[31] As Hong-Kong data was missing for the cloud policy index, we inputted the value of China for that country. Other missing values for the cloud policy index where those of Saudi Arabia and Russia, for which we inputted the sample averages by year.

Table 5-4: Asia Pacific: Maturity levels of Pro-cloud policy framework (2025)

Policy	Options		
	Low	Intermediate	Advanced
1. Cloud policy for public sector	**Restricted** • Indonesia • India	**Partially competitive** • Australia • Malaysia • Republic of Korea • New Zealand • Thailand • Philippines • Viet Nam	**Fully competitive** • Japan • Singapore
2. Data hosting policy for public sector (government) data	**Keeping data inside the country** • India • Indonesia • Republic of Korea • Malaysia • Viet Nam	**Hybrid (keeping data inside and outside the country)** • Australia • Japan • Singapore • New Zealand • Philippines	**Allow to process data outside the country** • Thailand
3. Government cybersecurity policy (score based on 2024 ITU Global Cybersecurity Index)	**Global Cyber Security Index value <85** • New Zealand (*)	**Global Cyber Security Index value between 85 and 97** • Australia • Philippines	**Global Cyber Security Index value >97** • India • Indonesia • Japan • Republic of Korea • Singapore • Thailand • Malaysia • Viet Nam

(*) New Zealand cyber security index value was assigned by the ITU because the country did not respond to ITU questionnaire

Source: World bank GTMI https://www.worldbank.org/en/programs/govtech/2022-gtmi; ITU Cybersecurity Index https://www.itu.int/en/ITU-D/Cybersecurity/Pages/global-cybersecurity-index.aspx; Telecom Advisory Services desk based research

As presented in Table 5-4, in all the countries there is room for improvement, something that will make their policy index scores increase, and consequently, raise cloud spending (Table 5-5).

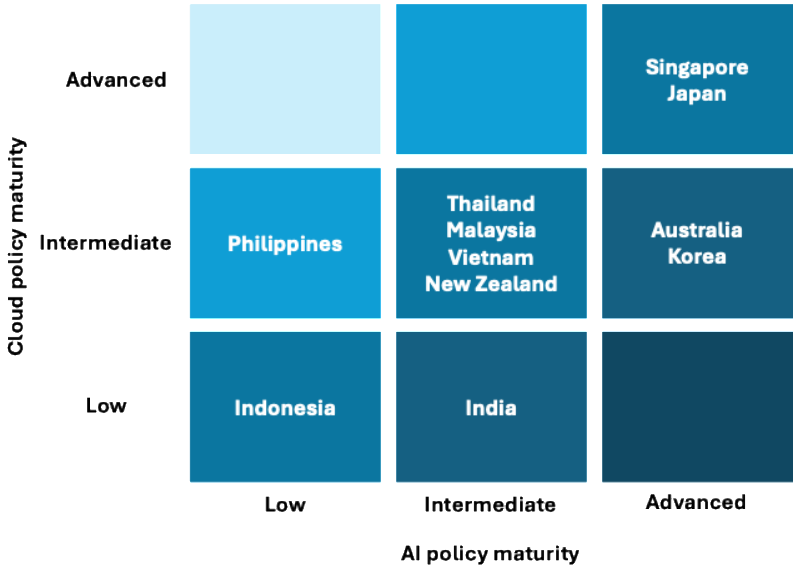
Table 5-5. Asia Pacific countries: Changes in pro-cloud policies

Country	Initial level (2025)				Reform simulation			
	Cloud policy for public sector	Hosting policy for public sector data	Cybersecurity Level (0-1)	Cloud policy index (2025)	Cloud policy for public sector	Hosting policy for public sector data	Cybersecurity Level (0-1)	Cloud policy index (simulated)
Australia	Partially competitive	Hybrid	0.962	2.00	Fully competitive	Allow data outside the country	0.970	3.00
Japan	Fully competitive	Hybrid	0.976	2.67	Fully competitive	Allow data outside the country	0.976	3.00
India	Restricted	Keeping data inside the country	0.985	1.67	Fully competitive	Allow data outside the country	0.985	3.00
New Zealand	Partially competitive	Hybrid	0.826	1.67	Fully competitive	Allow data outside the country	0.970	3.00
Singapore	Fully competitive	Hybrid	0.999	2.67	Fully competitive	Allow data outside the country	0.999	3.00
Malaysia	Partially competitive	Keeping data inside the country	0.988	2.00	Fully competitive	Allow data outside the country	0.988	3.00
Indonesia	Restricted	Keeping data inside the country	1	1.67	Fully competitive	Allow data outside the country	1	3.00
Philippines	Partially competitive	Hybrid	0.935	2.00	Fully competitive	Allow data outside the country	0.970	3.00
Republic of Korea	Partially competitive	Keeping data inside the country	1	2.00	Fully competitive	Allow data outside the country	1	3.00
Thailand	Partially competitive	Allow data outside the country	0.992	2.67	Fully competitive	Allow data outside the country	0.992	3.00
Viet Nam	Partially competitive	Keep data inside the country	0.997	2.00	Fully competitive	Allow data outside the country	0.997	3.00

Source: Telecom Advisory Services

These policies will have an impact on technology spending and, consequently, on spillovers. However, a wide variance in terms of policy maturity across countries in the region exists (see figure 5-2).

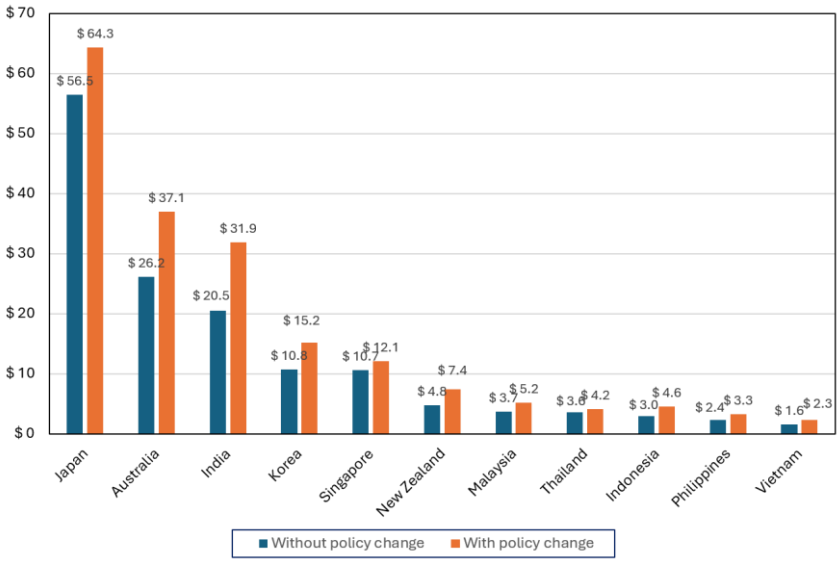
Figure 5-2. AI and Cloud policy maturity



Source: Telecom Advisory Services analysis (see appendices D and E)

By applying the reforms detailed in Table 5-5, we calculated the index increase for all countries. Taking the respective increases in the index and the coefficients estimated in the econometric regression, we calculate the potential cloud spending level that can be reached if policy reforms are conducted (graphic 5-4).

Graphic 5-4. Asia-Pacific: Cloud spending after policy reforms (in US$ billion)



Source: Telecom Advisory Services analysis

As presented in Graphic 5-4, in all cases significant improvements in spending arise. To cite a few examples, in Australia spending will increase from US$ 26.2 billion to US$ 37.1 billion, in India from US$ 20.5 billion to US$ 31.9 billion, in Republic of Korea from US$ 10.8 billion to US$ 15.2 billion, and in Singapore from US$ 10.7 billion to US$ 12.1 billion (to cite a few examples). These results demonstrate the relevance of creating a policy and regulatory environment aimed at maximizing the impact of cloud.

5.4. Simulation of AI policy reforms

A similar exercise can be done for AI policy reforms. From the country rankings presented in Graphic 5-2, we can establish some thresholds in terms of AI policy advancements, by splitting the sample in three levels: (i) Low (those countries reaching less than 30 points in the policy index), (ii) Intermediate (those economies reaching values between 30 and 50 points in the policy index), and (iii) Advanced (those countries reaching more than 50 points). In Table 5-6 we apply those thresholds to the Asia-Pacific countries.

Table 5-6: Asia Pacific: Maturity levels of AI policy (2025)

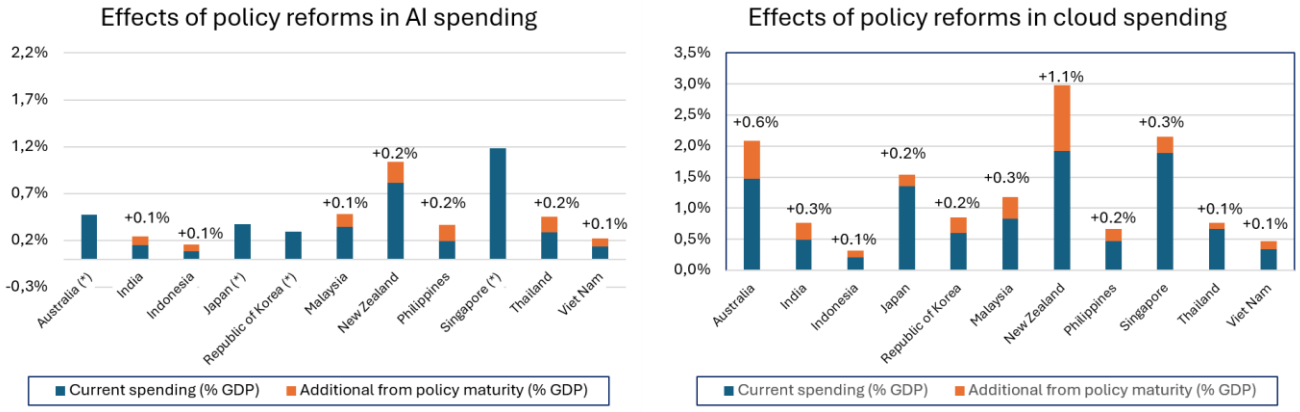
Policy	AI Policy Maturity Levels		
	Low	Intermediate	Advanced
AI Policy Index (TAS)	**AI Policy Index<30** • Indonesia • Philippines	**30<AI Policy Index<50** • India • Malaysia • New Zealand • Viet Nam • Thailand	**AI Policy Index>50** • Australia • Japan • Republic of Korea • Singapore

Source: Telecom Advisory Services analysis

Only Australia, Japan, Singapore and Republic of Korea are having an advanced maturity policy framework for AI development. Other countries in the region reach intermediate levels, such as Malaysia, New Zealand, Viet Nam, India and Thailand. On the other hand, the low-level AI policy maturity group includes Indonesia and Philippines. This means that, beyond the advanced maturity countries, there is plenty of room for improvement in terms of AI policy and consequently, on spending levels and economic impact from this technology.

Applying a hypothetical increase in policy maturity for each country, the impact on AI and cloud spending is estimated (see Graphic G).

Graphic G. Effects of increase in policy on AI and Cloud spending



(*) Country has already achieved the hypothetical increase in policy maturity
Source: Telecom Advisory Services analysis

These results demonstrate the importance of AI, cloud computing and cloud enabled AI for the economic development of the region, and the relevance of creating a policy and regulatory environment aimed at maximizing their impact. Asia Pacific countries have the opportunity of accelerating their technological development in cloud computing and AI. In order to do so, the region should re-think its digital policies to identify cloud and AI impediments to the fulfillment of development objectives.

On a final note, beyond the contribution to GDP, both technologies, especially AI, represent a critical input to improving labor productivity. The econometric model developed for this study indicates that the average annual incremental productivity derived from spending on AI and cloud computing in the countries under analysis is

equivalent to an additional US$ 544.37 per worker (from a current amount of US$ 14,776).

However, the study models also indicate that labor productivity enhancement will materialize primarily in the skilled workforce (i.e. workers with a tertiary educational level) combined with a process of substitution of unskilled workers. According to our econometric analysis, 1% increase in AI spending will increase the demand for skilled workers by 0.21% to 0.22% but will also decrease the demand for unskilled workers by 0.15% to 0.17% (in both cases, the exact magnitude will depend on the empirical model considered). If the number of skilled workers were equal to the number of unskilled workers in a given country, both effects would largely offset each other, and the net result would be close to zero. This is why, according to our models and assumptions, job creation in the Republic of Korea, Japan, and Singapore as a consequence of AI adoption more than compensates for the losses. On the other hand, in emerging economies, which tend to have a greater number of unskilled workers net job losses could be higher.

Furthermore, if demand for skilled jobs increases, so will their salaries. As firms compete to hire the best talent, wages should increase. On the other hand, if demand for low skilled workers reduces, so would their salaries. The net result, a potential excess supply of unskilled workers, would then may drive firms to pay them less. This means that, even in the eventuality of no overall effects on jobs, the change in the composition of employment, may augment the salary gap and increase inequality.

This detrimental effect should incentivize countries to implement policies focused on upskilling and reskilling the labor force that will be affected by the adoption of AI. Four of them are critical:

- Establishing clear metrics for assessing AI-related skills.
- Incorporating training in AI-centric skills taxonomies in education.
- Assessing/auditing the quality of existing "AI-readiness" training programs.
- Incentivizing employers and employees to participate in upskilling programs.

6. POTENTIAL IMPACT OF ARTIFICIAL INTELLIGENCE ON EMPLOYMENT AND INEQUALITY

The report has so far laid out the GDP and productivity impacts of AI across the economies of selected countries in Asia Pacific. In this context, it is relevant to consider the implications of the productivity gains if they also imply labor force disruptions leading to inequality effects. As pointed out in the results of the econometric model presented in chapter 4, the complementarity of skilled labor and physical capital under an increase in AI spending, particularly on generative AI, appears to drive the substitution of unskilled labor. If there is a trade-off between the contribution of AI to economic growth and its impact on the labor force and ultimately on inequality, are there policies that would mitigate some of the negative effects? Furthermore, what can countries do to effectively manage the trade-off, or what types of policies would help to boost productivity yet not worsen inequality?

This chapter discusses potential implications for employment that may result from the increasing diffusion of AI in Asia-Pacific countries. We begin by summarizing the evidence generated so far by the research literature regarding the labor impact of AI. After this, we present a quantitative analysis of potential labor force impact by AI diffusion in Asia Pacific. We also incorporate an empirical analysis to check the impact of AI in inequality levels. The estimated impact provides the context to discuss policy measures that can mitigate potentially negative effects.

6.1. Research literature on the impact of artificial intelligence on employment and inequality

The model presented in chapter 4 suggests the existence of substitutability between the complementarity of capital and skilled labor, and unskilled labor, predicting therefore a displacement effect. However, this result is based on an econometric model built with a panel data between 2020 and 2024, which captures primarily the impact of AI driven by use of machine learning, computer vision, and robotics, before the dramatic adoption of generative technology This evidence is consistent with the results generated by historical analysis and microeconomic research on the labor substitution triggered by early generations of AI. In fact, the original research on the impact of AI focused initially on what could be gleaned from the impact of prior technology waves.

For example, the historical trend analysis assessing the impact of robotics and machine learning coincides in stipulating the impact of automation in routine occupations, a trend validated by David Autor from MIT in successive papers. According to Autor et al. (2003), automation through robotics and machine learning in the US was associated with a reduction in routine tasks by 8.7%, and an increase in non-routine cognitive tasks by 11.5%, suggesting a functional restructuring of work as a result of technological change. Along these lines, Autor and Dorn (2013) concluded that between 1980 and 2005 a reduction of 1.80% of routine employment per decade took place in the United States. In manufacturing the job reduction in the same time span reached an aggregate 54%. Autor (2014) and Autor (2015) validated the asymmetric impact of AI, given that low-skilled jobs witnessed a reduction in demand due to process automation, which triggered an increase in

inequality. For example, Autor (2014) indicated that occupations based on human judgment have become more valuable, driving higher wages, while this trend was not compensated for wage losses of routine jobs. This is the reason why, according to Autor (2015), technology complements abstract cognitive tasks but replaces routine tasks, a trend that has led to a polarization of the labor market, in which incomes are growing for workers with higher cognitive skills but are declining or stagnating for the middle and low segments. Finally, Autor (2022) mentions that digital technologies, especially those associated with automation, have displaced routine tasks that were previously supported middle-income jobs.

Autor's research was also validated by Acemoglu, who estimated a 6.5% decline in low technology intensive population while Acemoglu and Restrepo (2019) calculated that automation drove an annual reduction of 1.1% of employment in the US, although this reduction did not occur constantly. During the period from 1947 to 1987, automation did not negatively affect net employment, as the displacement effect (-0.48% per year) was almost offset by the creation of new jobs (+0.47% per year). However, from 1987 to 2017, automation accelerated without generating enough new jobs, leading to a net reduction in employment. Subsequently, the same authors (Acemoglu & Restrepo, 2020) estimated that the increase in industrial robot density reduced employment by between 0.18% and 0.34% between 1990 and 2007. With a higher estimate, Acemoglu & Restrepo (2022) estimated that a 10% increase in task displacement caused by the adoption of robotic systems and machine learning in the United States was associated with a 4.4% reduction in the employment rate of the affected group in the period 1980–2016. Coincidently, Deloitte (2015) estimated that approximately 800,000 jobs in the United Kingdom were eliminated between 2001 and 2015, which could represent approximately 2.7% of the labor force. Both studies agree that automation and robotics have had a negative impact on total employment in the medium term, but with partial offsetting effects in high-tech sectors. Felten et al. (2023) also raised the impact of advanced technologies on routine jobs, calculating that 25% of workers in routine occupations in the United States face high levels of automation. Exposure in this research denotes potential for tasks to change, not confirmed job elimination.

Beyond the substitution impact of AI before the advent of generative technology, current research of the later wave points to two alternative potential employment effects, which have been labeled as the "displacement vs. enhancement of labor". The first effect points to the hypothesis that generative AI extends prior labor substitution trends, but now addresses also knowledge occupations, while the second effect posits that the technology has a differential effect across knowledge workers, actually enhancing productivity of primarily "high performing/highly trained workers".

The evidence regarding labor substitution triggered by generative AI has been generated on the basis of four empirical strategies: (i) microeconomic research of limited real-life effects (such as call centers, research laboratories, or software development units), (ii) experiments in restricted environments (such as management consulting professionals), (iii) theoretical models, and (iv) aggregated data series of emerging phenomena (such as job announcements).

Within the first empirical approach, substitution effects were identified, albeit with varying magnitude estimates in limited settings. For example, Toner-Rodgers (2024), estimated that AI adoption in a research lab resulted in 3% job reduction.

With regards to measuring effects of generative AI based on theoretical modelling of labor statistics, substantial work has been generated along the lines of the research tradition initiated by Frey and Osborne in 2017, albeit enhanced methodologically, by assessing exposure to AI of occupations likely to be affected by the technology. For example, Auer et al. (2024) relies on the O*NET job descriptions applied to 711 occupations, 35 cognitive abilities and approximately 19,000 tasks assessed with GPT-4. Their model simulated six levels of AI capability, distinguishing core from ancillary skills and accounting for time spent interacting with computers. The average share of exposed skills increases from 7% at low capabilities to 17% at moderate and 36% at high capabilities, reaching 45% in the top wage quartile. However, these estimates represented technical simulations, rather than measuring job losses.

On the other hand, Liu et al (2025) revealed that the rapid global adoption of generative artificial intelligence (Gen-AI) is profoundly altering digital activity patterns, especially in sectors intensive in cognitive and information processing tasks. Using traffic data and country-level regressions, the authors showed that the most affected sectors are concentrated in economies with high specialization in marketable digital services. The study documented how these AI tools have begun to displace traffic and usage of traditional platforms, affecting roles such as technical writers, translators, administrative assistants, junior programmers, and IT support operators.

Along these lines, Hatzius et al. (2023) assessed generative AI exposure using O*NET tasks for the United States and ESCO comparable occupations for Europe, weighted by OEWS and Eurostat-LFS employment data and extrapolated worldwide. The authors classified 13 of 39 work activities as AI-exposed and imposed assumptions about the difficulty of tasks AI can perform, without identifying a definite adoption year. They estimate that roughly two-thirds of jobs have some exposure, while 7% of US employment could face substitution.

Bridging the gap between substitution and enhancement hypotheses, Eloundou et al. (2024) measured US occupational exposure to large language models using O*NET 27.2 (1,016 occupations and 19,265 tasks), Bureau of Labor Statistics employment figures and demographic data. Human annotators and GPT-4 classified tasks based on whether AI could reduce completion time by at least 50%, either directly or with complementary software. The analysis concluded that about 80% of workers are in occupations where at least 10% of tasks could be affected, while 19% pertained to occupations where at least half of tasks could change. Again, this metric captured technical exposure rather than observed displacement.

Despite what has been identified in microeconomic, and theoretical modelling, there is limited aggregated empirical evidence so far of job losses due to AI-driven substitution. Eckhardt and Goldschlag (2026) detected that, while unemployment in AI exposed workers is rising, it is not doing so at a different rate than least exposed

occupations. Similarly, according to Liu and Webber (2026), no evidence exists that AI adoption has negatively affected companies' job demand. That said, Brynjolfsson et al (2025) reported a decline in announcements for jobs among early-career workers in AI-exposed occupations. The authors examined the observed employment effects of generative AI in the United States using monthly administrative payroll records for 3.5–5 million workers (2021–September 2025). They linked firm-level occupations to the exposure measures developed by Eloundou et al. (2024) and Anthropic and estimate firm and month fixed-effects models, and concluded that since late 2022, employment among workers aged 22–25 in highly exposed occupations has declined by 16% relative to their less-exposed peers, whereas employment among more experienced workers in the same occupations increased by 6%–9% over the observed period. Coincidentally, at least in the United States there is data that supports the fact that young workers (e.g. less trained) have more difficulty in finding work (Federal Reserve Bank of New York, 2026).

The above findings were confirmed by Hosseini Maasoum and Lichtinger (2026) when they examined the impact of firm-level GenAI adoption on employment in the United States, using employment records for 65 million workers across more than 280,000 firms between 2015 and 2025. Using difference-in-differences and triple-difference models, the authors identified firms integrating GenAI through job postings seeking specialists in its implementation and compared employment trends with those of non-adopting firms. The authors found that junior employment declines by approximately 9% in relative terms after six quarters, while senior employment shows no significant decline, and that this reduction is concentrated in occupations highly exposed to GenAI and is primarily driven by fewer entry-level hires rather than an increase in layoffs.

The negative impact on demand of early career workers has also been confirmed across countries. Initially, Teeselink (2025) reported similar results as those of the United States in the United Kingdom. In an extension of the prior study, Chandar and Teeselink (2026) examined the impact of firm-level GenAI adoption on employment across 41 countries, using 1.25 billion job postings and 154 million employment records from *Revelio Labs* between January 2021 and March 2026. Using an instrumental-variable event-study model, they compared employment trends in subsidiaries of multinational firms adopting GenAI with those of otherwise similar firms. The authors found that the share of junior workers declines by 1.9 percentage points relative to the control group, while senior employment increases by 6.7%. Likewise, total employment increases by 3.3%, indicating a shift in workforce composition in favor of more experienced workers rather than a widespread reduction in jobs.

In a similar finding, Khosravi and Liu (2026) examined the impact of GenAI on firms' labor demand across 186 countries, using 77.8 million LinkUp job postings corresponding to 37,395 firm-country pairs between 2021 and 2025. Using a difference-in-differences model and the C-AIOE index, they compared changes in job vacancies across occupations with different levels of exposure to AI-driven substitution following the launch of ChatGPT. The authors found that, for each

additional unit of occupational exposure, advertised hiring declines by approximately 9.6% in advanced economies and 19.1% in developing countries.

Beyond the substitution/labor displacement effect, a parallel body of evidence indicates that AI also augments workers' performance, raising the value of tasks that AI cannot perform and shifting labor demand toward higher-skilled roles. Microeconomic research of real contexts and experiments indicates that generative AI tools, particularly chatbots and coding support, tend to improve the performance of less experienced workers. For example, Brynjolfsson et al. (2025) study of worker performance in large call centers documented overall productivity improvement of recently hired and less skilled workers of 30% in the number of issues resolved per hour, although there was no improvement in highly skilled workers. Similar positive effect concentrated on low performing workers was documented by Peng (2023) in software development as a result of adoption of GitHub Copilot, although less positive effect was documented by Cui et al. (2025) in similar tasks. Noy et al. (2023) conducted an experiment aimed at measuring the impact of ChatGPT in professional writing tasks. In this case, productivity enhancement was registered in all workers, regardless of performance levels, while low ability writers improved the quality of their writing output.

Beyond differential impact by worker performance, research also indicates that productivity enhancement of generative AI varies by type of tasks. For example, in an experiment measuring impact on management consulting work, Dell'Acqua et al (2023) found positive effects on highly structured questions to be addressed, while the impact was not always consistent across workers, when management issues to be addressed were unstructured and based on qualitative information. In fact, the authors concluded that impact can be strong or limited depending on the task being addressed.

To sum up, the evidence compiled both in real world context and experiments indicates that the impact of generative AI on productivity enhancement varies by level of worker performance (high vs. low or novice) and type of task being addressed. From a prescriptive standpoint, the net labor outcome therefore depends less on the technology itself than on the approach chosen for implementation and how quickly the workforce is reskilled to complement it.

On a final note, it is critical for the purpose of this paper, to review the research evidence generated so far beyond advanced economies. Along these lines, it is important to ascertain that most of the research on overseas impact generated up to date corresponds to the measurement of substitution effects based on theoretical models applied to the occupations' exposure to artificial intelligence. For example, Ciaschi et al. (2025) simulate AI-related distributional impacts across 14 Latin American countries using harmonized household microdata (2018–2023) and PIAAC task profiles. They applied four exposure measures and imposed counterfactual shocks displacing 10% or 25% of workers into unemployment or informality. Under a 10% displacement scenario, regional unemployment rises from 4.1% to 13.8%, or informality rises from 51.4% to 56.3%, depending on the simulated transition.

Within the research focused on developing regions, Gmyrek et al. (2024) adapted ILO generative AI exposure measures to 16 Latin American and Caribbean countries using ILO microdata, mainly from 2022–2023. They combined PIAAC data with a logit model predicting computer use at work to capture barriers to actual adoption. Total occupational exposure ranges from roughly 26% to 38% across countries, but only 2%–5% of jobs fall into the potential automation category. Approximately 17 million workers across the Latin American continent whose tasks could be augmented face digital-access constraints, highlighting the role of infrastructure in realized employment outcomes.

Similarly, Benítez-Rueda and Parrado (2024) introduced the GENOE index, a measure quantifying the potential impact of artificial intelligence on occupations and their associated tasks, to estimate task-replacement exposure over one-, five- and ten-year horizons. Their analysis combines 1,016 occupations and 18,156 O*NET tasks with Mexico's National Survey of Occupation and Employment. In this case, average exposure rises from 0.28 at one year to 0.38 and 0.44 at five and ten years. As a result, they estimate 16 million highly exposed jobs in Mexico, although they do not interpret those figures as actual layoffs.

Similarly, Pizzinelli et al. (2023) compared AI exposure and labor complementarity, harmonizing worker-level surveys from the United States, United Kingdom, Brazil, Colombia, India and South Africa (2018–2022) into ISCO-08 occupations. Exposure is higher in advanced economies, but cross-country gaps narrow after accounting for complementarity. In the developing economies, 20% of employment in Brazil, Colombia, and South Africa would be at risk of AI substitution, although in the case of India the displacement risk drops to 12%.

Finally, focusing on the impact specifically in Asia Pacific, Hennig and Khan (2025), for the International Monetary Fund, estimated occupational exposure to AI in 21 Asia-Pacific economies, including Bangladesh, India, Indonesia, Cambodia, Laos, Mongolia, the Philippines, Thailand, and Viet Nam. They link the AIOE and C-AIOE occupational indices to ILO employment distributions to distinguish substitution from complementarity. Approximately 27% of jobs in emerging and developing economies are exposed, compared with nearly half in advanced economies.

Along these lines, World Bank (2025) researchers examined the effects of GenAI on employment in South Asia using 1.15 million observations from harmonized labor force surveys in Bangladesh, Bhutan, India, Nepal, and Sri Lanka, complemented by Lightcast job postings between 2020 and 2025. The study combined occupational exposure and complementarity measures using the ISCO classification and estimated event-study models around November 2022, finding that 7% of regional employment is concentrated in highly exposed to AI occupations with low complementarity, compared with 15% in occupations with potential for complementarity. In addition, the study also detected that vacancies in the most exposed and substitutable cognitive occupations declined by approximately 20% in relative terms.

The International Labor Organization (2026) assessed GenAI exposure in ASEAN labor markets using its refined global task-based index applied to national

employment and occupational statistics. The study also considered recent adoption and sectoral trends. For 2025, it estimated that 22.9% of ASEAN employment, equivalent to nearly 80 million workers, is in occupations with more than minimal exposure; 3.3% (11.7 million) falls within the highest-exposure category. Among countries with comparable data, exposure reached 28.1% in the Philippines, 21.7% in Indonesia, 20.8% in Viet Nam, and 20.6% in Thailand.

Huynh (2026) examined the Philippines using the ILO refined index of occupational exposure to GenAI, mapped to the national employment structure to identify differences by sex, age, region, and occupation, with particular emphasis on business process outsourcing services. The report estimated that 12.7 million jobs, more than one-quarter of total employment, are exposed, although only 3.6% of employment falls within the highest-risk category. Exposure among women is twice that among men. In the National Capital Region, approximately two in five jobs are exposed.

Weidenkaff and Huynh (2026) examine Viet Nam using the 2024 Labor Force Survey and the global index of occupational exposure to GenAI, disaggregated by age, gender, education, formality, province, and sector. They estimate that approximately 11.5 million employed persons, or one in five workers, perform potentially exposed tasks, while around one million workers (less than 2% of employment) are in occupations with the highest exposure. The exposure rate is 24.1% for women and 17.8% for men.

Lewandowski, Madoń, and Park (2026) developed a task-adjusted measure of AI exposure for the Asian Development Bank using O*NET, PIAAC, STEP, and the China Urban Labor Survey. The surveys directly cover 53 economies, including developing countries in Asia. The authors find that workers in low-income countries have an AI exposure level approximately 0.8 standard deviations below that of workers in advanced economies. Furthermore, low- and lower-middle-income countries, which account for 40.2% of global employment, represent only 16.7% of the world's most-exposed workers and 61.8% of the least-exposed workers. The study concludes that exposure differences mainly reflect task structures and access to technology, without quantifying the share of jobs potentially substituted.

In sum, microeconomic and time-series evidence on the employment impact of generative AI in developing economies remains limited. The studies reviewed here report a wide range of exposure and potential-automation estimates under different methodologies. These estimates should not be interpreted as observed job losses; infrastructure and access constraints also affect the scope for actual adoption.

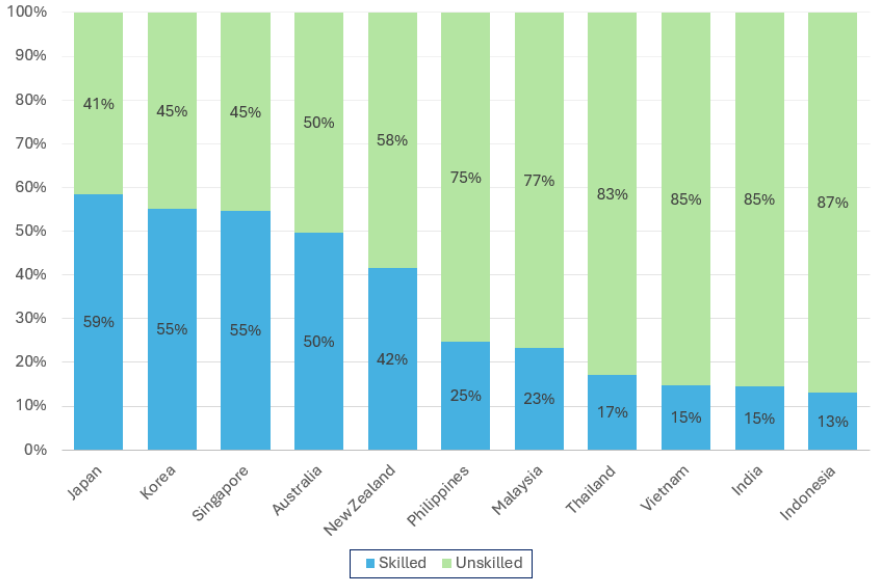
6.2. Initial estimations of potential labor force impact of AI in Asia Pacific

Considering the paucity of actual real time data on the employment effect of generative AI in the developing world and recognizing that the model presented in chapter 4 focuses primarily on the effect of prior AI technologies, the following analysis applies a model that analyzes how the combination of skilled labor and capital investment can be affecting demand for unskilled workers. The following estimation of the potential substitution impact of AI on labor force demand in the Asia Pacific countries under study is based on data compiled from the World Bank

data portal on the distribution of workers with and without tertiary education. Given the lack of statistics (as well as a consistent definition) for skilled and unskilled workers, tertiary education, defined as the highest level of training, represents an adequate indicator.

A descriptive analysis of workers with and without tertiary education depicts significant disparities in the composition of labor force by country in the Asia-Pacific region. The higher income economies, such as Japan, the Republic of Korea, and Singapore, have more than half of the workers with high skills, while, on the other hand, India and Indonesia do not reach 15% of the labor force (see Graphic 6-1).

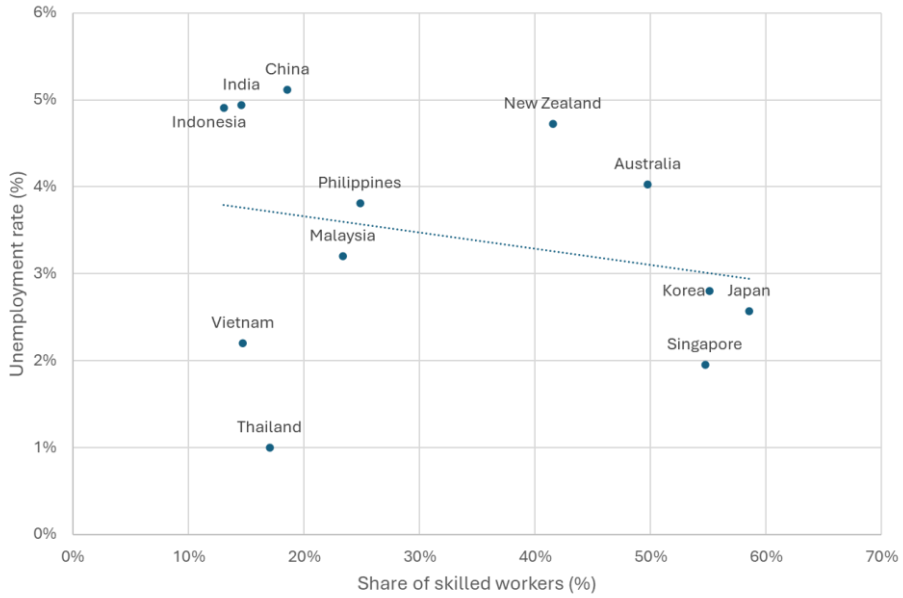
Graphic 6-1. Distribution of employment between skilled and unskilled (2024)



Source: The Conference Board, OECD, World Bank, Telecom Advisory Services analysis

If substitution between skilled and unskilled workers is occurring as a consequence of AI spending, the potential impact on the labor force is therefore likely to vary significantly by country. Countries with the lowest share of skilled workers, Vietnam and Thailand excluded, also tend to record higher unemployment rates, which may compound any differential impact. This association is descriptive and should not be read as a causal finding (see Graphic 6-2).

Graphic 6-2. Percentage of skilled workers and the unemployment rate (2024)



Source: The Conference Board, OECD, World Bank, IMF, Telecom Advisory Services analysis

To explain the variation in the level of skilled and unskilled employment, regression models were estimated in which these variables will be introduced as the dependent ones, while regressors include the level of spending on AI and other controls. Both dependent variables are introduced into the regression model measured as a percentage of the population. With respect to the control variables, in the first instance we include the average income (proxied by GDP per capita) and GDP growth. In the first case, the objective is to capture the influence of the wage level on the demand for labor, while in the second case, GDP growth aims to capture the expansionary or contractionary effects of the business cycle. Both variables have been compiled from the IMF database. Other controls include investment (as a percentage of GDP) from the IMF, the level of openness (trade with respect to GDP), as well as the percentage of the economy represented by the industry and services sectors (in the last three cases, the data are sourced from the World Bank). Finally, all estimates incorporate fixed effects by country and by year.

Estimates were made through the 3-stage least squares (3SLS) simultaneous equation system procedure (Table 6-1).[32] This methodology is considered more efficient than the separate estimation of both employment demands, since both decisions are expected to be correlated.

[32] Countries included in Table 6-1: Argentina, Australia, Brazil, Canada, Chile, China, Colombia, France, Germany, Hong Kong, India, Israel, Italy, Japan, Korea, Mexico, Peru, Russia, Saudi Arabia, Singapore, South Africa, Spain, Turkey, United Arab Emirates, United Kingdom, United States. Period considered: years 2020 to 2024

Table 6-1. Estimation of labor demand - 3SLS Simultaneous equation models

	System of Equations 1		System of Equations 2	
Dependent variable:	Log (Skilled)	Log (Unskilled)	Log (Skilled)	Log (Unskilled)
Log (AI spending)	0.21017***	-0.15483***	0.22430***	-0.17337***
	[0.01928]	[0.01530]	[0.02273]	[0.01844]
Income	-0.00001***	0.00000	-0.00001**	0.00000
	[0.00000]	[0.00000]	[0.00000]	[0.00000]
GDP growth (%)	0.18880**	0.11202*	0.17431**	0.12878*
	[0.07506]	[0.05955]	[0.08856]	[0.07183]
Investment			-0.00377	0.00345
			[0.00482]	[0.00391]
Openness			-0.00007	-0.00068
			[0.00112]	[0.00091]
Industry			0.01841*	0.00721
			[0.01088]	[0.00883]
Services			0.00166	0.00138
			[0.00505]	[0.00409]
Country FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Observations	130	130	97	97
R-squared	0.990	0.957	0.992	0.956

*Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses*
Source: Telecom Advisory Services analysis

The first system of equations model, which includes only the basic set of controls, suggests that AI spending positively impacts the demand for skilled labor, while at the same time it impacts negatively the demand for unskilled labor. This confirms the elasticity of substitution model explaining the economic impact of AI and cloud presented in chapter 4. In terms of elasticity, the coefficients suggest that a 1% increase in AI spending will increase the demand for skilled workers by 0.21% but will also decrease the demand for unskilled workers by 0.15%. If the number of skilled workers were equal to the number of unskilled workers, both effects would largely offset each other, and the net result would be close to zero. However, as seen in Graphic 6-1, most countries in the region have more unskilled than skilled workers, so the net result will have to be calculated for each specific case.

Despite the use of fixed effects and a simultaneous equation framework, the results should be interpreted with caution, as several sources of endogeneity may still affect the estimated coefficients. First, reverse causality is a concern: countries or firms with a larger or more skilled workforce may be better positioned to adopt and invest in AI, so that the observed positive association between AI spending and skilled employment could partly reflect the effect of skilled labor on AI adoption rather than the reverse. Second, omitted variable bias may persist even after including country and year fixed effects, since time-varying factors that are correlated with both AI spending and labor market composition may not be fully captured by the controls.[33] Although the 3SLS procedure addresses the correlation between the error terms of the skilled and unskilled labor equations, it is not resolving these further endogeneity concerns.[34] Therefore, we conduct as a robustness check a further

[33] This can be the case with broader ICT investment, trade, and sectoral shifts.
[34] As a side note, 3SLS models have been used to estimate technology economic impact and considered to endogenize technology effect (Roller and Waverman, 2001).

estimate introducing the AI regressor in lags (see detailed results in Appendix F), with estimates further confirming those presented above in Table 6-1.

With respect to controls, the average income level is negatively related to the demand for skilled labor, from which it can be inferred that increases in wages reduce the demand for these workers. On the other hand, economic growth is positively linked to both types of hiring, which accounts for the relevance of the business cycle for employment variations. In any case, it is worth noting that the effect of GDP growth is greater for skilled employment than for unskilled employment.

The second system of equations presented in Table 6-1 aims to verify whether the results are robust to the inclusion of additional controls. In most cases, these controls are not significant, possibly because some of them (openness or sector composition) mainly refer to structural aspects of the economy with little variation in a period as short as that of the sample, and these effects are surely absorbed by fixed effects.

The estimated elasticities can be applied to estimate the break-even point, that is, the threshold of skilled share that makes the net impact of AI on employment to be positive. Accordingly, it can be stated that the net result in terms of employment will be positive when the percentage of skilled workers over the total is greater than 42.3% or 43.6% (depending on the empirical model). In other words, all those countries with a percentage of skilled workers below this threshold would lose jobs due to a greater diffusion of AI.

In Table 6-2 we analyze the net labor force impact in the event of a hypothetical 1% increase in AI spending by country in the selected study group, using the results from both models of equations reported above in Table 6-1. Taking the 95% confidence intervals resulting from the estimated parameters of both regression systems, we choose the lowest and the highest possible value for the coefficients estimating the impact of AI on jobs. Therefore, we present the results in Table 6-2 as ranges between low/high bands.

Table 6-2. Net variations in employment after a 1% increase in AI spending

Country	Created jobs (skilled)		Displaced jobs (unskilled)		Net result on jobs		Net result (% employment)	
	Low	High	Low	High	Low	High	Low	High
Australia	12,091	18,909	13,144	9,734	-1,053	9,175	-0.01%	0.06%
India	141,172	220,786	889,450	658,674	-748,278	-437,887	-0.13%	-0.08%
Indonesia	32,014	50,069	229,225	169,751	-197,211	-119,682	-0.14%	-0.08%
Japan	69,243	108,293	52,730	39,049	16,513	69,244	0.02%	0.10%
Republic of Korea	26,834	41,968	23,490	17,395	3,344	24,572	0.01%	0.09%
Singapore	3,742	5,853	3,330	2,466	412	3,387	0.01%	0.09%
Malaysia	6,618	10,350	23,378	17,312	-16,761	-6,963	-0.10%	-0.04%
New Zealand	2,078	3,250	3,145	2,329	-1,066	922	-0.04%	0.03%
Philippines	20,022	31,314	65,162	48,255	-45,139	-16,941	-0.10%	-0.04%
Thailand	11,637	18,200	60,853	45,064	-49,216	-26,864	-0.12%	-0.07%
Vietnam	14,114	22,073	88,159	65,285	-74,045	-43,212	-0.13%	-0.08%
Total	339,566	531,066	1,452,067	1,075,315	-1,112,501	-544,249	-0.11%	-0.06%

Source: Telecom Advisory Services analysis

According to data in table 6-2, there are significant disparities in the net impact of AI depending on the percentage of skilled workers in total employment. According to these results, the cases of Japan, the Republic of Korea, New Zealand, and Singapore stand out, for which the model predicts a net effect between 0.01% and 0.10% increase in employment because of an increase in AI spending of 1%. In these cases, job creation more than compensates for the losses. On the other hand, in emerging economies, which tend to have a greater number of unskilled workers, such as India, Indonesia and Viet Nam, net job losses could be from 0.08% to 0.14% (depending on the model considered). If the whole region is considered, job loses largely outweighs the job creations, although this is mostly explained by the fact that India and Indonesia, which have a very low rate of skilled workers, are also the largest countries in the sample in population terms.

Another important aspect of analysis is the salary gap between skilled and unskilled workers. Unfortunately, there is no data available on salaries by skill group to incorporate in an econometric model. However, it can be hypothesized that if demand for skilled jobs increases, so will the salaries paid to them. This may happen as firms will compete among them to hire the best candidates, increasing wages offered in the process. On the other hand, if demand for low skilled workers reduces, so will their salaries. There will be an excess of supply of unskilled workers that will drive firms to pay them less. This means that, even in the eventuality of no overall effects on jobs, the change in the composition of employment, by augmenting demand for skilled labor and reducing that of unskilled ones, may also increase the salary gap, potentially increasing inequality.

Preliminary evidence suggests some increase in inequality (as measured through the Gini Index) because of a wider AI diffusion (see Table 6-3). The effect can be quantified as follows: a 1% increase in AI spending per capita is associated with a 0.03% increase in the Gini index the following year. We introduce the AI regressor in lags, as the potential effects from AI may take some time to materialize, as people who lose their jobs may receive temporal unemployment benefits from both the private sector and the government, meaning that inequality will not be immediately affected.

Table 6-3. Estimation of AI impact on inequality

Dependent variable:	**Log(Gini)**
Log (AIpc) t-1	0.030***
	[0.009]
Log(Income)	-0.049
	[0.046]
Unemployment	-0.004
	[0.004]
Population	-0.000***
	[0.000]
Education	-0.003
	[0.002]
Country FE	YES
Year FE	YES
Observations	72
R-squared	0.739

*Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses*

Source: Telecom Advisory Services analysis

These results have to be taken with caution, as the large number of missing data for the Gini Index in the World Bank dataset made us rely on only 72 observations to make the estimation presented in Table 6-3, mostly for 2024 or before. This limits the reliability of the results and should only be considered as illustrative of a potential effect that needs to be investigated further.

All in all, these findings will drive important social implications, given that the AI diffusion will generate winners and losers. It can be expected in some countries an increase in unemployment rates due to AI diffusion, while in all cases, the salary gap between skilled and unskilled individuals would increase. Two factors may temper this effect. First, since the model used for projecting labor force impact is based on panel data through 2024, it reflects primarily substitution effects and does not capture the worker productivity enhancement effect resulting from the adoption of generative AI, identified in developed economies and discussed above. Unfortunately, addressing this effect would require developing an econometric model based on temporal series through, at least 2026. Secondly, substitution dynamics assume a static profile of labor force education. An emphasis on reskilling training would yield workers that would be more amenable to adopt generative AI to improve their productivity. In summary, these results indicate the following conclusions:

- Employment impacts are likely to be contingent on policies rather than predetermined by technologies.

- Economies such as Japan, the Republic of Korea, New Zealand, and Singapore, with larger skilled workforces and proactive skills programs, may be better positioned for net job creation.

- Governments that invest early in workforce reskilling for AI-exposed roles, extend cloud and AI upskilling beyond IT functions, and partner with technology providers to build local talent may have stronger prospects to convert AI adoption into net employment and wage gains.

7. POLICY IMPLICATIONS

While some countries in Asia Pacific are implementing policies for the development of artificial intelligence and the migration to cloud computing, others need to promote policy initiatives that help them accelerate the adoption of cloud and AI technologies within the public and private sector organizations. Recommended policies have been aggregated around three levels (advanced, intermediate and basic) to have a positive effect on both technologies, although some of them (e.g. cybersecurity) are expected to influence both cloud migration and AI development.

7.1. Policies for stimulating the migration to cloud computing

These policies include:

- **Removing data localization requirements to enable customers to access the widest possible range of cloud and AI services.** This allows customers to benefit from economies of scale, increase access to the latest technology, and accelerate digital innovation and transformation.

- **Encourage enterprise cloud adoption**. Typically, unregulated industries are higher cloud adopters because they face less regulatory restrictions in terms of access to cloud computing platforms. On the other hand, regulated industries, such as financial services and healthcare, should benefit from accessing cloud services in terms of cost efficiencies. Public policies should stimulate cloud enterprise adoption in regulated industries by promoting standardized, risk-based cloud migration approval processes.
- **Modernize procurement for consumption-based cloud services. Public sector procurement rules should reflect the on-demand, pay-as-you-go nature of cloud services rather than assuming up-front purchases of hardware, so agencies can buy services as they are consumed.**

- **Invest in cloud and AI upskilling**. A key barrier in facilitating the migration to cloud service relies on limited human capital with expertise in transitioning applications from on premise to shared facilities. Governments should partner with cloud service providers in developing local talent. These entail multiple potential areas of collaboration:
    - Develop a framework of standardized skill taxonomies, harmonizing skills requirements, qualifications, and capabilities to support upskilling in AI.
    - Promote national programs to improve skills and retraining to prevent unemployment of workers in areas highly exposed to AI and promote their retraining in sectors that are complementary to AI.[35]
    - Establish strategic AI plans with cross-cutting coordination capacity to align educational, labor, scientific and productive objectives in a unified agenda.[36]

[35] The *SkillsFuture* program developed by the Ministry of Education and the Singapore Economic Development Board represents an international best practice to prepare the workforce for the impact of disruptive technologies.

[36] For example, the Pan-Canadian *Artificial Intelligence Strategy* (2022-2027) developed by the

- Develop systems for monitoring and evaluating the impact of AI on employment by sector and occupational profile in order to adjust public policies based on evidence.
- Encourage advanced training of engineers and researchers specialized in the design and management of hardware, networks and high-performance computing due to the need for low latency processing, data centers and connectivity in the AI adoption environment.[37]

- **Improve country Cybersecurity levels.** The maturity of cybersecurity policy is conceptualized across five components: (i) enactment of laws and regulations on cybercrime and cybersecurity; (ii) existence of technical capabilities in national agencies; (iii) presence of agencies measuring fulfillment and organizational implementation of cybersecurity; (iv) capacity development in cybersecurity domain; and (v) cooperation between government agencies and between the private and public sectors. Under the shared-responsibility model, cloud service providers secure the underlying infrastructure while customers retain control over their data, configurations, and access, so migration to the cloud is an opportunity for governments to strengthen their security posture and reduce operational risk. Raising cybersecurity maturity across these five components is a precondition for trusted adoption in sensitive and regulated sectors and strengthens this shared-responsibility model.

7.2. Policies for advancing development and adoption of artificial intelligence

The rapid adoption of AI in all economic and social sectors represents an opportunity for developing countries. However, its adoption presents risks of exclusion, reduction of employment through automation, concentration of knowledge and deepening of structural inequalities. This report analyzes actions and public policy recommendations for the inclusive, ethical, safe and productive adoption of AI. These are grouped into eight key areas:

- **Promotion of research in artificial intelligence economic impact**: promote policies to encourage research on the impact of AI related to social, economic and productive challenges to generate appropriation and appropriate use in sectors such as health, environment, education or food security. As a complement, it is necessary to develop national research and development networks around data science and AI to enable collaboration between universities, governments and companies. For example:

Canadian Institute for Advanced Research (CIFAR), drives the responsible development of AI through an initiative that involves public sectors, universities and companies under coordinated governance.

[37] The Jülich Supercomputing Center in Germany is an example of international best practice. It is one of the most advanced centers for training professionals in digital infrastructure and offers training in network design, parallel computing, hardware optimization and data center maintenance. It also collaborates with universities and public agencies to strengthen national capabilities in critical infrastructure, including systems applied to AI, scientific simulation and automation.

- Establish a centralized "AI Success Database" to document and share positive case studies of AI adoption in the public sector.
- Encourage standardized tools for measuring AI adoption across geographies, measuring differential rates of use and penetration between countries to identify laggard industries and departments.
- Create bridges for connectivity between business, academia and government where representatives can learn from one another, with an emphasis on promoting use of applications that do not necessarily require cutting-edge research capabilities or represent "frontier" systems.
- Develop an enterprise sandbox for testing software or changes without impacting live systems or data, capability for adoption and de-risk and reduce the financial costs of adoption of well-understood and proven tooling, to accelerate their adoption and use of artificial intelligence while building industrial confidence.

- **Education for AI skills development:** it is recommended to promote training in AI teaching for teachers, instructors and experts, given that the educational system requires trained personnel to teach practical topics on the use of technology. In terms of education of the population, it is necessary to implement digital literacy programs starting at school, and to certify skills applied to job retraining in order to improve the employability of adult workers in short training cycles adaptable to demand.
  - Incorporate training in adoption-centric skills taxonomies in education: to ensure that more students get an initial education in the "AI-ready" skill set that supports adoption, with the opportunity to deepen it in tertiary education programs.
  - Conduct an audit of existing "AI-readiness" training programs to assess the need for changes that are enterprise-relevant and identify where more opportunities could be supported by grants, tax credits and other schemes. This audit should consider the full roadmap for industry-specific skills, and map out supplementary measures related to occupations with high exposure to automation and public-private partnership programs.
  - Incentivize employers to participate in AI skills programs through public subsidies.
  - Incentivize AI Skills Training by framing programs as a vehicle for career growth and security. Additionally, firms should prioritize internal training programs that empower workers to use AI tools effectively in their roles.

- **Cybersecurity**: it is recommended that regulatory frameworks and specialized training be created to protect critical infrastructures, systems and data based on AI. In addition, it is necessary to promote international cooperation on cybersecurity standards and AI interoperability regulations in order to establish a coherent governance system between countries' incident response centers to avoid regulatory gaps on the limits of AI use within a broad geographic space. Finally, it is critical to ensure AI-oriented cybersecurity training in technical and professional education in order to

design curricula and certification programs that combine computer security, machine learning and ethical data management.[38]

- **Training and social inclusion programs**: it is recommended to promote national programs to improve skills and retraining to prevent unemployment of workers in areas highly exposed to AI and promote their retraining in sectors complementary to AI, as well as to incorporate criteria of equity, gender and territory in all AI adoption policies in order to reduce the deepening of structural gaps. As a complement, AI strategic plans should be established with cross-cutting coordination capacity to align educational, labor, scientific and productive objectives in a unified agenda. Finally, it is critical to develop systems for monitoring and evaluating the impact of AI on employment by sector and occupational profile in order to adjust public policies based on evidence.

- **Promotion of AI innovation**: Regarding the implementation of specific public policies, it is important to incentivize the adoption of AI that complements the interaction with employment through certifications or best practice frameworks that expand the capabilities of less experienced professionals or those entering the labor market. Finally, it is important to establish specific regulatory frameworks for the establishment of limits to the use of AI and automated algorithms that promote misinformation or plagiarism in sensitive areas such as law, health, education, research and content generation. These frameworks should be flexible and risk-based, reflect different risk levels and roles across the AI value chain, and avoid unnecessary barriers to adoption.
    - Bilateral research agreements and "sister city" partnerships to foster international collaboration on AI diffusion can enhance global cooperation on AI-driven solutions for shared challenges. These partnerships would facilitate joint research funding, knowledge exchange, and the creation of shared data repositories and AI governance frameworks. Through collaborative pilot programs in cities, these initiatives can build technical capacity, promote the responsible deployment of AI technologies, and harmonize global standards, contributing to equitable and sustainable development.

- **Human capital development**: it is critical to promote advanced training of engineers and researchers specialized in the design and management of hardware, networks and high-performance computing due to the need for processing, data centers and low-latency connectivity in the AI adoption environment. In the same vein, it is required to promote the learning of non-automatable skills (social, creative, analytical) that complement the skills of professionals who are highly exposed to AI.

- **Infrastructure development**: the strategic deployment of infrastructure such as AI labs, should be encouraged to sustain the growth of AI. These

[38] This can include approaches similar to the Veritas program in Singapore, a national cybersecurity initiative that focuses on developing and enhancing the capabilities of cybersecurity professionals through a combination of hands-on training, advanced tools, and real-world threat simulations.

elements are the physical foundation for training AI models, hosting data and ensuring real-time responses, especially in intensive applications. To this end, it is important to establish the use of open interoperability standards for public and private AI infrastructure in order to facilitate collaboration between actors and avoid closed solutions. All this must be complemented with strategies that ensure the accessibility of AI tools with adequate connectivity.

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In sum, Asia Pacific countries have the opportunity of accelerating their technological development in cloud computing and AI. In order to do so, countries should rethink their digital policies to identify cloud and AI impediments to the fulfillment of development objectives.

7.3. Singapore: a case study of policy good practice

As presented in chapter 2, Singapore is the country in the study sample with one of the highest performances in the development of AI and cloud computing. Furthermore, the country scores in the highest position in the AI policy index and one of the most advanced in the cloud policy index. In light of this evidence, it is pertinent to analyze in depth the policies implemented by the country for the promotion of both technologies. The case study is structured around the various areas of recommended policy interventions presented above.

7.3.1. Promotion of national R&D (public and private) and development of academic capacity in the field of AI.

Singapore has developed the **National Artificial Intelligence Research and Development Program** (AISG)[39] , to drive research and development through AI deployment in partnership between academia, industry and international partners. It offers programs such as the "100 Experiments"[40] to solve business challenges through AI solutions. Thus, co-funding of up to SGD $150,000 per project will be provided for its engineering team to work for 6 months to develop and implement a minimum viable AI model to manage the organization's problem statement. In addition, PhD scholarships have been encouraged to develop local talent in the area.

Moreover, in December 2023, the **National Artificial Intelligence Strategy 2.0** (NAIS 2.0)[41] has also been generated, which sets out the vision of "AI for the Public Good, for Singapore and the World". This strategy focuses on developing demonstration of AI research excellence in specific areas where Singapore can compete globally, such as personalized recommender systems, urban intelligence, and AI-based advanced manufacturing. It also seeks to foster a robust ecosystem through a number of key enablers, including: (i) talent (which aims to strengthen academic training and advanced AI research), (ii) industry, (iii) infrastructure, and

[39] Source: AI Singapore. (n.d.). AI Singapore. Retrieved in: https://aisingapore.org/
[40] Source: op. cit.
[41] Source: Smart Nation and Digital Government Office. (2023). National AI Strategy: AI for the Public Good, for Singapore and the World [PDF]. Retrieved in: https://file.go.gov.sg/nais2023.pdf

(iv) trust. The strategy explicitly establishes, as one of its pillars, the promotion of advanced capabilities in AI research and development within Singapore; as well as the realization of partnerships between universities and industry to accelerate the production of new knowledge in artificial intelligence. Similarly, the strategy also encourages funding for R&D projects involving more than SGD $500 million to promote public-private collaboration to support fundamental AI research and strengthen existing research centers.

Along the same lines, the Singapore government has developed the *Research, Innovation and Enterprise* (RIE) Plan[42] to strengthen investment in new research capabilities and innovation platforms to take advantage of opportunities in AI and digital technologies. Through this instrument, a fund called *Industry Alignment Fund - Pre-Positioning* IAF-PP has been created, which represents a mechanism to finance research projects aimed at facilitating early partnerships between public researchers and private companies with the objective of ensuring that scientific discoveries are rapidly converted into innovative products and services. In addition, the plan encourages the expansion of academic centers of excellence specialized in AI, promoting interdisciplinary research programs that combine AI with other strategic sectors such as biomedicine, urban sustainability and advanced manufacturing.

Also, other initiatives related to research and development (R&D), including: (i) the promotion of the "Visiting Chair in AI" to attract top AI researchers and establish collaborations with Singapore; and, (ii) the investment of SGD $ 7 million in an Accelerated Master Program in AI, in collaboration with local universities, to develop a pipeline of Singaporean AI researchers (to reach 15,000 in 5 years).

7.3.2. Development of AI start-ups and implementation of the necessary infrastructure for training AI models

On the one hand, SGInnovate is an initiative of the Government of Singapore, whose core purpose is to develop and invest in Deep Tech startups that can have a global impact[43] . SGInnovate supports various branches and in recent years has placed particular strategic emphasis on Artificial Intelligence (AI), machine learning and data science. It also ties in with the country's digital transformation priorities. One of its key functions is investing in startups based on scientific and technological research, including the design, training and deployment of AI models. To this end, it manages and co-invests through the Startup SG Equity program, which corresponds to a public fund of SGD $200 million to support innovative ventures in strategic sectors, including AI[44]

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[42] Source: National Research Foundation Singapore. (2021). Research, Innovation and Enterprise 2025 Plan [PDF]. Retrieved in: https://file.go.gov.sg/rie-2025-handbook.pdf

[43] Source: SGInnovate. (2022). Emerging Tech Startup Landscape Report 2022. https://www.sginnovate.com/sites/default/files/gated_content_pdf/SGInnovate_Emerging%20Tech%20Startup%20Landscape%20Report%202022%20%281%29.pdf

[44] Source: Enterprise Singapore. (2024). Additional S$440 million in funding to drive growth of deep tech through partnerships with prominent global VCs. Retrieved in: https://www.enterprisesg.gov.sg/-/media/esg/files/media-centre/media-releases/2024/october/mr04424_additional-s%24440-million-in-funding-to-drive-growth-of-deep-tech-through-partnerships-with-prominent-global-vcs.pdf

SGInnovate also provides access to specialized networks, technical advice and infrastructure support for AI startups. In collaboration with entities such as the *National Supercomputing Centre* (NSCC) and cloud computing platforms, it facilitates these startups' access to processing-intensive resources needed for training machine learning models.

Along the same lines, the National Supercomputing Centre of Singapore (NSCC) is the country's first national supercomputing facility. According to its official website, its explicit mission is: "to provide high-performance computing (HPC) resources to support the advanced research needs of the public, academic and industrial sectors"[45] . In addition, it constitutes a critical infrastructure for training advanced artificial intelligence models, as it enables computationally intensive tasks necessary for training machine learning algorithms, deep learning and large-scale data modeling.

Another initiative is related to the National Multimodal Language Modeling Program (NMLP), which is a strategy endowed with an initial budget of SGD $70 million to develop research, engineering and deployment capabilities for multimodal large-scale language models (LLMs); that is, models that can simultaneously process text, images, audio and other types of data.

7.3.3. Implementation of general infrastructure (e.g., high-speed broadband) and advanced cybersecurity standards.

First, the Government of Singapore through the Ministry of Communications and Information and the regulatory authority (*Infocomm Media Development Authority* - IMDA) has conceived connectivity as an enabling right for its economy through the issuance of the *Digital Connectivity Blueprint* (DCB) strategy.[46] This document targets the expansion of 10 Gbps fiber links to all homes by 2030, based on the expansion of the national next-generation broadband network that reaches more than 95% of homes and businesses. This policy consolidates the first layer of infrastructure on which AI-intensive services and cloud computing are built.

On the other hand, high-speed mobile connectivity has materialized in the deployment of 5G Standalone networks. Mobile operators achieved population coverage of over 95% by the end of 2022, three years ahead of the official target. This ensures adequate bandwidth and latency for real-time artificial intelligence applications, connected vehicles and smart industrial environments.[47]

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[45] Source: National Supercomputing Centre (NSCC) Singapore. (s.f.). NSCC Singapore. Retrieved in: https://www.nscc.sg/

[46] Source: Infocomm Media Development Authority (IMDA). (2023). Singapore pioneers S$70 million flagship AI initiative to develop Southeast Asia's first large language model ecosystem. Retrieved in: https://www.imda.gov.sg/resources/press-releases-factsheets-and-speeches/press-releases/2023/sg-to-develop-southeast-asias-first-llm-ecosystem

[47] Source: Infocomm Media Development Authority (IMDA). (2023). Digital Connectivity Blueprint. Retrieved in: https://www.imda.gov.sg/-/media/imda/files/programme/digital-connectivity-blueprint/digital-connectivity-blueprint-report.pdf

Along the same lines, the national strategy incorporates the promotion of critical storage infrastructure that includes sustainability criteria. Thus, the government established the *Data Centre - Call for Application* program, through which 80 MW of new energy capacity was awarded exclusively to projects that demonstrate high-efficiency cooling and a predominant use of low-emission energy. In doing so, Singapore preserves its position as a regional data center hub without compromising its climate commitments.[48]

[49]On the regulatory front, the *Cybersecurity Act,* as amended in 2024, is a framework that promotes oversight of "critical digital infrastructure," which encompasses large public clouds, specialized data centers and critical service providers that host third-party AI payloads. The Act empowers the Cyber Security Agency (CSA) to conduct mandatory biannual audits on model governance and protection of training datasets; as well as impose criminal penalties for serious breaches, strengthening the resilience of the digital ecosystem against advanced threats. This strengthens the resilience of the digital ecosystem and reduces the risk of model manipulation or leakage of sensitive data during the AI lifecycle.

Likewise, the *Safer Cyberspace Masterplan* 2020 articulates a preventive strategy that makes use of AI-based analytics to detect anomalies in broadband networks and 5G cores. Within this framework, the *Cybersecurity Labelling Scheme* (CLS-IoT) introduces a four-tier label that obliges manufacturers of smart devices, which power machine learning systems, to demonstrate good security practices by design. Mutual recognition agreements with Finland, Germany and Republic of Korea have thus facilitated the creation of trusted supply chains for hardware powering AI applications.[50]

Finally, Singapore, through the launch of the *National Quantum-Safe Network*, has endowed SGD $23.5 million, for the preparation of cryptographic research to prepare for future quantum attacks, while the Digital Trust Centre (DTC) channels SGD $50 million to research in AI verification and algorithmic governance.[51] These initiatives strengthen the trustworthiness of the environment and make it easier for locally trained AI models to scale with guarantees of security and international compliance.[52]

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[48] Source: Infocomm Media Development Authority (IMDA). (2021). Next Wave of 5G Growth & Deployment in Singapore: Policy and Regulatory Design for 2.1 GHz Band. Retrieved in: https://www.imda.gov.sg/-/media/imda/files/regulations-and-licensing/regulations/consultations/2021/next-wave-of-5g-growth-and-deployment-in-singapore/imda-decision--21-ghz-policy-and-regulatory-framework.pdf

[49] Source: Singapore Parlement. (2024). Cybersecurity (Amendment) Act 2024 (No. 19 de 2024). Singapore Statutes Online. https://sso.agc.gov.sg/Acts-Supp/19-2024/Published/20240704?DocDate=20240704

[50] Source: Cyber Security Agency of Singapore. (2020). Safer Cyberspace Masterplan 2020. https://isomer-user-content.by.gov.sg/36/f085f3e2-dbe3-4427-a5ac-1f36de21c866/Safer-Cyberspace-Masterplan-2020.pdf

[51] Source: Channel News Asia

[52] Source: Infocomm Media Development Authority. (2024). Digital Trust Centre designated as Singapore's AI Safety Institute. Retrieved in: https://www.imda.gov.sg/resources/press-releases-factsheets-and-speeches/factsheets/2024/digital-trust-centre

7.3.4. Implementation of policies and governance conducive to AI adoption

In this area, Singapore generated a policy of early adoption of AI with the development of the National AI Strategy 1.0 (2019), in which the government committed resources for five national projects (transport and logistics, smart cities, health, education and security); it also articulated a governance system that includes the entire state; and, in which academia, companies and public agencies converge. [53]In four years of implementing the initiative, it has brought together nearly 150 research teams and supported the work of 900 startups exploring new commercial uses of AI.

Moreover, in December 2023, Singapore updated the National AI Strategy 2.0 (NAIS 2.0). $The new plan mobilizes more than SGD 1 billion to ensure sovereign access to advanced GPUs, train specialized talent and anchor sectoral centers of excellence. The governance model is based on a scheme where strategic leadership is articulated from the *National AI Office* (NAIO), created within the *Smart Nation and Digital Government Office* (SNDGO). This office sets the national agenda and synchronizes ministries, regulatory agencies and the private sector. At the operational level, applied research and talent training falls under the "*AI Singapore*" (AISG), which represents a national program funded by the *National Research Foundation* and acts as a link between universities and companies for the implementation of its pillars (AI Research, AI Technology and AI Innovation). [5455]With the emergence of the current strategy, the *Economic Development Board* SGInnovate anchor Centers of Excellence (CoE) within leading companies and, when appropriate, constitute sectoral CoEs that bring together "industrial champions", academic labs and startups around high-impact use cases. In this way, the government encourages access to incentives (grants, access to sovereign GPUs, public data) while each CoE assumes autonomy in research and development (R&D), intellectual property creation and product scaling.

Also, according to the first AI Strategy issued in 2019, the ethical governance and trust scheme is underpinned by several standing bodies. The *Advisory Council on the Ethical Use of AI and Data*, made up of leaders from industry and academia who advise the Executive on emerging risks and algorithmic accountability policies, while the *AI Ethics and Governance Steering Committee* of the Singapore Computer Society oversees professional certification on these issues. In parallel, the AI Verify Foundation (a public-private partnership hosted by IMDA) maintains the open-source AI Verify testing tool, which companies use to audit their models against 11 international principles, reinforcing transparency throughout the chain. This web of

[53] Source: Smart Nation and Digital Government Office. (2024). AI initiatives launched to uplift Singapore's economic potential and build a trusted AI ecosystem. Retrieved in: https://www.smartnation.gov.sg/media-hub/press-releases/20240301a/

[54] It functions as a permanent corporate laboratory: recruiting researchers, equipping GPU nodes, defining model roadmaps and sharing best practices with the rest of the corporate group and the national ecosystem.

[55] They are a collaborative variant, where the government and the *Economic Development Board* propose to create hubs not within a single company, but around entire value chains (advanced manufacturing, logistics, financial services, healthcare, etc.). There, several firms, research institutes and startups come together to solve a set of common use cases, share data and reuse models. The aim is to intensify value creation with AI in strategic sectors.

headquarters, corporate centers of excellence and multi-stakeholder committees allow public policy, R&D and regulation to move forward in a coordinated manner.

7.3.5. Development of competencies in AI workforce development training and professional upgrading.

Singapore promotes human talent in AI through the articulation of policies ranging from basic literacy to the training of researchers. [56]Thus, NAIS 2.0 sets the goal of reaching 15,000 "AI Practitioners" in five years; to this end, the redesign of the "*AI Apprenticeship Programme*" (AIAP) is proposed. In addition, industrial research links are being expanded with graduate fellowships and an accelerated Master program funded with SGD $7 million with the support of the *National Research Foundation* and autonomous universities. These initiatives aim to ensure professionals capable of conceiving, training and deploying advanced models in both corporate Centers of Excellence and sectoral CoEs.

On the other hand, the Government through IMDA in collaboration with industry, SkillsFuture Singapore (SSG), Workforce Singapore (WSG) and the National Trades Union Congress (NTUC) drive professional upgrading or re-skilling through the *TechSkills Accelerator* (TeSA) programs, which have fostered an ecosystem of professional conversion and intensive bootcamps that have already re-deployed more than 2,700 professionals in AI and data analytics roles. [57]In addition, the "*GetReadySG*" initiative conducted in partnership between Microsoft and Generation complements this offering with the aim of enhancing the skills and boosting the employment of up to 1,000 Singaporeans.

Considering non-technological profiles and with basic digital skills, the "SkillsFuture Digital Workplace 2.0" program offers two-day courses that introduce fundamentals of generative AI, analytics and IoT, ensuring that any worker can acquire concepts of AI tools applied to their job.[58] These actions are complemented by the "*Jobs Transformation* Maps" initiative produced by sector leaders from 23 industries. Each map identifies how AI alters tasks and skills in order to establish the specific courses that could be covered by the SkillsFuture program.[59]

Finally, it is important to note that Singapore will invest more than $20 million to enhance the training of AI professionals to boost "SG Digital" scholarships to students for three years and for Singaporeans to pursue undergraduate, master's

[56] The AIAP is designed as a 9-month, full-time, company-led in-depth skills training program that helps trainees acquire AI capabilities by working alongside industry teams on real business problems.

[57] Source: I Infocomm Media Development Authority. (2020). Microsoft and Generation partner Singapore Government to launch #GetReadySG to upskill and boost employment for up to 1,000 Singaporeans. https://www.imda.gov.sg/resources/press-releases-factsheets-and-speeches/press-releases/2020/microsoft-and-generation-launch-getreadysg

[58] Source: SkillsFuture Singapore. (n.d.). SkillsFuture for Digital Workplace. Retrieved in: https://www.skillsfuture.gov.sg/initiatives/mid-career/digitalworkplace

[59] They are roadmaps developed for 23 industries in six clusters to systematically increase productivity, develop skills, drive innovation and promote internationalization in order to catalyze transformation.

and doctoral degrees in AI and related careers at top universities. It also facilitates access to overseas internships in AI-related positions.[60]

[60] Source: Smart Nation and Digital Government Office. (2024). AI initiatives launched to uplift Singapore's economic potential and build a trusted AI ecosystem. Retrieved in: https://www.smartnation.gov.sg/media-hub/press-releases/20240301a/

8. CONCLUSIONS

The purpose of this study was to assess the economic contribution of artificial intelligence (AI) and cloud computing in the 11 Asia-Pacific economies analyzed, excluding the PRC and Hong Kong, China. AI as stand-alone technology (not including Generative AI) contributed on average US$ 179.7 billion during 2025 to the region's GDP. In turn, cloud computing as a stand-alone technology contributed US$ 156.4 billion to the annual GDP. The complementarity between both technologies was identified as a crucial source of economic value, yielding US$ 140.9 billion. Generative AI, in turn, contributed on average US$ 118.3 billion annually. After counting the shared component once, the combined contribution is US$ 595.3 billion, or 3.68% of the GDP of these economies.

The Asia-Pacific AI and cloud computing market is evolving fast, having reached US$ 117.3 billion and US$ 245.9 billion respectively in spending in 2025 (US$ 53.0 billion and US$ 150.2 billion if we exclude the PRC and Hong Kong). In turn, spending by Asia-Pacific businesses in purchasing AI technology from cloud service providers for 2025 amounts to US$ 10.2 billion (or 8.7% of the total AI market), having grown 44% with respect to the previous year. This CSP-delivered AI component forms part of the wider US$ 48.17 billion shared cloud-enabled AI spending component.

On the basis of the estimates presented above, the differential economic impact by country was calculated. Results indicate that countries that increase AI and Cloud spending will generate important economic gains, while on the other hand, economic spillovers depend on the complementarity between both technologies. From a sector viewpoint, the industries that are leading the adoption of cloud and AI in the region are information and communication, real estate, and professional, scientific and technical activities.

Accordingly, these results suggest that the countries which support a more proactive approach to cloud development will outperform in terms of AI economic impact. These results also demonstrate the importance of AI, cloud computing and cloud enabled AI for the economic development of the region, and the relevance of creating a policy and regulatory environment aimed at maximizing their impact. A relevant aspect to address is the still low adoption of AI, which should be accelerated to maximize its economic effects.

While some countries in Asia Pacific are developing sound policies, others need to promote reform frameworks that help them accelerate the adoption of cloud and AI technologies within the public and private sector organizations. The priorities include modernizing cloud procurement, enabling protected cross-border data flows, adopting flexible, risk-based AI regulation, investing in skills, and strengthening cybersecurity.

In particular, governments should focus on upskilling and reskilling the labor force that will be affected by the adoption of AI. Four of them are critical:

- Establishing clear metrics for assessing AI-related skills.
- Incorporating training in AI-centric skills taxonomies in education.

- Assessing/auditing the quality of existing "AI-readiness" training programs.
- Incentivizing employers and employees to participate in upskilling programs.

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APPENDICES

A. RESEARCH LITERATURE REVIEW

Three bodies of research literature have been identified as framing this study: (i) investigations of the economic impact of cloud computing; (ii) research on the contribution of AI to economic growth and productivity, and (iii) the analysis of technological complementarity between both technologies. The following review examines each area and relies on it to frame the current study hypotheses.

A.1. The economic contribution of AI

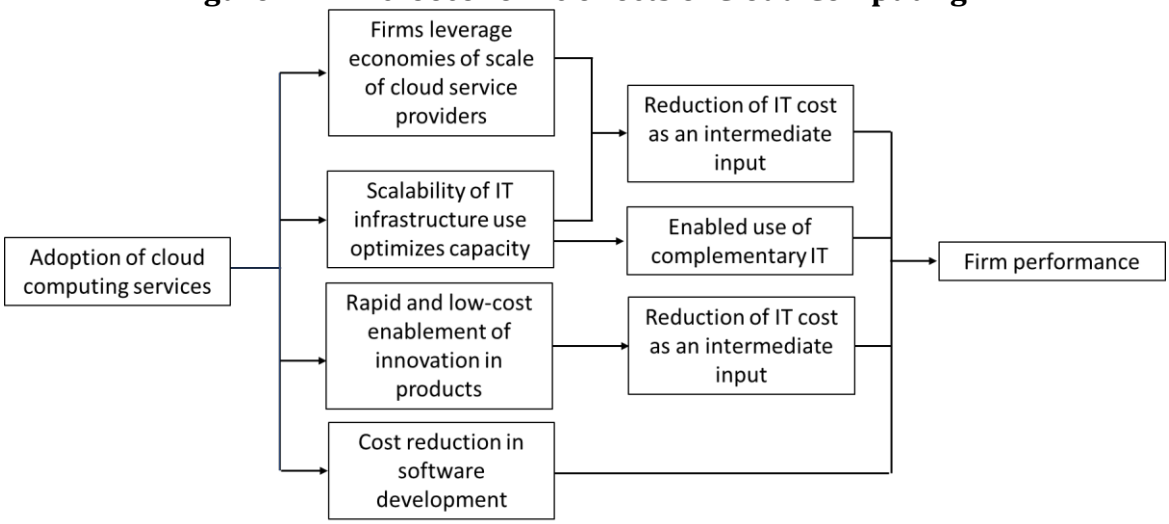
While research on the economic effect of AI has primarily focused on the impact on labor substitution (Acemoglu and Restrepo, 2018a; 2018b; Lane and Saint-Martin, 2021; Felten, Raj, and Seamans, 2023), studies have recently started addressing the contribution to productivity. Initially, such studies have been affected by the lack of firm AI adoption data. In fact, many studies measure the use of AI among firms by relying on proxy variables, such as job postings (Alekseeva et al., 2020, 2021; Babina et al., 2021), or patent registration data (Damioli et al., 2021; Alderucci et al., 2020.; Yang, 2022). For example, Alderucci et al. (2020) measure the intensity of AI patent grants in the US as a metric of firm AI innovation. They found that this metric is positively associated with firm growth and labor demand. Firms with high level of AI innovation appear to have 25% faster employment growth and 40% faster revenue growth than the rest of firms in the sample. A consistent conclusion is generated by Bessen and Righi (2020). The metric they rely in this case is large custom software investment and estimate that these events are associated with 7% increase in employment and 11% in revenues. While still affected by the paucity of data, other studies have emphasized innovations in their empirical approach. For example, Lu (2021) relies on a three-stage endogenous model where AI is assumed to have the capability to accumulate through resource allocation and based on the elasticity of substitution between labor and capital. The study concludes that if the accumulation of AI leads to a rising productivity in the firms, the technology drives a positive contribution to economic growth.

More recent studies on the economic impact of AI have benefitted from the availability of data captured in national surveys. For example, Czarnitzki, Fernandez and Rammer (2022) built a classical production function incorporating AI adoption as another term and implemented an instrumental variable approach within a two-stage regression to control for endogeneity. Data on AI adoption was captured from a panel survey of German firms for 2018. In this case, the authors found positive and significant effects in the range of 6% and 4% caused by the increase of the use of AI on German firms' productivity, when measured by sales. That being said, the impact of AI on productivity based on national statistics of AI adoption has not always consistently proven to be positive. Song and Cho rely on AI adoption in Korean firms, according to Statistics Korea data for 2017 and 2018, and implement OLS and IV models. Recognizing that their approach could be limited by small sample size and endogeneity, the authors conclude that not all firms exhibit productivity improvements as a result of AI adoption although multi-plants firms appear to benefit from efficiency gains.

A.2. The economic impact of Cloud Computing

Cloud Computing is a crucial contribution to firms' digitization process, through several internal effects that can be summarized as depicted in Figure A-1.

Figure A-1. Microeconomic effects of Cloud Computing



Source: Telecom Advisory Services

Supported by cloud computing, the provision of IT-based services has experienced a significant transformation. The ability to share and access computing resources such as servers, storage areas, and network service applications remotely with high reliability and scalability is one of cloud computing's primary advantages (Park and Ryoo, 2013; Ebadi and Jafari Navimipour, 2019; Naseri and Jafari Navimipour, 2019; Khayer et al., 2020; Vu et al., 2020). Moreover, these computational resources can be accessed online at a minimal additional cost thanks to cloud technology. This means that businesses will not have to spend significant resources developing their own infrastructure.[61] As a result, firms that use cloud services can gain from advantages like cost savings, flexibility, and scalability. Businesses can also automatically scale software and storage in response to load by utilizing cloud computing, which helps them save resources (Armbrust et al., 2010). Spending less on resources improves a company's margins and, as a result, its monetary value, which is, in turn, translated into economic contribution.

Moreover, SaaS cloud services can have a potential impact on firm-driven ICT-enabled innovation (e.g., product development) (Chou et al., 2017; Kathuria et al., 2018; Chen et al., 2022), although the effect appears to be modest, according to some authors (Loukis et al., 2019; PWC, 2021).

Lastly, the economic impact of cloud services on software development is expected to be significant. According to Byrne et al. (2018), software development work is made easier when cloud vendors implement technologies that allow them to create

[61] In the past, businesses had to build their own data centers, acquire the necessary hardware and software, and hire skilled personnel to manage them when cloud computing was not commercially available. This limited the benefits of this technology primarily to large companies.

products "higher up the stack" and provide services with higher abstractions. This is because companies can now concentrate solely on writing code and deploying it, which reduces development costs. This ultimately results in increased margins and possibly higher sales.

Initially, the empirical research on the economic effects of cloud computing concentrated on firm-level analysis and frequently on specific economic sectors. These studies gauged the performance of the company using a variety of factors, including financial indicators, productivity, and innovation. Schniederjans and Hales (2016) used transaction cost economics to examine how cloud computing facilitates supply chain cooperation and enhances businesses' financial and environmental performance. The authors gathered survey-based information from 247 supply chain and IT professionals, and they used structural equation modeling (SEM) to demonstrate how cloud computing can improve business performance and foster greater cooperation among supply chain participants. Similarly, Loukis et al. (2019) found that SaaS cloud technologies' operational and innovative benefits have a positive impact on business performance, leading to enhanced operations and higher rates of innovation. The study surveyed 102 Dutch firms, identifying the significance of a firm's absorptive capacity, defined as its capacity to identify, obtain, and assimilate important new knowledge from the external environment. Interestingly, Chou et al. (2017) discovered a positive correlation between cloud adoption and service innovation after analyzing data from 165 companies across a range of Taiwanese industries, including IT, travel and tourism, finance, and banking. Bolwin et al. (2022) measured the effect of AWS cloud computing on business performance through a comprehensive survey of 1,504 German companies. By extending the survey findings to all businesses, they calculated that 1.25 million German enterprises depend on the cloud, generating 11.2 billion euros in additional value growth using AWS technologies.

The goal of another research body has been to understand the factors that enhance cloud computing's influence on firm performance. Garrison et al. (2015) used SEM to analyze a survey of 302 Korean firms, determining that the impact of cloud computing on firm performance is positively influenced by managerial, technical, and relational IT capabilities, with managerial capability having the largest impact. On a global scale, Chen et al. (2022) estimated the relationship between cloud computing and firm-level performance metrics (e.g., ROA and Tobin's Q) using Difference-in-Difference econometric techniques on a world sample of firms from 2010 to 2016. Their analysis revealed a positive correlation, indicating that firms adopting cloud computing experienced significantly improved profitability and market value. The authors also identified variations in the impact of cloud computing on performance based on industry type and firm size, with manufacturing firms showing greater profitability gains after adopting cloud services compared to service firms.

Complementing the research on the economic contribution of cloud to firm performance, the focus has moved to understanding the impact at a macroeconomic level. Gal et al. (2019) estimated the impact of cloud computing (among other

technologies) on multifactor productivity[62] growth for a sample of 20 European countries, applying a combination of firm-level and industry-level data to a Neo-Schumpeterian growth approach that links innovation and technology diffusion. Their results suggest that a 10-percentage point increase in adoption of cloud computing would translate into an increase in multifactor productivity growth by 0.9 percentage points. PWC (2021) studied the effects of cloud computing on productivity in Indonesia, by applying a methodology based on Yusuf (2020). Their research uses a recursive-dynamic multi-regional computable general equilibrium model and applies sector-specific labor productivity shocks to it, representing the effect of the new technological changes on the economy. Overall, they estimated that the cumulative productivity benefit to the Indonesian economy of cloud adoption will be US$ 10.7 billion over the period 2021 - 2025.

The authors of this study have produced several studies estimating the economic impact of cloud computing in the Middle East and North Africa (Katz and Jung, 2023a), Sub-Saharan Africa (Katz and Jung, 2023b), and Southeast Asia (Katz, Jung and Berry, 2024). All studies rely on a 3-stage least squares model incorporating cloud adoption as a term in a production function, measuring the impact on GDP growth. Cloud's contribution is verified in all studies through a positive and significant elasticity coefficient of cloud adoption ranging from 0.299 to 0.271.

A.3. Technological complementarity between AI and cloud computing

The ability of cloud computing to scale IT infrastructure also makes it easier for businesses to use other cloud-enabled technologies like big data, AI machine learning, and the Internet of Things. Because these technologies allow for a fundamental transformation of business management practices, they play a significant role in some of the economic impact that digitization generates.

Despite the above-mentioned advances in the research literature, there is still a lack of analysis regarding the role of cloud computing and its complementarity effects with other cutting-edge technologies. Cloud service providers might offer database management software, content delivery, analytics (which might include real time video and data streams analysis, and using third party data), machine learning (including deep learning inference, identifying insights and relationship in text), and security applications. Because of that, cloud computing and AI can be conceptualized as complementary technologies.

Complementarity has been initially studied as an enabler of interdependencies supporting the stimulation of demand for capital goods. This effect operates in the technology field at two levels: (i) a given technology enables the production of another one by lowering manufacturing and distribution costs (Dosi et al., 1990; Schmookler, 1966), and (ii) one technology addresses bottlenecks in the diffusion and adoption of a second one (Rosenberg, 1976). The first effect focusses on reducing the cost of intermediate inputs, while the second one addresses user needs.

[62] Multifactor productivity is a measure of economic performance that compares the amount of output to the amount of combined inputs, which includes labor, capital, energy, materials and purchased services.

The study of sector interdependencies has been extended to address the complementarity within value chains (Mäkitie et al., 2022). The authors analyze three mechanisms by which complementarity emerges: (i) **synchronization**, which depicts "the simultaneous and mutually supporting development between the input and user sectors in a technology value chain"; (ii) **amplification**, where a technology accelerates the adoption of a another one; and (iii) **integration,** whereby technological advances in one sector spill in accelerating the development and adoption of technology in another one. In particular, the principle of "amplification" is defined as follows:

> *"Diffusion of a novel technology in a user sector creates demand for products and services in the input sectors of the [technology value chain], making it imperative that input sectors are scalable enough to ensure a balance between supply and demand. Thus, economies of scale may emerge, driving further development and deployment in the user sector due to reduced costs, network effects, and increased availability of necessary services and products." (p.9)*

The case under study of complementarity between cloud computing, and AI appears to be a clear example of amplification. Each technology was developed independently, although their combination acts as a multiplier of demand and impact.

Beyond the direct impact it may generate, cloud is also expected to enable infrastructure for the use of other technologies such as AI and machine learning, which in turn, should positively influence output. This has been highlighted by Pop (2016), who argues that since machine learning is a resource-consuming task, cloud computing can provide valuable alternatives to speed-up the execution times. In turn, Omurgonulsen et al. (2021) emphasizes the increasing adoption of AI in cloud computing and the challenges associated with equipping workers with the necessary skills to make the most of it. The study also underscores the importance of ensuring enough security measures and compliance requirements before deploying cloud-based AI services.

Soni and Kumar (2022) discuss the integration of machine learning techniques in emerging cloud computing paradigms, emphasizing the study of "intelligent" AI systems. This research presents a detailed taxonomy of AI and cloud computing integration, highlighting the potential for enhanced performance through the combination of these technologies. Furthermore, Collins et al (2021) provides insights into the strategic potential of AI, emphasizing the importance of organizational resources, including technical and non-technical aspects, to fully exploit the benefits of AI. Their study also mentions the provision of infrastructure for machine learning in the cloud by large companies, such as Google, Amazon, and Microsoft, further underlining the integration of AI and cloud computing (Enholm et al, 2022). Additionally, El Khatib et al. (2019) presents a case study on the integration of cloud computing with AI in the telecommunications sector, highlighting the benefits of leveraging cloud services with network function virtualization (NFV) and machine learning to improve customer experience and

operational efficiency. The study emphasizes the correlation between cloud computing and AI, showcasing their interrelated nature and the support they provide to enhance agility, deploy services faster, and improve operational intelligence.

Complementarity between cloud and other technologies has already been studied by the authors of this research. In a study of economic spillovers of cloud computing in OECD countries, Katz and Jung (2023c) determined empirically that the economic impact of cloud computing depends on fixed broadband adoption. To estimate cloud economic spillovers, the authors combine high speed broadband and cloud adoption in a production function estimating gross value added and productivity. The results suggest that broadband effectively enhances cloud's economic contribution. In a similar vein, Katz, Jung and Goldman (2023) studied the economic impact of cloud computing, big data and machine learning in Israeli firms. By relying on SEM, the authors determined that cloud computing indirectly leads to more reliance on machine learning and big data applications, although the impact of these technologies on productivity is only positive and significant for large firms.

In summary, the literature review findings underscore the potential of integrating cloud computing and AI to enhance firm-level performance, emphasizing the need for skill development, security measures, and the strategic utilization of organizational resources to fully exploit the benefits of this integration. However, despite these theoretical arguments in favor of the complementary nature of both technologies, empirical research is still lacking in this field.

A.4. Conclusions of research literature review

The review of the research literature has highlighted the progress and opportunities for further development (see table A-1).

Table A-1. Research on the economic impact of cloud computing, AI and their complementarity: Progress and development of opportunities

	Progress	Development for further research
Economic impact of AI	• Impact of AI on labor substitution/creation • Link between AI adoption and firm productivity, albeit for multi-plant firms • Association between AI adoption and revenue growth	• Impact of AI on aggregate firm performance indicators (e.g., sales growth and profitability) • Impact of AI on GDP growth and productivity based on national industrial statistics
Economic impact of cloud computing	• Contribution of cloud to firm performance (productivity, product development, IT cost efficiency, profitability) • Impact of cloud on GDP growth in high- middle- and low-income economies	• Factors driving differential GDP impact of cloud within sub-sovereign geographies in high income economies
Complementarity between AI and cloud computing	• Precision in the definition of complementarity between cloud and AI (resource optimization, time required for product development) • Economic impact of cloud computing, big data and machine learning on firm performance	• Marco-economic impact of the complementarity of AI and cloud computing

In summary, this study will address the gaps in the research literature along the following objectives:

- Understand the bases of differentiated cloud economic contribution within countries
- Base analysis in panel data derived from reliable databases on AI and cloud adoption in enterprises
- Impact of AI on GDP growth based on national industrial statistics
- Focus the empirical strategy on exploring the complementarity between both technologies

Appendix B. Countries included in general econometric model

- Argentina
- Australia
- Brazil
- Canada
- Chile
- China
- Colombia
- France
- Germany
- Hong Kong
- India
- Israel
- Italy
- Japan
- Republic of Korea
- Mexico
- Peru
- Russia
- Saudi Arabia
- Singapore
- South Africa
- Spain
- Turkey
- United Arab Emirates
- United Kingdom
- United States

Appendix C. ChatGPT use indicators (monthly averages)

Country	ChatGPT visits (in million)	ChatGPT unique users (in million)	ChatGPT visits per inhabitant	ChatGPT unique users per inhabitant
Argentina	22.927	4.453	0.503	0.098
Australia	30.637	7.268	1.149	0.273
Brazil	134.556	25.642	0.637	0.121
Canada	45.006	7.830	1.122	0.195
Chile	16.125	2.977	0.820	0.151
China	45.763	10.402	0.032	0.007
Colombia	38.840	5.987	0.742	0.114
France	43.722	8.377	0.640	0.123
Germany	56.480	13.162	0.678	0.158
Hong Kong	4.390	0.915	0.583	0.121
India	237.747	55.227	0.165	0.038
Israel	7.191	1.896	0.737	0.194
Italy	27.776	7.032	0.471	0.119
Japan	47.983	11.886	0.385	0.095
Republic of Korea	28.763	9.087	0.556	0.176
Mexico	48.013	8.832	0.370	0.068
Peru	25.343	4.540	0.749	0.134
Russia	14.625	5.150	0.102	0.036
Saudi Arabia	8.705	3.340	0.262	0.100
Singapore	13.765	3.110	2.326	0.526
South Africa	10.954	2.629	0.173	0.042
Spain	42.974	9.706	0.889	0.201
Turkey	20.767	6.504	0.243	0.076
United Arab Emirates	10.619	2.285	1.013	0.218
United Kingdom	58.735	11.437	0.859	0.167
United States	319.501	77.396	0.954	0.231

Source: Semrush; Telecom Advisory Services analysis

Appendix D. Cloud Policy Index

Country	Index	Pillar 1: type of Cloud platform	Pillar 2: Hosting policy	Pillar 3: Cybersecurity
Australia	2.00	2	2	2
India	1.67	1	1	3
Indonesia	1.67	1	1	3
Japan	2.67	3	2	3
Republic of Korea	2.00	2	1	3
Malaysia	2.00	2	1	3
New Zealand	1.67	2	2	1
Philippines	2.00	2	2	2
Singapore	2.67	3	2	3
Thailand	2.67	2	3	3
Viet Nam	2.00	2	1	3

Source: Telecom Advisory Services analysis

Appendix E. AI Policy Index

Country	Index	R&D and Academic Strength	AI Industry & Advanced Tech Infrastructure	Digital Infrastructure & Security	AI Governance & Policy	Education & Skills
Australia	55.55	40.58	49.38	92.32	29.26	66.22
India	32.06	7.23	25.96	55.77	21.08	50.24
Japan	55.54	32.82	55.93	96.87	62.04	30.04
Republic of Korea	60.86	55.20	56.28	100.00	70.64	22.16
Singapore	76.94	79.79	100.00	99.82	25.41	79.69
Indonesia	23.97	6.28	9.97	59.88	21.00	22.72
Malaysia	38.00	14.22	11.97	81.17	48.80	33.84
New Zealand	41.25	21.67	31.29	77.51	22.40	53.39
Philippines	22.31	2.71	9.98	59.06	21.00	18.78
Thailand	31.47	8.99	12.52	75.40	41.00	19.45
Viet Nam	31.09	4.86	11.14	99.66	21.00	18.80

Source: Telecom Advisory Services analysis

Appendix F. Robustness check – 3SLS estimation of labor demand using AI regressor in lags

Dependent variable:	Log (Skilled)	Log (Unskilled)
Log (AI spending)	0.13005***	-0.12441***
	[0.04107]	[0.03175]
Income	-0.00001	0.00000
	[0.00000]	[0.00000]
GDP growth (%)	0.24228**	0.08615
	[0.11940]	[0.09232]
Investment	-0.00207	0.00173
	[0.00653]	[0.00505]
Openness	0.00130	-0.00160
	[0.00150]	[0.00116]
Industry	0.01901	0.00596
	[0.01472]	[0.01138]
Services	0.00289	0.00051
	[0.00680]	[0.00526]
Country FE	YES	YES
Year FE	YES	YES
Observations	97	97
R-squared	0.985	0.927

*Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses*
Source: Telecom Advisory Services analysis