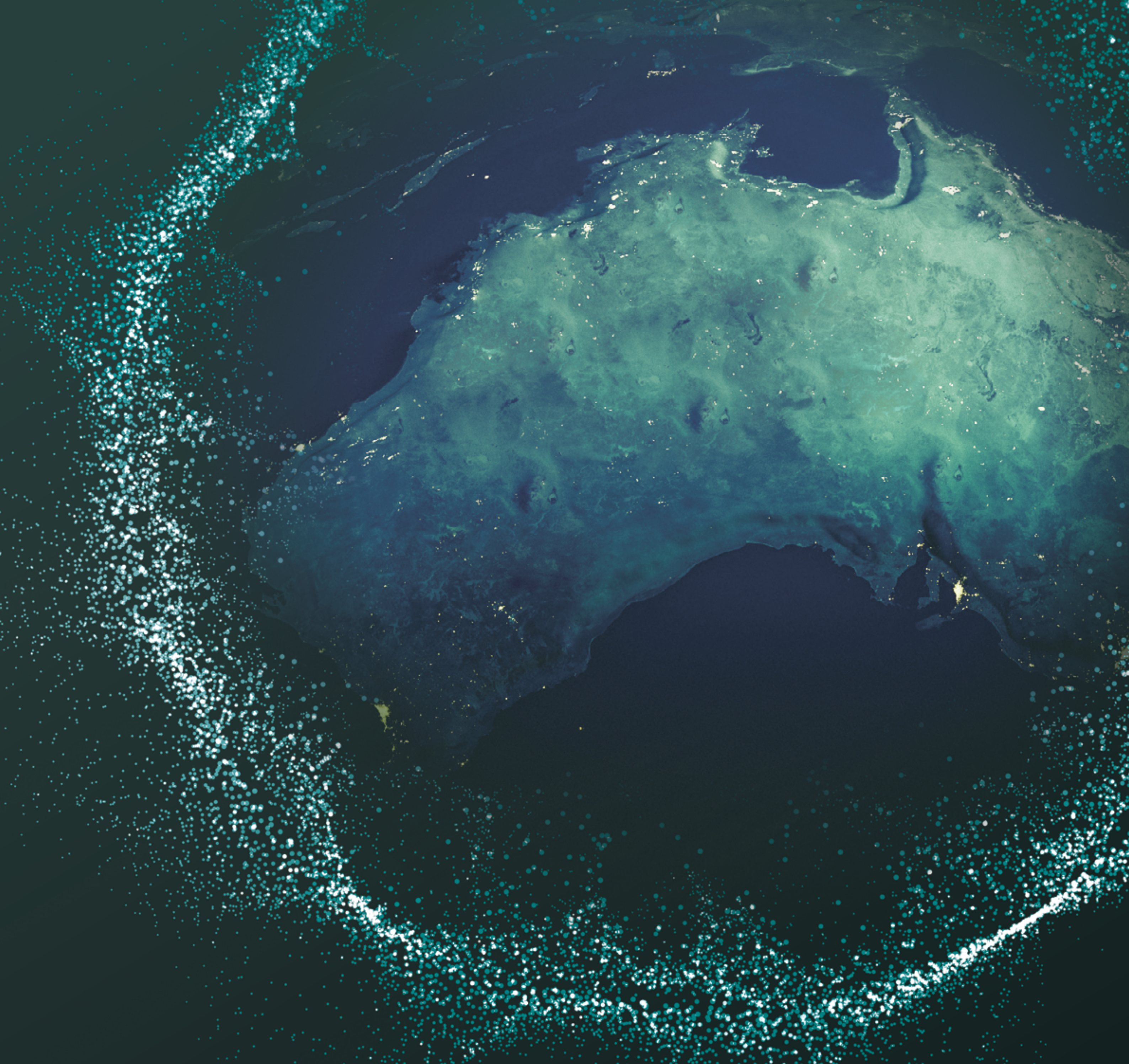

Australia's AI **Opportunities**

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acs.org.au

aiia Australian Information Industry Association

BCA Business Council of Australia

COSBOA Council of Small Business Organisations Australia

Women in Digital

This research report has been prepared by Shahar Merom for the purpose of providing information and insights on the economic potential of AI in Australia.

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WOMEN IN DIGITAL

Executive Summary

Artificial Intelligence (AI) will offer transformative economic opportunities for Australia. The critical choice for Australia today is which of these economic opportunities does Australia want to realise.

The purpose of this report is to articulate and model the three main economic opportunities Australia could realise from AI to inform the choice about the future Australia wishes to aim for. It leverages original research, generative AI for data classification, and stakeholder consultations with over 40 representatives from a wide range of industries and industry bodies including technology, data centres, governments and small businesses. The research was overseen by an independent advisory committee of five industry bodies heavily involved in Australia's AI opportunity.

The opportunities examined in the report are:

1. **AI adoption:** Where Australia is primarily an adopter of AI technology across industries, leading to increased labour productivity
2. **Developing Domestic AI capabilities:** Where Australia captures value in the supply chain, to deliver AI products and services domestically
3. **Becoming a Regional Hub:** Where Australia strives for regional leadership, and aims to become an exporter of AI products and services

The report finds that if Australia aims for all three of these opportunities, it could add $142bn per annum to the Australian economy by 2030.

We estimate that adopting AI across industries could add up to $112bn to the economy by 2030, with the gains largest in Australia's industries with the lowest productivity. As AI diffusion is possible across industries, it would have broad-based benefits, spurring average wage growth of 7% across industries and alleviating workforce shortages in critical areas such as the care sector by freeing up time for high-value activities. Women would be especially likely to see wage gains, as they are more likely to work in occupations that benefit from AI adoption. Small businesses would also be winners, experiencing productivity uplifts up to 22% greater than for large businesses, because small businesses are concentrated in industries with some of the highest potential for AI-led productivity gains.

However, focusing solely on benefits from AI adoption would see Australia miss an additional $30* billion in economic activity.

Doubling-down on building new AI sovereign capabilities in AI compute and applications could add an extra $18 billion to Australia's economy by 2030. Becoming a regional AI Hub in the Asia Pacific could add a further $11bn per annum, with Australia particularly competitive in exporting compute and education.

These opportunities play to Australia's competitive advantages in data centre infrastructure due to its large landmass, access to renewable energy, and stable political system. Australia could also be competitive in AI applications, leveraging its emerging new crop of AI start-ups and base of already established, globally successful software companies, and Australia's high-quality research and education system.

They would enable innovators and researchers to make new discoveries and to build new businesses, products and jobs. It would improve Australia's global and regional competitiveness, and create new export markets and opportunities. They would also bring non-quantifiable benefits, including improving Australia's national security, gaining greater agency over sensitive data and applications, and improving economic and supply chain resilience. Using AI in citizen services could see better outcomes and high public value as long as implemented with appropriate guardrails in place.

While Australia is well-positioned to realise each of these opportunities, they will require concerted action to achieve. This includes investment in new data and compute infrastructure and AI research, workforce skills and training initiatives, and ensuring the development of safe, responsible and democratic AI applications that support public trust and confidence. With coordinated action across government, industry, and education, Australia can position itself as a trusted, capable, and regionally significant AI economy by 2030, securing long-term productivity and inclusive growth.

Key Data Points

By 2030, AI could deliver annual benefits worth*

$142bn p.a.
In Economic value

$112bn p.a.
In gains through adoption

$18bn p.a.
domestic AI industry

$11bn p.a.
In export opportunities

AI will deliver benefits across the entire economy

7%
Wage growth across the economy

35%
Higher wage growth for women

6%
Productivity uplift in benefitting industries

22%
Greater productivity gains for small businesses

* totals can differ from components sums due to rounding errors

AI presents a $142 bn p.a. economic opportunity for Australia by 2030

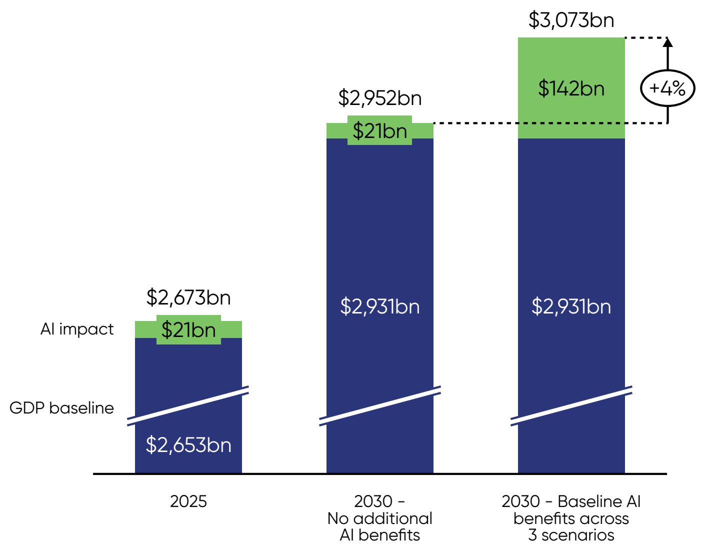
Today, the Australian economy is benefitting by up to $21bn p.a. through increased labour productivity in select areas, by using AI for tasks such as proofing documents, ideation, or more efficient search. This is equivalent to every worker in Australia benefitting by up to an additional $7 of value per day. This figure is consistent with macroeconomic data in the US which shows one-in-five Americans are using generative AI at work, allowing them to complete a week's work 2.2 hours faster.[1]

By 2030, Australia could increase the value it gains from AI by 7x, with annual benefits worth up to $142bn. Australia can do this by realising three significant economic opportunities related to AI that Australia is well-placed to capture:

- **Broad-based AI adoption:** Benefits that come from Australian businesses across many industries integrating AI into their business models.
- **Developing domestic capabilities:** Benefits accruing to a domestic AI industry delivering compute and AI applications.
- **Becoming an AI regional hub:** Benefits from becoming an export hub for regional neighbours and for training compute.

Australian economic opportunity from AI opportunities

Australian GDP, Constant 2025 $bn, 2025-2030



Source: ABS, O*Net data, Author's analysis
totals may differ due to rounding

Growing the local AI industry and becoming a regional hub adds $30bn p.a. to the economy

Most estimates of the economic opportunity related to AI in Australia focus exclusively on benefits from AI adoption that lift productivity. This opportunity is certainly significant - worth up to $112bn pa by 2030. It's also timely, with labour productivity in Australia stagnating at 0.7%p.a. since 2020[2].

However, Australia could realise a further $30bn p.a. by also targeting two additional opportunities Australia is well-placed to seize. Firstly, Australia can play to its competitive advantages to build sovereign domestic AI capability in key areas such as data centre compute and AI software and applications. This could be worth an additional $18bn p.a.

A further $11bn in benefits can be realised through exporting AI products and services, including education, AI applications and computational power. If Australia develops these export capabilities, there is also significant upside across many of these markets, as these figures are based on Australia accounting for under 1% of global compute needs, compared to Australia's contribution to global economic activity of ~1.7%.

> ***"Application development, education and training, these are the sorts of things that we've been very good at for a long time… that competitive advantage is going to have some linkage to the adoption of AI" - Workshop participant***

Australia can realise an extra $30bn per annum from AI opportunities in addition to AI productivity gains

Annual GVA contribution of AI, Constant 2025 $bn, 2030

Source: ABS, O*Net data, Author's analysis
totals may differ due to rounding

Adoption benefits will flow to women and small businesses

The benefits of AI adoption are likely to flow to workers at a higher rate than the rest of the economy. While AI could lift GDP by 4% by 2030, wages could increase by 7% overall, as less capitalised industries will experience higher productivity gains, which will flow through to workers.

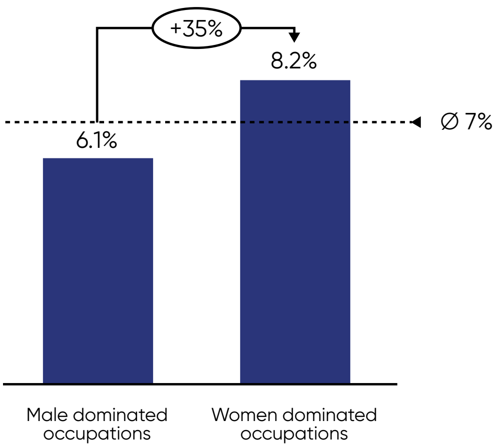
The benefits will disproportionately flow to key groups with lower wages: women will experience 35% higher wage growth, and small businesses will experience 22% higher productivity growth between 2025-2030.

Communities also stand to benefit from AI adoption by the public sector, with a range of potentially beneficial use-cases for citizen services, e.g. using real-time AI systems to monitor street parking. Such use cases also present new opportunities for value creation, such as the provision of real-time capacity data to citizen applications.

"Women will experience 35% higher wage growth, and small businesses will experience 22% higher productivity growth between 2025-2030."

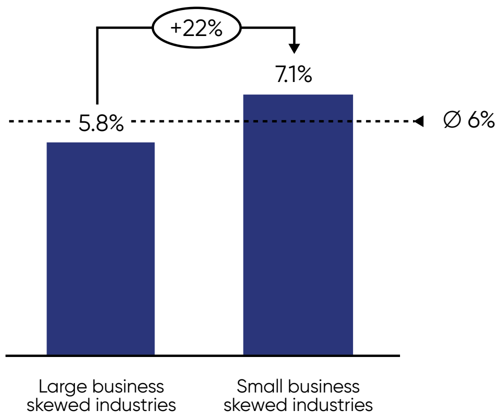
Wage growth from AI by gender

Projected wage growth by occupation gender skew, %, 2025-2030



Productivity increase by business size

Projected productivity growth by business size skew, %, 2025-2030



Source: ABS data, O*Net data, Author's analysis

AI adoption will primarily benefit low productivity industries

Industries with lower labour productivity are generally more likely to benefit through AI adoption. This means AI will have significant impact in areas that are highly labour intensive. These include public sector focused industries, export services and the health and care sector. Lifting productivity in these sectors is critical given they are significant contributors to stagnating productivity growth (e.g. Professional, scientific and technical services experienced a 2.4% multifactor productivity decline in 2023-24)[2].

For example, in health and social services, productivity benefits from AI could reach 7% by 2030, which could help alleviate significant workforce shortages that impact 50%-70% of occupations in these industries.

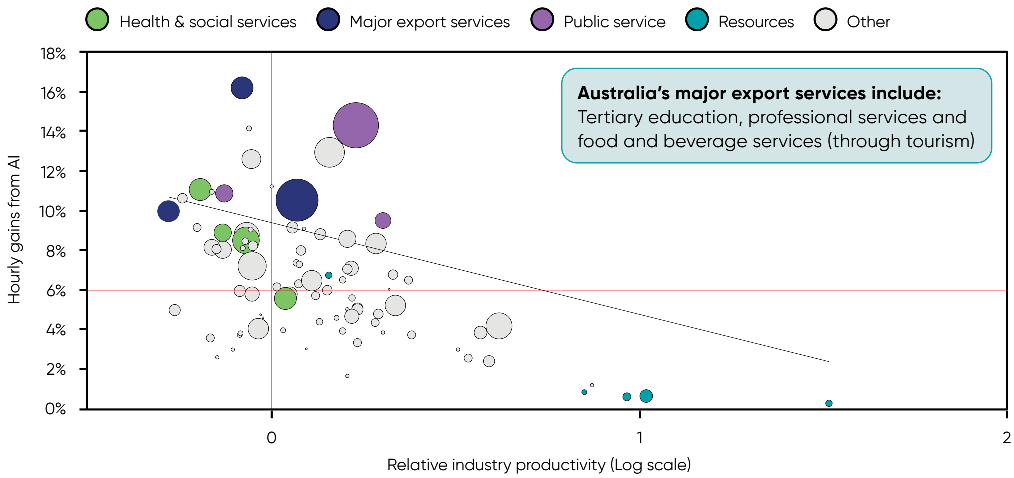
On the other hand, traditional Australian strengths such as resources are proportionally less likely to benefit from AI for several reasons:

1. Resource businesses have already experienced benefits, being early adopters of AI
2. Resource industries are highly capitalised, mean labour productivity improvements have smaller relative impacts
3. The resources sector benefits are still significant ($2bn p.a.) but small relative to the current GVA of the sector.

Overall, the labour productivity enhancing impacts of AI are less pronounced in industries that are already heavily capitalised.

Adoption opportunity benefits – Industry productivity vs. benefit intensity

X-axis: Relative industry productivity, log-index (median = 0), 2030
Y-axis: Productivity benefit from AI adoption, %, 2025 - 2030
Bubbles represent industries, Size indicates scale of benefit potential, red lines reflect median values



Source: ABS, O*Net data, Author's analysis
totals may differ due to rounding

Developing Australian AI capabilities could capture an additional $18bn of GVA by 2030

To enable AI adoption benefits, Australia will need to either import or develop homegrown AI capabilities in compute and AI product development. This itself presents an opportunity for Australia of $18bn p.a. by 2030.

Australia should aim to domestically host the required compute for the nation's needs - worth an estimated $6bn p.a. - which will help assure control over Australian data and ensure Australia maintains low latency for AI inference production.

However, most of the benefits ($12bn p.a.) for a domestic AI industry would accrue to businesses that develop user-ready AI products and services using AI inferences as inputs.

This layer of the supply chain will be competitive, but if Australia develops a domestic AI product/service at similar rates to domestic software development, Australia will capture most of the benefits in this layer.

Australia can increase exports by $10.6bn through applications, compute and education

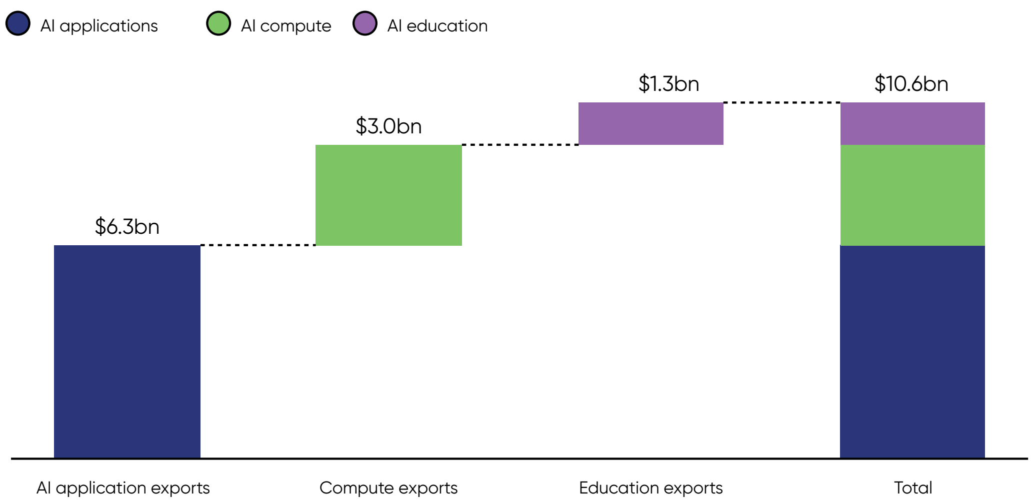
The third economic opportunity requires Australia to develop sufficient domestic capabilities to become a regional technology hub. If an Australian AI industry can match its software exporting capabilities, Australia could generate $6.3bn p.a. in GVA through AI exports.

Australia also has the potential to generate additional export value through providing compute to Asia-Pacific neighbours for regular business use, or compute for global training loads for frontier model developers. This market could be worth $3bn p.a. to Australia.

Lastly, Australia can build on its strength in education exports. Since 2022, Australian international enrolments in AI specific higher education degrees has grown by 69% p.a., from a nearly 700 in 2022, to 3,300 as at 2025. By 2030 this market could be worth $1.3bn p.a., with significant growth potential for future years.

Australian export opportunities through AI

GVA by export opportunity area, Constant 2025 $bn, 2030



Source: ABS, Department of Education data, Author's analysis
totals may differ due to rounding

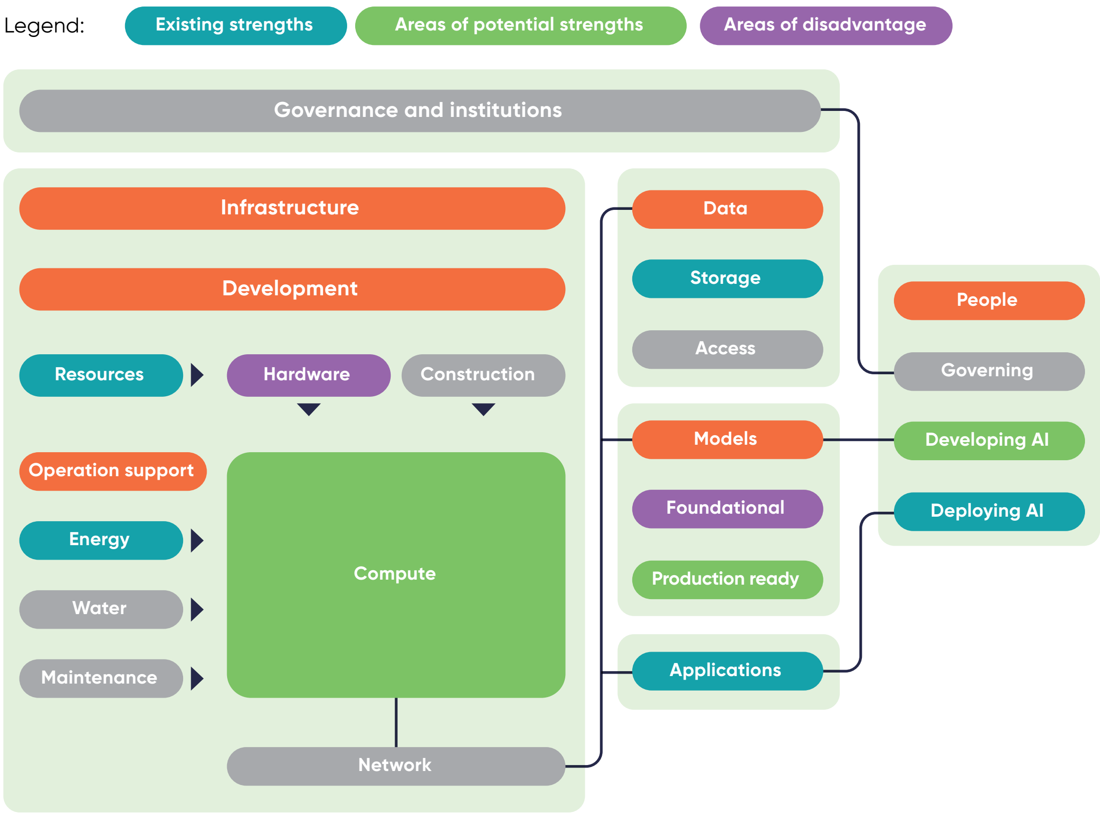
Australia will need to either secure supply, or build capacity to realise AI benefit potential

Securing benefits from AI will require access to key components of the value chain as well as supporting infrastructure, governance structures, data, models and a skilled workforce.

Australia already has significant strengths in parts of the AI value chain. This includes data centre infrastructure, where Australia has available land, comparatively affordable renewable energy and skilled operators, and AI applications, building on Australia's successful start-up and software industry.

Australia is currently less competitive in areas such as hardware and foundational models. However, Australia may be able to identify segments where it can specialise, e.g. in the intersection between quantum hardware and data centres, in the development of narrow, finetuned or lightweight foundational models in areas where Australia has domain strengths, and/or in the development and curation of locally representative and significant datasets and the models trained on them.

AI capabilities supply chain



Supporting requirements

In addition to developing AI capabilities, Australia needs to ensure **enabling infrastructure** can deliver on needs, including energy delivery for operation, **water infrastructure** for cooling, **low latency & high bandwidth network** that can handle data transmission needs between servers and clients, supported by appropriate data access that balances privacy needs with usability.

Australia faces five key barriers to realising benefits from AI

Developing the necessary capabilities without having the appropriate supporting capabilities in place will prevent Australia from realising many of the outline benefits. This report has identified five key barriers to benefit realisation:

1. Australia needs to develop clarity around which capabilities it wants to cultivate.
2. Growing infrastructure needs: increasing model complexity driving compute demand: Australia's compute capacity needs to increase by 50% compared to the current pipeline to serve export markets. This will require investment in supporting infrastructure such as energy, and network transmission
3. A need to upskill and improve AI literacy, with high skill workers needing to spend significant hours interacting with AI products and services.
4. Addressing a decline in AI research and development activity with Australia under-performing Asian neighbours in model development
5. Building public trust and confidence in safe, responsible and democratic AI tools and use cases.

1	**Defining clear strategy and vision**	Australia will need to develop a clear vision for where in the value chain it wishes to specialise, attract investment and build domestic capabilities
2	**Growing Infrastructure needs**	AI adoption may require an additional $14bn in data centre infrastructure to serve export opportunities. Australia will need to consider supporting infrastructure through timely planning approvals, access to energy needs and supporting fibre networks
3	**Upskilling and AI literacy needs**	The Australian workforce will need to significantly upskill, with managers needing to interact with AI for up to 44% of their work hours by 2030
4	**Declining AI research strengths**	Since 2022, Australia funding for AI research has declined by 46%, curtailing our ability to innovate and contribute to global model development. Australia lags regional peers in model development, accounting for just 0.2%, of AI large models trained since 2022, behind most Asia-Pacific neighbours.
5	**Public trust**	While Australians are eager adopters of AI, they also care deeply about AI safety and trustworthiness. Building confidence, and addressing public concerns, is critical

Australia's AI adoption opportunity

AI adoption benefits the economy by increasing productivity, spurring economic expansion and growing GDP.

The analysis undertaken for this report suggests AI has the potential to lift Australian GDP by nearly 4% (0.9% p.a.) or $112bn higher by 2030, providing Australia keeps pace with global AI adoption rates.

This forecast is consistent with previous work undertaken in Australia, while noting there is still debate amongst economists globally about the likely productivity impacts of AI. At the lower end, it has been estimated that the AI could cause as little as a 0.07% p.a. productivity uplift over 10 years[3]. At the higher end, it is estimated AI could trigger a productivity increase of up to 1.3% p.a. for advanced economies like the US and UK.[4] The primary drivers of this variation is uncertainty surrounding the pace at which AI can be integrated cost effectively into production, the capabilities and cost of AI (both of which have evolved rapidly), and how people and industries will adopt AI in practice.

This report finds that AI adoption will deliver particularly strong benefits in Australian industries where productivity growth is most urgently needed. In particular, industries with lower productivity and skill shortages, such as Australia's critical care industries.

The benefits from AI adoption will flow to much of the Australian economy. However, the data suggests that some of the most likely beneficiaries will be groups that may have been overlooked in previous productivity growth cycles. Lower productivity sectors such as health and social assistance will experience greater benefits in this wave as well as accompanying wage growth. Overall, wage growth from 2025-2030 due to AI could total 7% across industries by improving the speed at which workers can complete tasks and unlock potential for new types of work by making previously impossible tasks feasible. For example, AI can rapidly classify items in large datasets to create new analytical opportunities for businesses.

On an occupational level, women are more likely to be employed in jobs that have the potential to benefit from AI adoption and could experience wage growth due to AI that is 35% higher than what occupations skewed towards men experience.

Small businesses also stand to benefit – where previous productivity booms required significant capital investment, AI can deliver productivity gains through "as a service" business models. This makes AI more scalable across multiple small businesses, compared to productivity gains requiring significant investment in machinery and other hardware.

Lastly, AI benefits can enhance the quality of public goods, with the primary barrier often being trust. Australian companies are trialling solutions that can address the barriers by implementing guardrails that ensure AI outputs deliver relevant and reliable outputs. Once these solutions are scaled, complementary benefits may also be unlocked, such as the delivery of citizen services that leverage real-time data and AI outputs.

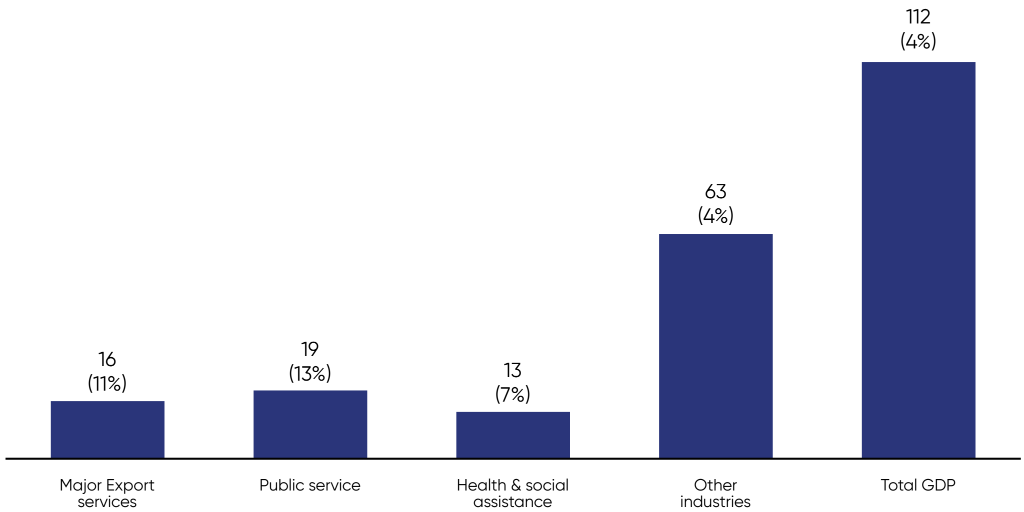
Australian benefits accruing to users of AI products and services are worth $112bn p.a.

Of the $112bn in annual benefits flowing to AI adopters, 43% of benefits accrue to three key - and critical - industry groups:

1. **Major export services:** Professional services, Tertiary education and food and beverage services together account for 10% of Australia's non-mining exports. Productivity uplifts are important to preserving their value to the Australian economy. Without productivity gains, these industries could become globally uncompetitive and fall behind countries that successfully adopt AI.
2. **Public Service:** These industries have faced challenges in productivity growth, which could be alleviated through AI adoption.
3. **Health and social assistance:** These industries have significant benefits from AI adoption, as well as facing significant workforce shortages, which AI could partially alleviate.

Australian economic opportunity – Adoption opportunity

Annual GVA contribution of AI by industry groups, Constant 2025 $bn (% uplift 2025-2030), 2030



Source: ABS, O*Net data, Author's analysis
totals may differ due to rounding

Australia's key services export industries have significant opportunity

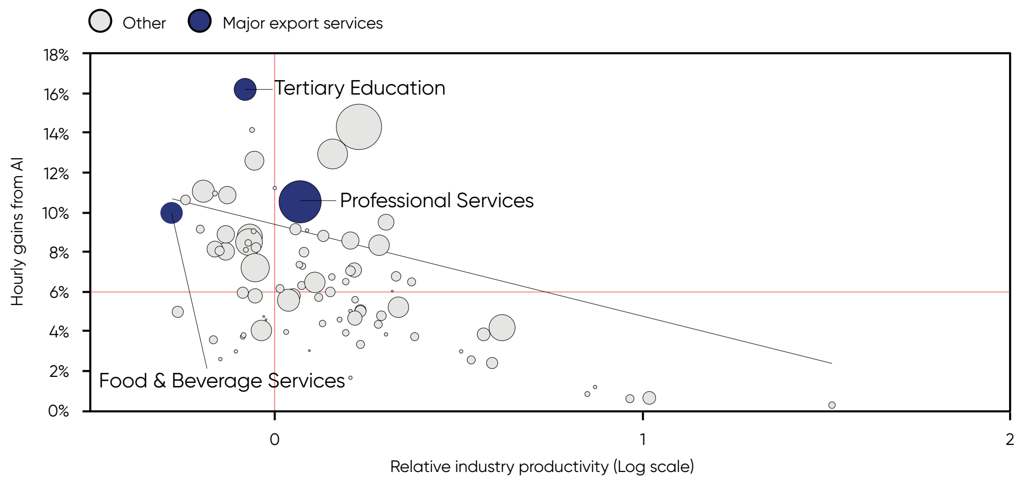
Australia's major service export industries, including higher education, professional services and tourism will be significant beneficiaries of AI adoption. Although less productive than many other Australian industries, they could realise some of the greatest potential gains from AI adoption.

Initial evidence suggests AI adoption in accounting increases weekly client support by 55% while reallocating roughly 8.5% of time from data entry to high-value tasks like quality assurance.[5] Material productivity improvements can also be observed in marketing services, with IBM reporting that through the use of Adobe's AI tools, the time to develop a campaign was cut from two weeks to two days, freeing up time for brainstorming and storyboard creation.[6]

By 2030, AI adoption is estimated to lift productivity by 11% across higher education, professional services and tourism. This could increase GVA by up to $15bn p.a.

Adoption opportunity benefits – Industry productivity vs. benefit intensity

X-axis: Relative industry productivity, log-index (median = 0), 2030
Y-axis: Productivity benefit from AI adoption, %, 2025 - 2030
Bubbles represent industries, Size indicates scale of benefit potential, red lines reflect median values



Source: ABS, O*Net data, Author's analysis

Healthcare and social services shortages could be partially addressed through AI

AI adoption can particularly benefit industries that face the dual challenges of low worker productivity and significant workforce shortages.

Across health care and social services industries, at least 50% of workers are employed in occupations experiencing staff shortages. AI adoption could lift labour productivity in these industries by 8%, helping mitigate the impact of workforce shortages, and lifting GVA by $14bn.

For healthcare professions facing shortages in rural, regional and remote areas, such as radiology[7], AI has strong potential to reduce workload and mitigate significant delays in diagnosis and treatment. Evidence from European pilots is promising – AI in mammography screening cut radiologist screen-reading volumes by 44%-50%, while maintaining accuracy and safety.[8]

Improved clinician utilisation can also be achieved through AI applications. AI-powered software that predicts missed appointments was trialled in the UK's NHS. Over the 6 months trial, there was a 30% fall in non-attendances, and an additional 1,910 patients were seen.[9]

"AI adoption could lift labour productivity in these industries by 8%, helping mitigate the impact of workforce shortages, and lifting GVA by $14bn."

Adoption opportunity benefits – Industry shortages vs. benefit intensity

X-axis: Industry shortages, % of work hours employed in shortage occupations, 2025
Y-axis: Productivity benefit from AI adoption, %, 2025 - 2030
Bubbles represent industries, Size indicates scale of benefit potential, red line reflects median values

Source: ABS, Jobs and Skills Australia, O*Net data, Author's analysis

Australia's public sector productivity would benefit strongly from AI adoption

Increases to productivity are also expected to accrue to the public sector, which has been associated with weak productivity growth in recent years (compared to average growth over the past 20 years)[10]. By 2030, AI adoption could lift public sector GVA by 13%, delivering $19bn in annual value.

Internationally, adoption of AI across the public service is already delivering benefits. Pair, a suite of AI products for public officers in Singapore, has saved employees an estimated 46% of time spent on administrative tasks.[11] PairChat, a secure version of ChatGPT, also assists with tasks such as summarisation, research, brainstorming and coding. With more than 20,000 active weekly users, Pair is a leading example of how the public sector can embrace AI, while ensuring data is stored safely by government.

Experience to date reveals three key lessons for public sector adoption:

1. Workers need adequate training on the use of AI
2. Legacy software products can limit benefits from AI tools
3. AI model training on government data could help ensure outputs are fit-for-purpose and aligned to government standards

"By 2030, AI adoption could lift public sector GVA by 13%, delivering $19bn in annual value."

Adoption opportunity benefits – Industry productivity vs. benefit intensity

X-axis: Relative industry productivity, log-index (median = 0), 2030
Y-axis: Productivity benefit from AI adoption, %, 2025 - 2030
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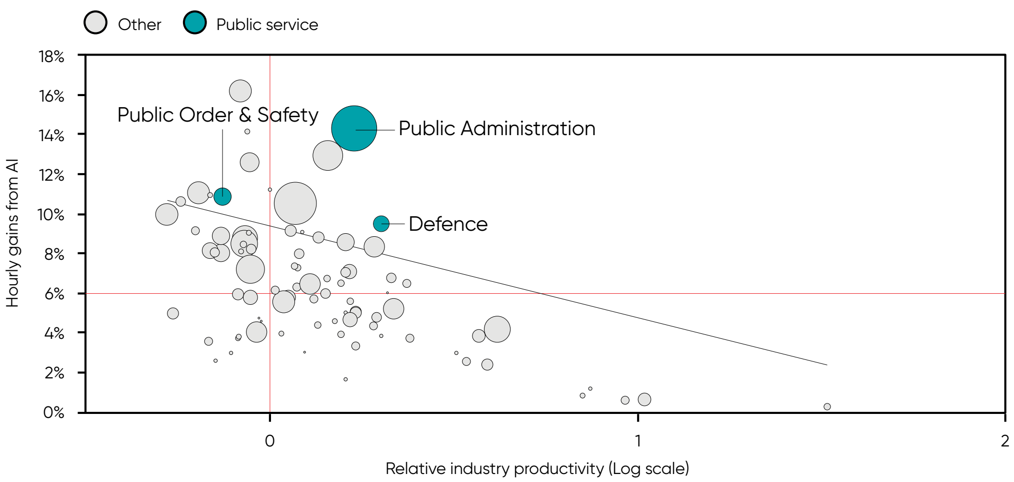


Source: ABS, O*Net data, Author's analysis

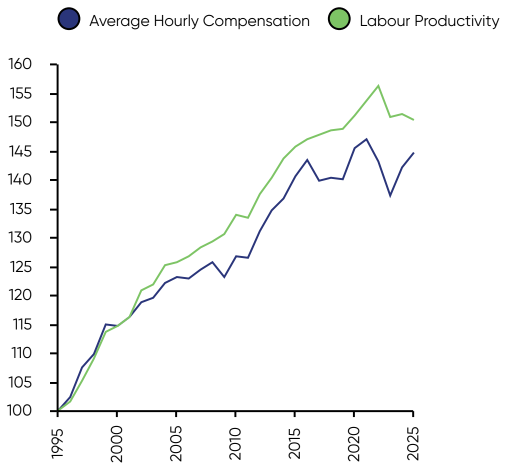
Increased labour productivity remains a key driver of wage growth

A significant share of benefits from AI adoption is set to flow to wage growth, via labour productivity improvements. Analysis by the Australian Productivity Commission finds the relationship between wages and productivity growth is close to 1 to 1 with some sectoral skews in mining and agriculture.[12]

Our analysis aligns closely with the Productivity Commission estimate, finding that for every 1% increase in labour productivity, wages increase 0.92%.

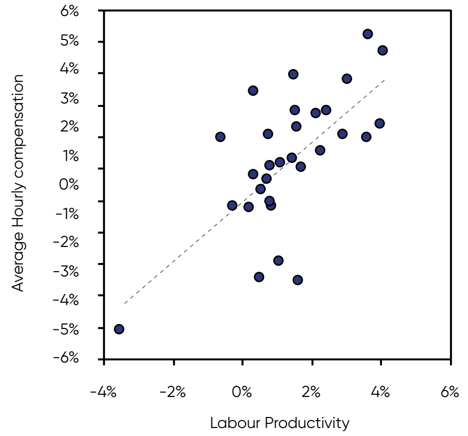
Labour productivity (LP) and Hourly Compensation

Index, 1995 = 100,1995-2022



Change in LP vs. Hourly compensation

YoY change in index, %, 1996-2022



Source: ABS National Accounts, Author's analysis

Productivity gains from AI adoption will flow to workers, lifting wages by 7% on average

Across all but one of the identified ANZSIC industries with strong uplift potential and/or benefits (Section 1), the expected wage growth flowing from AI adoption is above the economy wide average impact of 7% over 5 years.

Aside from lifting wages, AI has the potential to alter wage dynamics in a way that reduces inequality across the workforce.

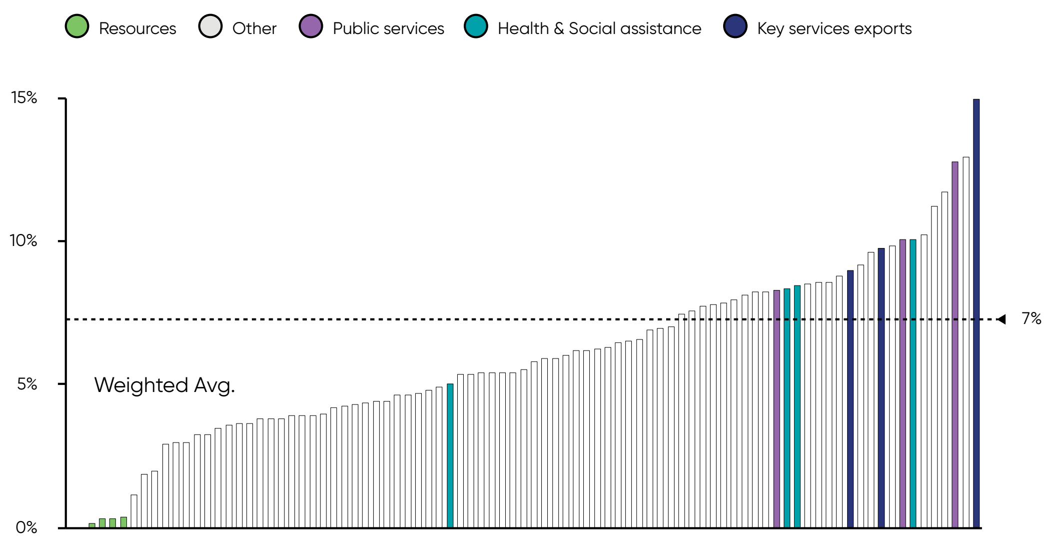
This finding is consistent with recent research across developed economies:

1. A longitudinal study of German workers found that higher AI exposure by occupation was positively associated with wages growth[13].
2. This finding was attributed to workers either substituting away from tasks where AI can reduce work-load or increasing worker productivity by complementing how workers perform tasks.

There is also a growing body of work showing that less productive workers benefit more from AI adoption than more productive workers[14,15], further demonstrating AI's potential to alleviate inequality.

Wage growth impact of AI adoption by industry

Predicted growth in worker compensation, %, 2025-2030



ANZSIC industry subdivisions
Source: ABS, O*Net data, Author's analysis

Women could experience 35% faster wage growth due to AI adoption

Women are also more likely to benefit from AI adoption, working in occupations with greater productivity gains. Over 2025-2030 women have projected wage increases of 8.2% from AI adoption compared to 6.1% for men.†

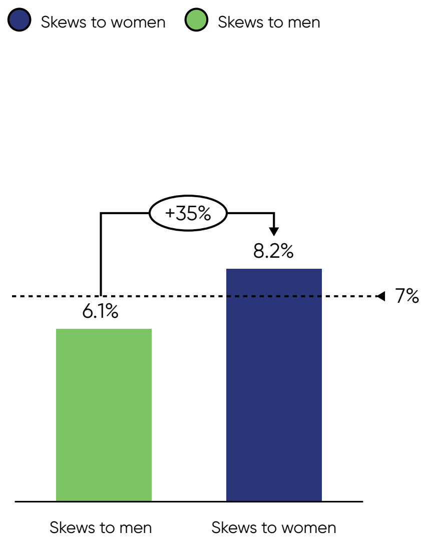
However, despite potential for benefits, women are typically more hesitant to adopt AI tools. For example, women are 10%-40% less likely than men to use generative AI according to published studies.[16]

A key reason for disparity is concern around ethical AI tool use, highlighting the importance of considered implementation of AI adoption in the workplace. AI adoption goes hand in hand with strong AI literacy and capabilities, to ensure workers use AI effectively and confidently.

Recent research suggests the gender gap may be closing, with analysis of ChatGPT users showing that over 50% of weekly users had typically female names as at July 2025.[17]

Wage growth from AI by occupation and gender

Average projected wage growth by occupations gender skew*, %, 2030



Bubbles represent occupations, Size indicates Number of employees

* Occupations where more than 50% of hours are worked by women are "skewed to women" and vice-versa
Source: ABS industry GVA data, ABS Table Builder, ABS input output tables, O*Net data, Author's analysis

† Assumes task split within occupations does not differ across gender

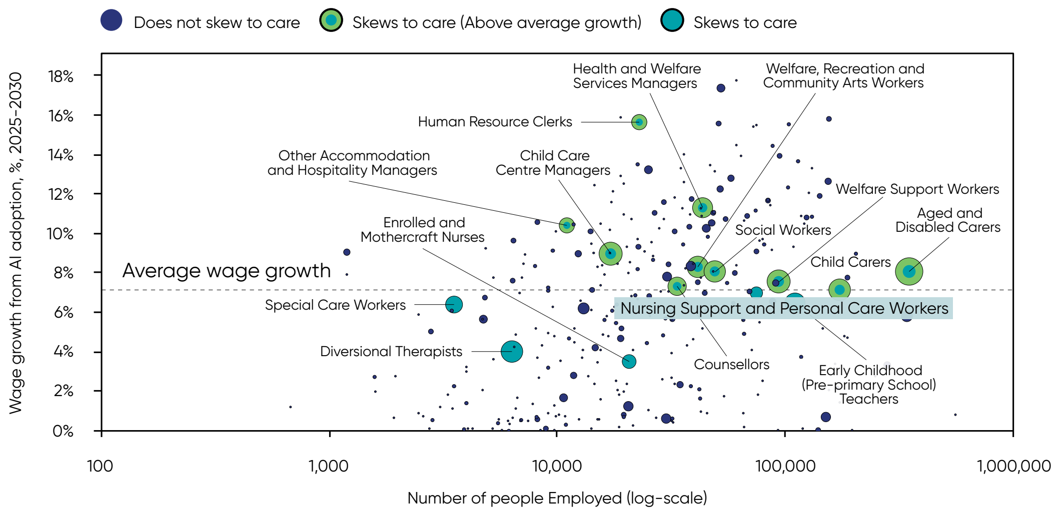
AI adoption will raise wages among care workers by 10% more than other occupations

Care sector workers are also likely to benefit from AI adoption, with 67% of occupations and 84% of workers set to experience above average wage growth to 2030 due to AI adoption.

Overall, occupations skewing to the care industry will experience 7.84% average wage growth between 2025-2030 stemming from AI, compared to 7% across the economy.

Wage growth across occupations by presence in care workforce

Bubbles represent occupations, Size indicates care industry x occupation Quotient*



* A location quotient measures the relative skew towards a particular population in a "location". While typically locations are geographical, they can be any variable stratifying a population. In this dataset, the location quotient measures the share of care industry (Social assistance or Residential care industries' employees) in an occupation vs. the share of total employees in that occupation. A location quotient greater than 3 is "skewed to care" in the above chart.
Source: ABS industry GVA data, ABS Table Builder, ABS input output tables, O*Net data, Author's analysis

Small businesses operate in industries that stand to benefit more from AI adoption

AI benefits show a skew to small businesses, as these are often more labour intensive than large businesses. Census data shows that individuals operating as sole traders, or running businesses employing fewer than 20 people disproportionately operate businesses in lower labour productivity industries.

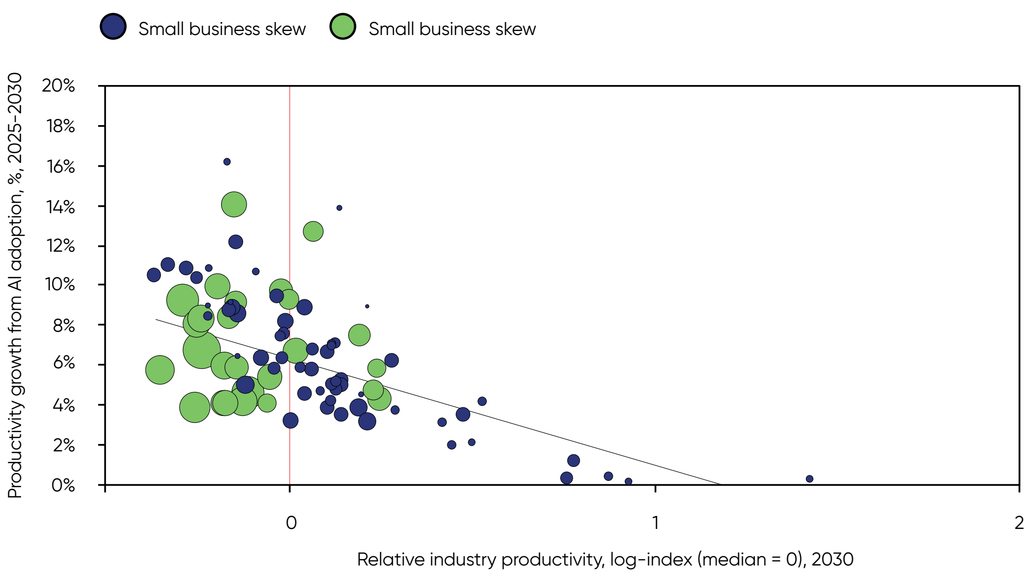
"AI as a Service" business models will allow small businesses to experience productivity uplifts without unaffordable capital outlays. Our data shows that between 2025 and 2030, industries with a "small business skew" will experience AI driven productivity growth of 7.1% on average vs. 5.8% for large business skewed industries (weighted by industry GVA).

The benefits for small businesses are also becoming more evident in research. A 2025 UK study found small businesses experience productivity gains between 27%-133% through AI adoption.[18]

In Australia, a Salesforce survey found 86% of small businesses report a boost in revenue from the use of AI, highlighting the growth potential from improving productivity.[19]

Adoption opportunity benefits – Industry productivity vs. benefit intensity

Bubbles represent industries, Size indicates Small enterprise "Location Quotient"*, red lines reflects median



* A location quotient measures the relative skew towards a particular population in a "location". While typically locations are geographical, they can be any variable stratifying a population. In this dataset, the location quotient measures the share of small businesses in an industry vs. the share of total employees in that industry, with values greater than 1 indicating a significant skew towards small businesses
Source: ABS Census data, O*NET, Author's analysis

AI implementation pilots show AI can deliver quantifiable benefits to the public

Beyond direct benefits to workers and businesses, AI has the potential to deliver substantial public value, through enhancing delivery of public goods. Often the major barrier is trust, even if production ready solutions can be developed.

ISG (A member of AiiA) is piloting three AI products through their clients with public benefit use cases across (1) education, (2) council services and (3) legal arbitration. The critical enabler for these use cases is the inclusion of strong guardrails to ensure accuracy and relevance of outputs using a dual model approach:

1. A primary AI model which generates the required output for service delivery (e.g. NESA compliant subject plans)
2. A supervising AI (e.g. IBM "Guardrail"), designed to monitor and assure primary AI output quality and accuracy

The adoption of these solutions can also create new economic opportunities that would not otherwise be possible. E.g. using AI to streamline parking revenue collection generates analytical data that can support services such as dynamic pricing, or delivering citizen service apps that provide real-time parking data.

EdgiTeach

Education

An LLM - driven platform for micro-schools, that helps teachers in "micro-schools" deliver individualised lesson plans, track student engagement and helps students by tailoring content to their progress.

This system can save time spent on administration, generate NSW Education Standards Authority (NESA) complaint curriculums and lesson plans, and could readily be adapted for other jurisdictions.

This removes administrative burden for teachers, supporting enhanced interaction time with students.

Comprehensive AI governance framework ensuring safe implementation

CityParkAI

Council services

AI can be readily used to improve how councils determine and collect parking revenue. AI can scan cars as they park, automatically calculate fees, and use non punitive escalating fees when vehicles overstay parking limits (as opposed to steep fines).

There is further potential to expand the scope of what this system can deliver, including allowing for dynamic pricing based on areas demand, supported by real-time analytics from the CityParkAI system.

Expansion of scope would generate additional economic activity and new job opportunities to develop and implement such a system, that would not be possible without AI.

Reduces conflict, improves citizen experience

Resolvia

Legal Services

AI assisted arbitration can deliver outcomes that have 98% satisfaction rates for disputing parties.

The system uses guardrails (powered by IBM) to ensure that advice meets quality and accuracy standards before being delivered to disputing parties.

Implementation saves time and allows humans to focus on more complex cases, rather than spending time on lower value-add work.

Creates new legal service delivery model

Source: Information Systems Group (ISG) – member of AiiA

Building a domestic AI industry

Building a domestic industry will allow Australia to capture a further $18 billion of GVA in the supply chain on top of AI adoption. About one-third of the benefit will be captured by compute provision, where Australia may have an advantage. Australia has a strong data centre industry, with Sydney's operational IT load ranked 5th in APAC and 16th globally[20]. Provided the right hardware is installed, domestic data centres could support much of required AI compute.

The domestic application market also presents a significant opportunity. Australia has already proven it is globally competitive at creating software-based companies, with Australia creating over 100 companies valued at $100m or greater in this sector, and 35 global tech unicorns (companies valued at $1bn or greater), including Atlassian, Canva and Employment Hero.[21] Australia is particularly strong in the Software-as-a-Service (SaaS) market, specialising in B2B applications.

If the AI application market develops in a similar fashion to the SaaS market, it could generate $12.3bn in GVA for Australia by 2030. As the next section explains, it could also create $6.3bn in export value, for a total benefit of $18.6bn annually for local developers and the Australian economy. There is already evidence that Australia's existing software leaders, such as Atlassian and Canva, are utilising AI to create new products and ensure their competitiveness, and that Australia is creating a new generation of AI-based companies, such as HediAI, HarrisonAI and Lorikeet.

Critically, building a domestic AI industry delivers important benefits that have not been explicitly quantified, including quality gains from low latency, create economic and supply chain resilience, and the ability to adopt AI in sensitive areas, such as healthcare and national security applications, where locally hosted and processed data is important.

Australia could achieve compute self-reliance, and deliver most domestic AI applications

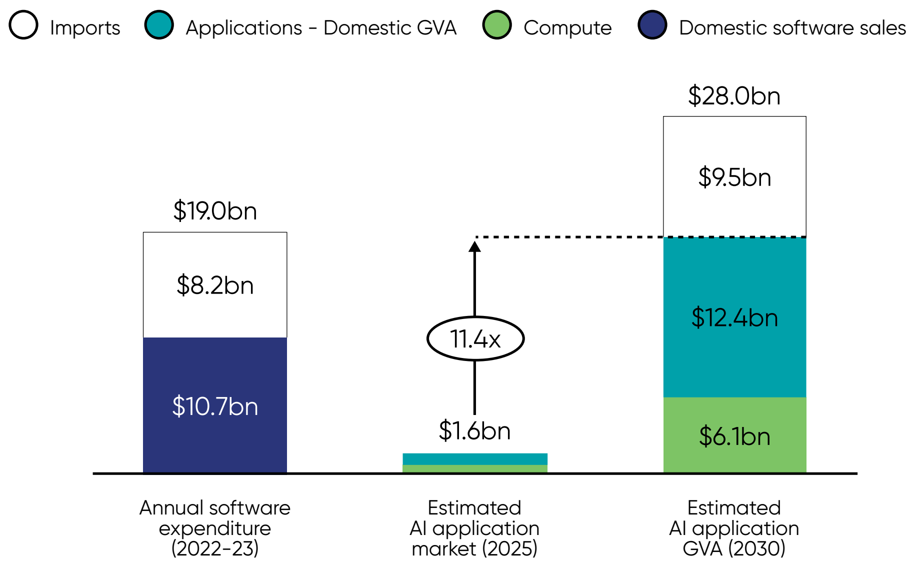
Australian activity in the AI supply chain could increase 11.4x compared to current levels, to $18.5bn p.a. through the provision of compute, and AI application development.

Low latency needs gives Australian data centres an advantage. Latency refers to the delay between sending an instruction and receiving a response. Low latency can be critical for consumers, in use cases such as spoken conversation with chatbots, but even more so in industry where precision is essential. An AI system in a factory setting may need to send instructions to machinery to change operating speeds, temperatures or other dynamics. Delays in this process may render production lines inoperable.

Australia has a strong track record in SaaS, producing 35 unicorn companies since 2000.[21] Demand for enterprise-specific AI applications could support domestic AI applications development. There is evidence of appetite for custom builds which may favour domestic suppliers and workers, with companies such as Telstra[22], BHP[23] and Commonwealth Bank[24] already developing in-house AI platforms and applications.

Annual value accruing to AI developers

Annual GVA contribution of AI, Constant 2025 $bn, 2030



If Australia can match its share of domestic SaaS penetration, it could capture $12.4bn in AI application GVA[1]

Low latency needs provide Australia a natural advantage in the provision of compute inference for Australian users

Source: ABS, O*Net data, Author's analysis
totals may differ due to rounding

Premier Australian companies are integrating AI into their products

Successful Australian companies are already incorporating AI into their products.

Canva is bringing advanced AI features to over 175 million global users, transforming how people design, communicate, and create. Through Magic Studio, a suite of AI-powered tools, users can instantly generate content, translate copy, edit images, and turn rough ideas into polished outputs. These tools are deeply embedded in Canva's workflows, making AI feel less like a separate tool and more like a natural extension of the creative process. By reducing friction and boosting speed, Canva is helping users – from students to marketers to major enterprises – focus more on creativity and less on complexity.[a]

> ***"Providing powerful and safe AI technology is critical to Canva's ability to further the world of design."***
> ***Danny Wu, Head of AI Products at Canva.[b]***

a OpenAI. (2025, July). OpenAI Australia Economic Blueprint [PDF]
b OpenAI. (n.d.). Creating an AI-powered Magic Studio [Web page]. OpenAI.

Domestic AI can deliver other unquantified benefits in the national interest of Australia

Building domestic AI capabilities will support additional benefits that have not been directly quantified but may be critical to realising identified benefits. These include:

1. **Securing low latency:** Real-time applications such as AI conversations will require local computation.
2. **Supporting adoption in sensitive industries:** Local capabilities can ensure industries with strict privacy requirements can utilise data in AI applications without ever sending data offshore.
3. **Supporting adoption in areas with distinct needs:** Domestic models may reduce bias for populations underrepresented in global datasets, such as tailoring medical diagnostics to reflect local genetic and environmental factors affecting specific communities..

While some of these barriers can be overcome through appropriate controls/ relationships with trading partners, domestic capabilities may offer the most robust approach to securing benefits in the national interest of Australia.

Secure low latency

Many AI applications will require real-time response rates. Using foreign compute may increase latency, due to:

1. **Distance:** minimal, but non-negligible impact depending on round-trip distance.
2. **Switching and routing delays:** routers add additional overhead to travel time.
3. **Congestion (high risk):** Increasing AI workloads may lead to bottlenecks in high demand networks (particularly if compute I geographically concentrated).

Support adoption in sensitive industries

Sensitive industries such as healthcare, finance, or defence are some of the most likely to benefit from AI, but also carry significant data privacy requirements. Having domestic capability can enable the use of sensitive data for AI applications in these industries. Further capability in tuning/ developing models can also ensure that data use is less likely to display bias/ inaccuracies in use.

Support uptake in industries with distinct needs

Developing domestic model training/tuning capabilities may support industries with specialised needs. For example, a Legal AI provider may need access to a lightweight model, that can maintain high accuracy with reference to Australian law.

This could be achieved through selectively distilling or quantising a high-performance foundational model in a way that predominantly sacrifices accuracy/quality in irrelevant domains.

Australia as a Regional Hub

On top of building capability for domestic industry, Australia can aspire to become a regional hub exporting AI products and services to neighbouring countries in the Asia-Pacific region and the rest of the world. Australia is strategically positioned to become a regional hub for AI innovation and exports, leveraging its strengths in education services, critical minerals (which are seeing increasing demand from AI chip manufacturers), and digital infrastructure. By 2030, Australia could generate over $10 billion in new annual export value through AI-related opportunities. Growth will be driven by three primary channels: AI applications, AI compute services, and AI education.

Across AI applications, Australia is already showing early signs of potential strength, with existing SaaS exporters such as Canva integrating AI heavily into their products, and new startups such as Lorikeet achieving international market penetration. For AI compute, opportunities may be limited to heavy, batched inference workloads that do not require real-time transmission, as well as training compute which is less affected by proximity.

In education, Australia has seen rapid growth (69% p.a.) in tertiary enrolments in AI degrees since 2022. There is further potential for Australian tertiary education providers to support upskilling the existing workforce across the APAC region through a mix of micro-credentialling and industry- or enterprise-specific training programs. Globally, AI training offerings are not keeping pace with AI adoption expectations. In the Asia-Pacific region, 92% of employers expect their organisations to use AI tools by 2028, yet 79% do not know how to implement AI workforce training programs, and 74% of workers lack knowledge about available AI training programs.[25] This suggests that, despite the significant number of online AI training courses offered through providers such as Coursera (~700 GenAI courses)[26] there is a need for more specialised, applied offerings tailored to specific domains, industries, and organisational objectives. Training demand will also likely intensify to meet employer AI adoption expectations.

Lastly, an important consideration that cannot be quantified in this report is the need to integrate AI into Australia's existing export strengths. The Australian tertiary sector may face increasing competition from other jurisdictions that invest more heavily in AI. As foreign universities integrate AI training into their courses more rapidly than Australia, they may displace Australian universities as a preferred destination for international students. In such a scenario, the true value of becoming a regional AI hub is not only the incremental value Australia can gain from today's exports, but also the potential value it stands to lose to global peers by acting too slowly.

Australia could generate $10.6bn in exports through three opportunities

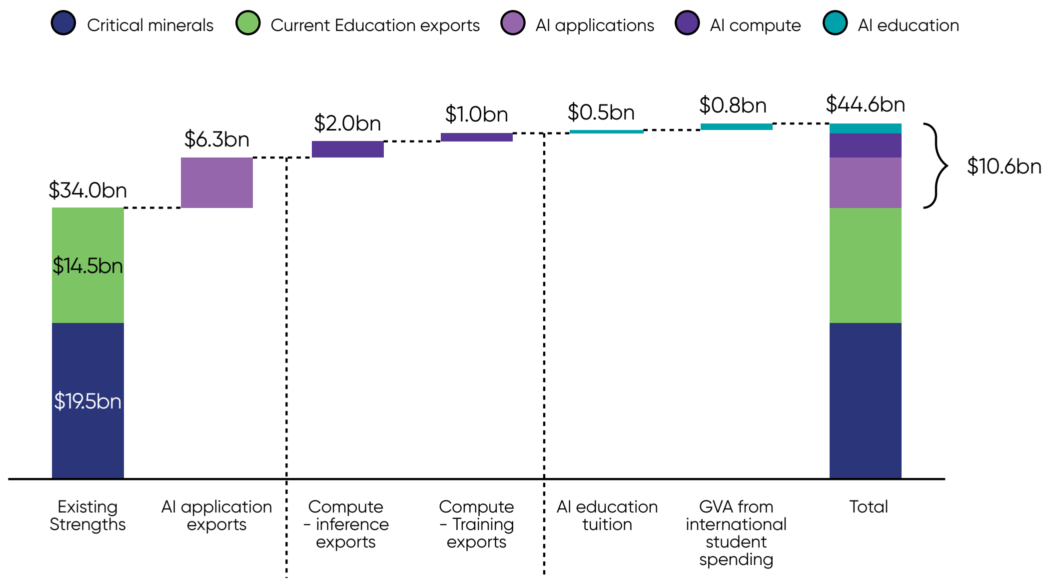
Australia already exports in parts of the AI value chain including higher education and critical minerals*. Although most of these exports are not AI-oriented, there is opportunity to capitalise on our existing strengths in these industries to increase our market share in the AI value chain.

While we expect that there is potential for critical minerals exported from Australia to integrate in the AI supply chain as demand for accelerator hardware grows, limited available data on volumes of critical minerals necessary for AI chip production makes it challenging to value this opportunity.

Across new opportunities, Australia can derive benefits from 3 sources (1) AI applications, (2) Compute, and (3) education. We find that Australia has potential export opportunities of $10.6bn by 2030 from these specific opportunities

Australian export opportunities through AI

GVA by export opportunity area, Constant 2025 $bn, 2030



Source: ABS, Department of Education data, Author's analysis
totals may differ due to rounding

* Non-ferrous metal mining exports have been used as a proxy for critical minerals, though these only form part of this industry's output (Exports are not available at a more detailed level)

Converting existing SaaS strength to AI applications could unlock $6.3bn p.a. in GVA

Australia is demonstrating emerging strength in "AI applications as a service", with two Australian companies ranking in Andreesen Horowitz's (one of the largest VC funds in the world) top 50 sources of AI spend among startups (Canva #17 and Lorikeet #8).[27]

These two companies also reflect distinct sources of AI product development:

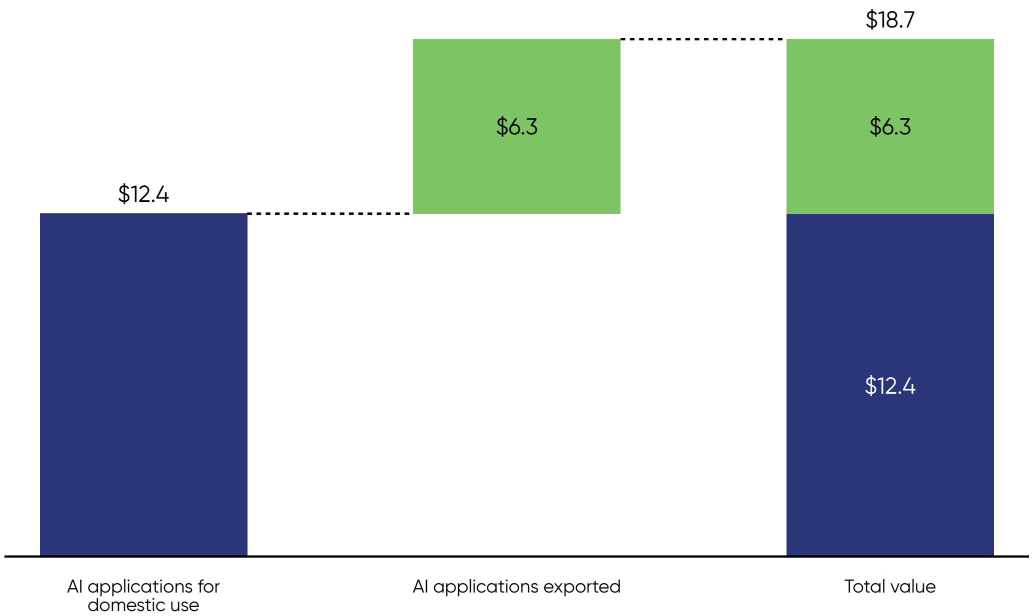
1. Existing SaaS companies integrating AI into their products (Canva)
2. New startups innovating in the AI industry (Lorikeet)

While it is likely that AI companies will emerge in domains other than SaaS, it is also clear that SaaS is becoming increasingly AI centric.

If Australia can continue to build on this strength, by 2030 AI exports could add over $6bn p.a. in GVA to the Australian economy.

Australian AI application industry value

GVA, Constant 2025 $bn, 2030



Source: ABS, O*Net data, Author's analysis
totals may differ due to rounding

Australia could capture $3bn of a global compute market worth $398bn p.a. in 2030

Global computational needs for AI are expected to be significant, with a total value of nearly AU$400bn dollars by 2030.

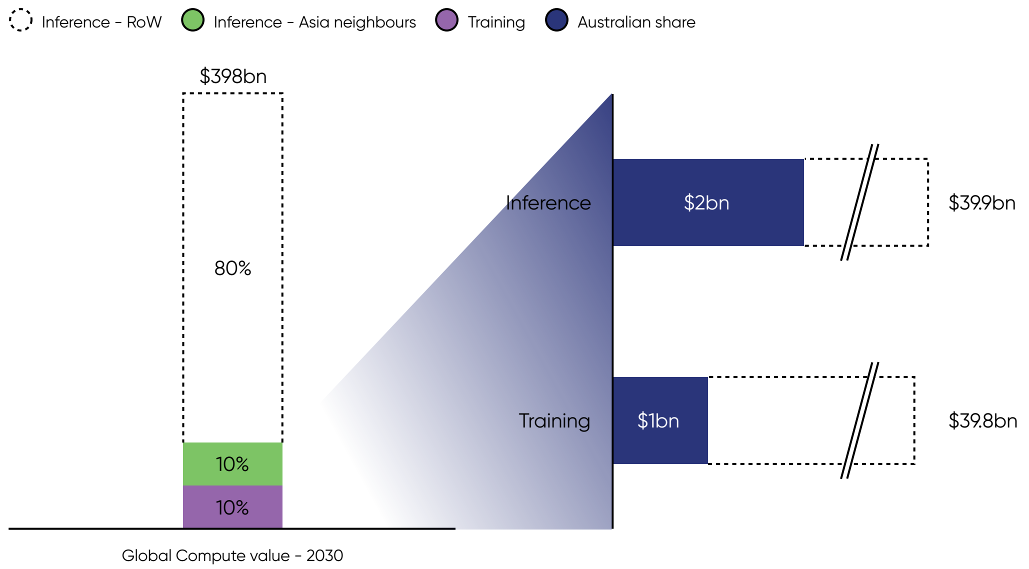
However, the capability to tap into this export market will be constrained by latency requirements, which will favour countries developing data centers locally. There are two potential caveats to this:

1. **Asia Pacific neighbours:** may be proximate enough for Australia to economically provide compute at competitive speed for more intensive inference workloads, where computation time means real-time inference is not feasible. This is particularly true in high density cities with insufficient space.
2. **Training compute:** Global training needs will expand due to growing model complexity. Model training can take multiple days at minimum, and as such is not impacted by latency bottlenecks.

Australia could capture $3bn p.a. of the global compute market, with $2bn p.a. attributable to inference exports and the remaining $1bn p.a. from training exports.

Australian capture of Global AI compute market

Annual expenditure on AI compute, Constant 2025 $bn, 2030



Source: Compute market modelled based on data from multiples sources: Goldman Sachs, McKinsey, Mandala Advisors, Author's analysis; Australia assumed to capture 5% of Asian inference demand, and 2.5% of global training demand

By 2030, International enrolments in AI education could be worth $1.9bn p.a.

Demand for AI specialist occupations is accelerating, with significant skill shortages already being reported in up to 72% of businesses across the APAC region.[28]

The share of enrolments in AI courses by international students in Australia has grown rapidly in recent years, reflecting awareness among the future workforce of employer demand for AI capabilities.

Maintaining this growth rate to 2030 will be challenging as neighbouring countries are likely to present competition to Australia's education sector. To remain competitive with other higher education destinations and keep pace with employer expectations regarding AI literacy, Australia will also need to integrate AI skills into other degrees. Australia will also need to address traditional competitive factors such as prices, speed and quality of educational experience.

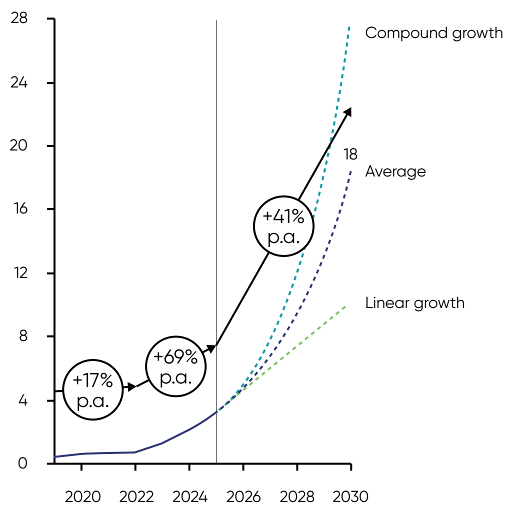
Leading Australian universities have begun this process, including providing AI training opportunities for staff and students[29], as well as creating new subjects to support AI fluency regardless of discipline.[30]

If Australia can maintain 41% p.a. growth in specialist education to 2030, Australia could derive $1.3bn in annual benefits.

> ***"I like the idea around training and education... where would we land from having overseas students be trained here... can we provide AI literacy more than what other countries are?"- Workshop participant***

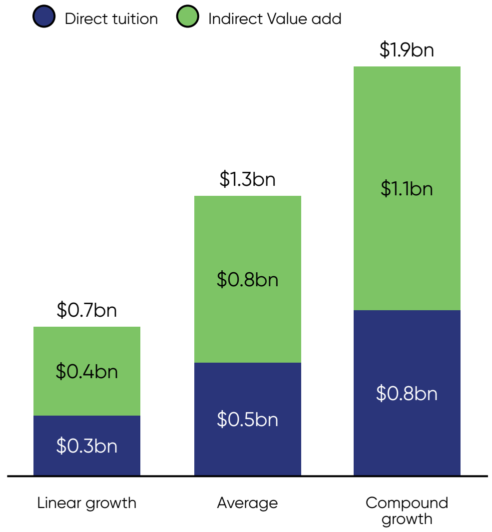
Projected international enrolments in AI degrees

Number of enrolments , 000s, 2030



Projected GVA impact

GVA from AI education, Constant 2025 $bn, 2030



Source: Australian Department of Education, International student monthly summary and data tables, Author's analysis

Barriers to realisation

Realising benefits through the three economic opportunities explored in this report is not a guaranteed outcome. Through our analysis, research and consultations with stakeholders from more than 40 different companies operating across government, technology consulting, data centers, tech firms and industry bodies we have identified six significant barriers that Australia would need to overcome to become regional leader in artificial intelligence:

1. Australia needs to define its vision and strategy: where does Australia wish to specialise, attract investment and build domestic capabilities in the AI value chain.
2. Australia will need to consider infrastructure needs to complement existing strengths in data centres. The AI workloads outlined for the three opportunities could require raising Australia's projected data centre investment through to 2030 to over $40bn. While total required investment is not seen as a barrier by leading data centres, being able to deploy capacity in a timely matter could become a challenge. Network capacity may also pose significant challenges depending on the nature of AI workloads in 2030. If AI workloads take in an increasing volume of heavy data (e.g. High-Definition videos and images) as inputs, upstream network demands could rise faster than historical rates.
3. Workforce capability is also critical, as by 2030 over 40% of work hours for managers and professionals will involve AI, yet leadership and technical readiness remain uneven. How leaders engage with AI is instrumental to successful adoption, with better leaders taking a strategic view, and leaving direct oversight to specialists.
4. Australia's AI research capability is declining, with Australian Research Council annual funding for AI dropping by 46% on average since 2022. Lack of research capability may curtail Australia's ability to build high quality AI education programs. Australia also lags in translating research to model development: Australia contributes just 0.2% to global AI large model training, lagging most significant countries in the Asia-Pacific region, except for Indonesia and Vietnam. Lack of model development capability may limit Australia's opportunity in applying AI to sensitive use cases where Australia's needs may differ from what foreign models deliver.
5. While Australians are eager adopters of AI in their personal lives, they also care deeply about AI safety and trustworthiness. Building confidence, and addressing public concerns is critical to AI adoption and local development, particularly in sensitive sectors and for sensitive applications.

Australia will need to secure access, or develop capability across the entire AI supply chain

Australia needs to decide where it will specialise and build sovereign capability in the AI value chain:

Existing strengths

(1) Australia has strengths in critical minerals, (2) a well-established data centre industry, and (3) a strong software industry and emerging AI start-up ecosystem supporting AI application development

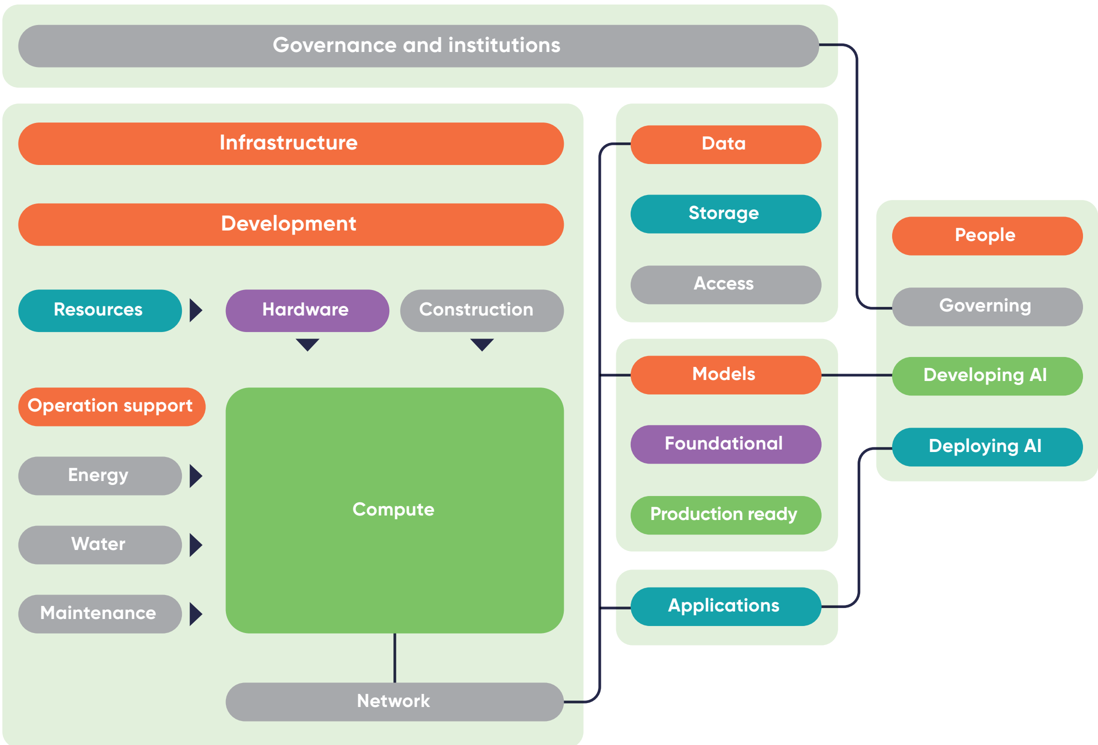
Areas of disadvantage

(1) AI requires advanced chips, to manufacture advanced GPUs/TPUs, an area where incumbents have a significant edge, (2) Foundational models require significant investment to develop, and Australia is several years behind market leaders

Areas of potential strengths

(1) Australian data centre advantage could be expanded (2) Australia has historically been able to build cutting edge research strengths, and could do the same for AI, and (3) Australia could focus on fine-tuning and quantising domain specific, or otherwise specialised production models

AI capabilities supply chain



Supporting requirements

In addition to developing AI capabilities, Australia needs to ensure **enabling infrastructure** can deliver on needs, including energy delivery for operation, **water infrastructure** for cooling, **low latency & high bandwidth network** that can handle data transmission needs between servers and clients, supported by appropriate data access that balances privacy needs with usability.

Model complexity growth is driving increasing energy needs, despite improving efficiency

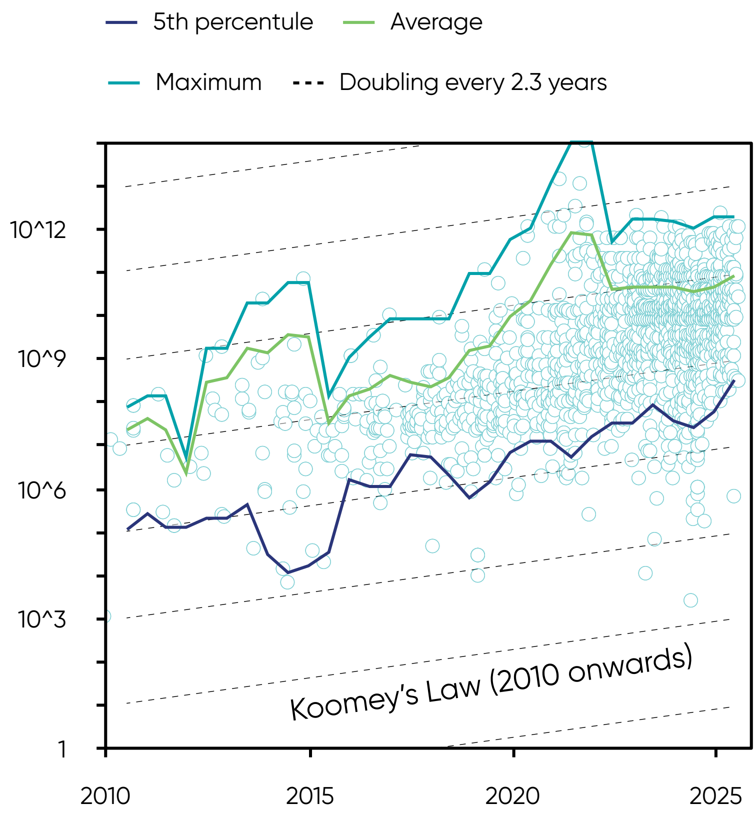
Improvements in computational efficiency are not keeping up with demand for more complex models.

While computational efficiency has been improving at a very rapid pace (energy requirements per computation halving every 2.3 years)[31], model complexity has been doubling every 1.3 years. This has been true for smaller models too, lifting the definition of "lightweight" over time.

While the relationship between model complexity and compute can be mitigated by other factors such as quantization and architecture, the benefits of better-quality results will continue to drive demand for more complex models, offsetting much of the affordability benefits of increased compute efficiency.

AI model* complexity over time

Model parameter count, log scale, 2010-2025



The frontier of AI models has been growing at a rapid pace, with **the most complex models doubling in parameter counts** every year

On average, model parameter count has been doubling every 1.3 years, and what is considered a "lightweight" model has been increasing in complexity at similar rates

Computational efficiency has been doubling every 2.3 years since 2010 (Koomey's Law). Across both lightweight models (bottom 5% in parameter counts) and heavyweight, parameter count has increased by orders of magnitude more than energy efficiency.

* Only includes models with estimated parameter counts; Includes models across 14 domains: 3D modeling, Audio, Earth science, Games, Image generation, Language, Mathematics, Medicine, Multimodal, Other, Robotics, Speech, Video and Vision
Source: Epoch AI, 'Data on AI Models'. Published online at epoch.ai. Retrieved from 'https://epoch.ai/data/ai-models' [online resource]. Accessed 3 Oct 2025, Author's analysis

Prompt approvals and utility connections can enable the $40bn investment of data centre capacity needed to become a regional hub

Compared to 2024 baseline, Australia is expected invest an additional $26bn in data centres by 2030, to increase total deployed capacity from 1.35GW to 3.1GW.[32]

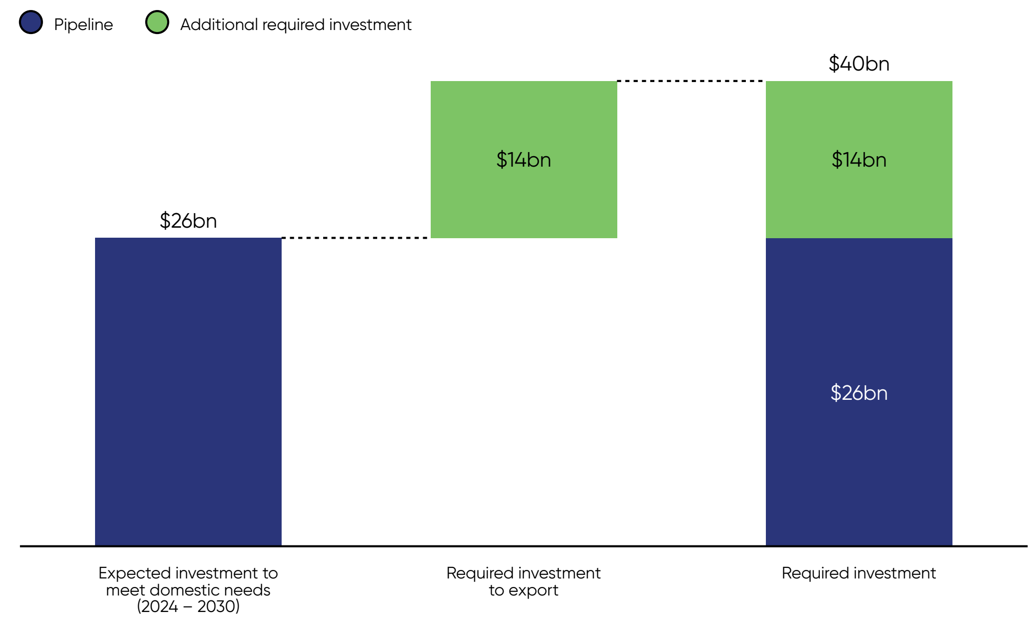
Australian data centres could invest an additional $14bn to export 0.9% of global compute requirements (worth $3.0bn in GVA p.a.) - this would increase total capacity to 4.1GW.

This significant investment comes with key caveats:

1. **It excludes hardware:** The accelerators (GPUs/TPUs) required to provide computational power could cost an additional $29bn.[†] These may be in short supply depending on global demand.
2. **Time to realisation:** Data centres have sufficient access to capital for this level of investment, but planning and approval hurdles can prevent investment from coming online in time.
3. **Need for supporting infrastructure:** Data centres require supporting infrastructure, including energy and water (where data centres are already investing), as well as network capacity.
4. **Training vs. inference needs:** Australia would need to balance training demand with inference demand, despite specialised accelerators typically required for training.

Required data centre investment to meet AI compute requirements

Total investment, 2025 Constant $bn, 2025-2030



† As at 2025, an 8x NVIDIA H100 GPU cluster costs US$216,000. At peak demand in 2030, Australia may need 708,690 such units running concurrently for domestic use, implying total required CAPEX of at least $29bn. These units are increasingly becoming deprecated, but we assume that pricing for newer units will remain similar in 2025 constant dollars
Source: Mandala Advisors, Lucius Advisory analysis

Australia will need to ensure workforce readiness, particularly among skilled workers

All occupations will need to engage with AI to some degree, but managers and other professionals will likely need to engage the most.

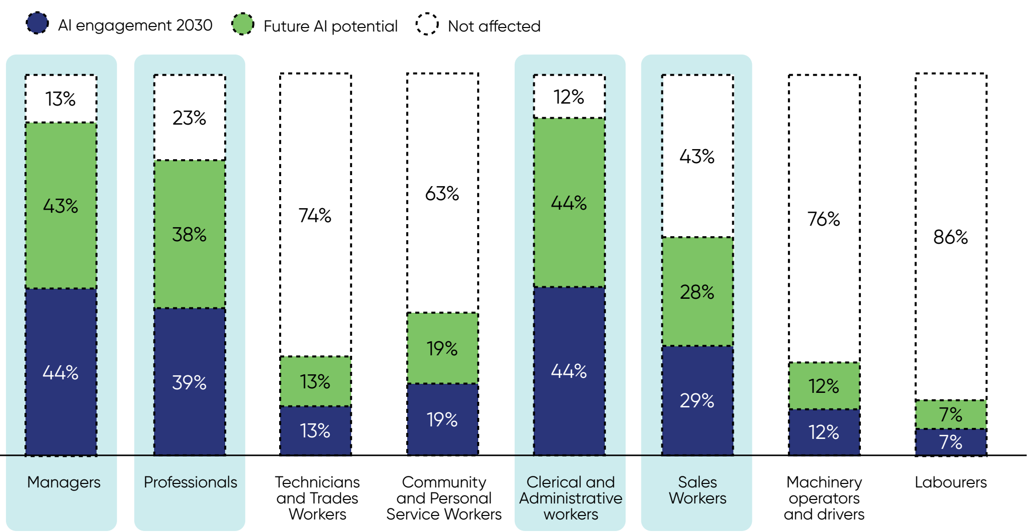
Managers will be engaging with AI in some capacity for 44% of work hours by 2030, and will need to have the right skills to effectively integrate AI into their organisations.

Improving AI skills at business leadership level will enable more successful adoption, with research showing that leaders with strong AI literacy are better able to implement AI in their organisations.[33]

However, how leaders engage with AI is critical with direct control of implementation better left to specialists. A Kearney survey found that among high performing firms, only 59% of CEOs maintain direct oversight over AI implementation, compared to 92% in lower performing firms.[34]

AI engagement by occupation groups

% of work hours with AI engagement, 2030



Productivity uplift among managers, professionals, and administrative workers will be key to driving benefits in Health & social assistance, Public service, and Major export services

Source: ABS, O*Net, Author's analysis

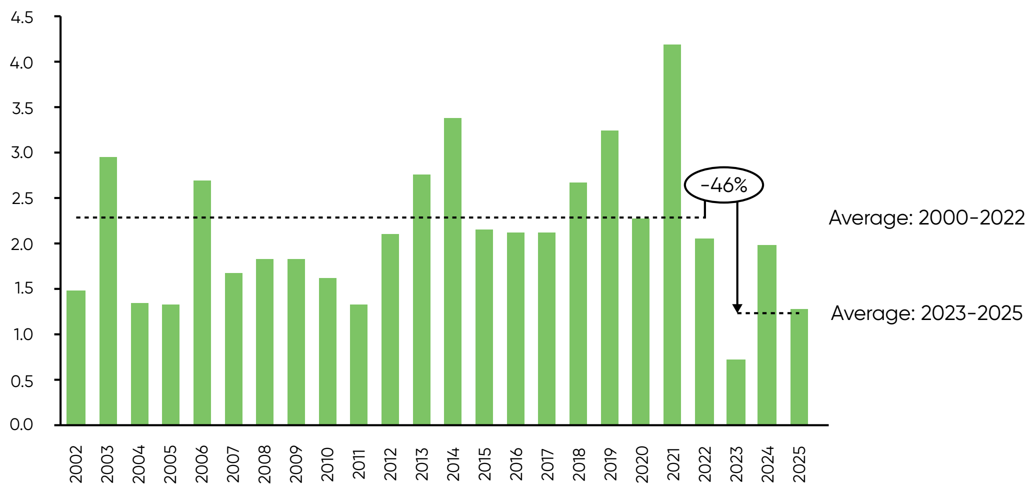
In recent years Australia has begun losing its AI research strengths

Australia has historically been well represented in AI research, with CSIRO research showing that between 2000-2022 Australian peer-reviewed publications represented 2.2% of AI-related global publications, compared with 1.5% of all global publications. This research strength however is not typically translated into products, with Australia only representing 0.24% of global AI patent applications.[35,36]

Further, Australian Research Council (ARC) grants data suggests a decline in AI related research since 2023, with AI's share of ARC grants declining by 46% in 2023-2025 compared to the 2002-2022 average. While the CSIRO dataset is more comprehensive, as it includes AI publications in a greater variety of fields, ARC grants are a forward looking indicator that suggests this historical strength may be eroding.

AI share of Australian research funding†

Share of ARC grant funding for AI research, %,2002 - 2022



† AI grant funding includes all projects in one of the following 4 digit fields of research categories: Artificial intelligence and image processing (2002-22), Machine Learning (2023-25), Artificial intelligence (2023-25), and Computer vision and multi-media computation (2023-25)

Source: ARC Grants data

Australia lags peer countries in AI research and development

Consistent with the Australian gap between research and product development, Australia lags most of our Asia Pacific neighbours in AI model releases.

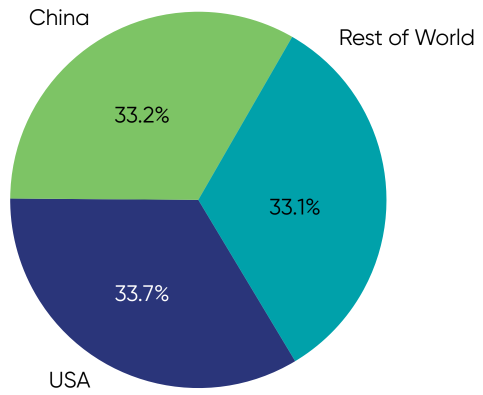
The USA and China dominate AI model development, accounting for roughly 67% of models trained globally since 2023. However, among other countries, many of Australia's Asia-Pacific neighbours (Hong Kong, Japan, Singapore, South Korea, Taiwan and Thailand) all rank well head of Australia in contribution to global model development.

Lack of training capability could impede Australia in several ways:

1. Use of foreign models could limit application in sensitive industries (such as Health, or Defence) where strict privacy requirements exist.
2. Models trained on foreign data may demonstrate biases in Australian contexts; for example, a foreign trained medical model may under diagnose conditions prevalent in Australia.
3. Lack of exposure to AI training may limit Australia's opportunities to become an AI education destination, particularly as neighbours capitalise on their greater level of capability in model development.

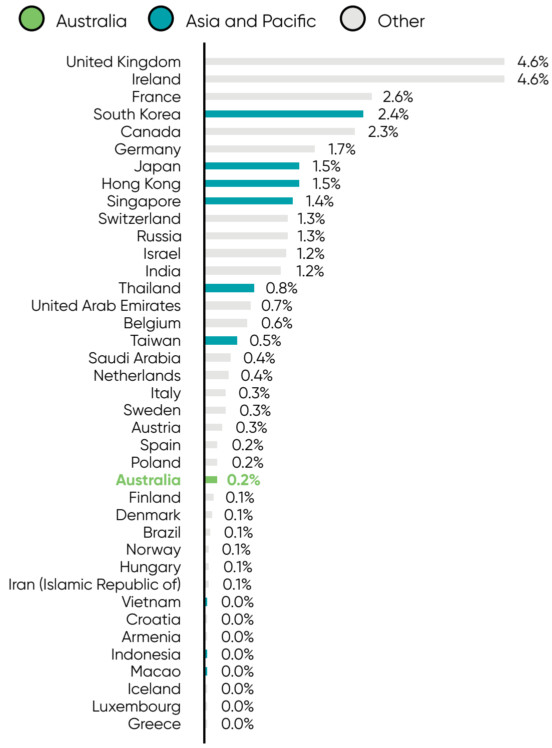
Share of AI model training†,* US, China and RoW

Share of models trained †,*, %, 2023- July 2025



Share of AI model training †,* Ex. USA and China

Share of models trained†,*, %, 2023- July 2025



† Includes models across 14 domains: 3D modeling, Audio, Earth science, Games, Image generation, Language, Mathematics, Medicine, Multimodal, Other, Robotics, Speech, Video and Vision
* Where multiple countries are involved in model development contribution has been equally divided among countries
Source: Epoch AI, 'Data on AI Models'. Published online at epoch.ai. Retrieved from 'https://epoch.ai/data/ai-models' [online resource]. Accessed 3 Oct 2025, Author's analysis

Increasing public adoption, confidence, skill and trust in AI applications is key.

Approximately 50% of Australians use AI on weekly basis, a similar proportion to peer countries such as the UK, US and New Zealand. However, adoption is lower compared with many other nations , including in the Asia Pacific region.[37]

Relative to other countries, fewer Australians report that they have undertaken AI training, and they are less confident in their AI knowledge and efficacy. Less than 25% of Australians report they have undertaken AI training, which is lower than the global and advanced countries average, and significantly lower than emerging countries.[37]

While most Australians regularly use AI in their daily lives, they are more likely to question the trustworthiness of AI applications relative to citizens in other countries. Ensuring safe and responsible AI deployments, and building citizen trust, particularly where AI is used in critical and sensitive settings, is vital.

> ***"while Australians in particular are happy to use AI in their life...they are very skeptical about government using AI" -Workshop participant***

Conclusion

AI offers many economic opportunities for Australia over the next decade.

At the more ambitious end of the scale, Australia could add $142bn per annum to the local economy by 2030 if it seeks to increase AI adoption, build a thriving local AI industry, and become a regional AI hub.

This would increase productivity, lift wages and living standards, address skills shortages, create new businesses and jobs, improve citizen services and strengthen Australia's economic and supply chain resilience.

Critically, many of the beneficiaries of these opportunities could be industry sectors and groups in the community that have been more likely to be overlooked in previous technology-driven productivity uplifts. This includes small business, the care and public sectors, and women.

However, while these opportunities are feasible, they are not inevitable.

Australia is well-positioned to realise each of these opportunities, but they will require concerted action to achieve. This includes investment in new data and compute infrastructure and AI research, workforce skills and training initiatives, and ensuring the development of safe, responsible and democratic AI applications that support public trust and confidence.

With coordinated action across government, industry, and education, Australia can position itself as a trusted, capable, and regionally significant AI economy by 2030, securing long-term productivity and inclusive growth.

AI Economic opportunities Methodology overview

The following details the steps that were undertaken to estimate the economic impact of AI on the Australian economy. Whereever a variable in the style $A.x$ is listed, the corresponding value can be found in Table 7 at the back of this document.

1. Estimating expected task Frequency

O*NET data[38] does not contain direct estimates of task frequencies, and instead contains estimated proportions of workers performing tasks across various frequency bins using the following scale:

Table 1. O*NET Frequency categories and assumed boundaries

bin	Description	Key assumption	Lower bound	Upper bound
1	Yearly or less	Performed at most once per year	0	2
2	More than yearly	Performed at most 12 times per year	1	12
3	More than monthly	Performed at least 12 times per year 12	12	100
4	More than weekly	Performed at least twice per week, 50 working weeks per year 100	100	250
5	Daily	Performed at least once per day, 250 working days per year 250	250	750
6	Several times daily	Performed at least 3 times per day 750	750	1500
7	Hourly or more	Performed at least 6 times per day, 250 days per year 1500	1500	N/A

The methodology assumes that actual task frequencies performed by workers are drawn from some distribution that accounts for the proportion of workers falling into each category according to the bounds informed by key assumptions in Table 1. To estimate the prior distribution from which observed proportions are drawn, we consider the possibility that observed proportions are the result of sampling from one of three distributions:

Distribution	Probability mass function	Rationale for use
Negative binomial	$\phi^{NB}\left(r, \frac{r}{r+\mu}\right)$	1. Has positive domain 2. Allows for high variance to capture spread in observed proportions
Log-normal	$\phi^{LN}(\mu,\sigma)$	1. Has positive domain 2. Can model very long tailed distributions, where some workers can perform task orders of magnitude more frequently other workers
Poisson	$\phi^{P}(\lambda)$	1. Has positive domain 2. Can be modelled using only one parameter (but restricted to variance equalling mean)

Given some set of parameters θ describing a distribution ϕ_d the expected proportion falling under category c is given by:

$$q(c|\theta) = \frac{\int_{l(c)}^{u(c)} \phi_d(x|\theta)dx}{\int_0^{\infty} \phi_d(x|\theta)\,dx}$$

The likelihood of observing the empirical distribution of frequencies $Pr(.|\theta)$ is given by:

$$\Pr(n(1), \dots, n(7)|\theta) = \frac{N!}{\prod_{c=1}^{7} n(c)!} \prod_{c=1}^{7} q(c|\theta)^{n(c)}$$

We estimate the parameters $\hat{\theta}$ that maximise the log-likelihood of our observed distribution, by minimising the equivalent negative log-likelihood:

$$\hat{\theta} = \arg\max_{\hat{\theta}\in\Theta_d} \sum_{c=1}^{7} n(c)\log\left(q(c|\hat{\theta})\right) \equiv \arg\min_{\hat{\theta}\in\Theta_d} \sum_{c=1}^{7} -\frac{n(c)}{N}\log\left(q(c|\hat{\theta})\right)$$

For each task we estimated the relevant parameters and associated negative log-likelihood for the three hypothesised distributions, retaining the estimated distribution that returned the lowest negative log-loss, we then estimate an expected frequency for each task t:

$$E[t|d] = \begin{cases} \hat{\mu} \mid d = NB \\ e^{\hat{\mu}+\frac{\hat{\sigma}^2}{2}} \mid d = LN \\ \hat{\lambda} \mid d = P \end{cases}$$

to construct a vector of average frequencies for tasks 't'

1.1. Estimating time per task from frequencies

To estimate time shares spent on tasks, each task is mapped to one or more corresponding "Detailed Work Activities" (DWAs - 2,087 in total). Assuming that on average a detailed work activity takes the same amount of time to perform across occupations, we can express a system expressing total working time across occupations:

$$J\mathrm{t} = \mathrm{h}$$

Where J is m×n matrix, with m rows for each occupation and n columns for each DWA h reflects a vector of hours worked in each occupation (all entries normalised to 1; this assumes that O*NET task frequencies across occupations reflect distributions for a standard US 2,000 hour working year (eight hour days, five days per week, fifty weeks per year). We solve for $\hat{t}$ through constrained linear optimisation:

$$\frac{1}{2}||J\hat{t} - h||^2 \; s.t. \frac{1}{250 \times 8 \times 30} < t < c$$

Where:

$$c_i = \frac{1}{\max_j J_{ij}}, \qquad c = (c_1, c_2, \dots c_n)^T$$

The constraints reflect that no single DWA can take less than two minutes, or add up to more than 2,000 hours per year on average (The minimum value of c_i was equivalent to 6.4 minutes).

In theory, because such a system has more parameters (2,087) than equations (894), there could be infinite solutions, however the addition of lower and upper bounds on task times can lead to convergence to a unique solution. In our setup, a unique global minimising solution for $J\hat{t}=\hat{h}$ existed, because a sufficient number of high frequency tasks were restricted to the boundary conditions.

As a final step, for each occupation m, we normalise time spent on task n:

$$share_{m,n} = \frac{J_{m,n} \times t_n}{\hat{h}_n} \tag{1}$$

Such that each occupation is represented by a length n vector of time shares per task

2. Concording SOC occupations to ANZSCO occupations

To convert O*NET time shares into Australian occupations, we concord US SOC occupations to ANZSCO 4-digit occupations in a three-step process:

1. Use correspondence tables to link SOC occupations and ISCO occupations codes, and ISCO codes to ANZSCO codes. This yields a many-to-many matching (with some poor matches)
2. We refine the concordance with fuzzy matching on cosine similarity between SOC and ANZSCO occupation names, by encoding occupation names using a sentence transformer (The model used was "all-MiniLM-L6-v2"). For each ANZSCO/SOC occupation pair i,j we calculate a similarity score $s_{i,j}$, keep the best matching SOC code for each ANZSCO code, and any other matches that satisfy the following condition:

$$s_{i,j} \in \left\{ s | s_{i,j} \geq \max_i s_{i,j} - \frac{1 - \max_i s_{i,j}}{2} \right\}$$

3. The final step is to generate a weighting where many matches exist, we apply cosine similarity from the same sentence transformer on the SOC job descriptions and ANZSCO job descriptions, and use a softmax to weight each SOC to similarity score within an occupation, so for a given ANZSCO/SOC pair i,j

$$w_{i,j} = \frac{e^{\alpha \cdot s_{i,j}}}{\sum_{s_{i,j} \in \{s | s_{k=i,j}\}}^{o} e^{\alpha \cdot s_{i,k}}} \tag{2}$$

With α acting as a temperature parameter, with lower values favouring equal weights, and higher values favouring unequal weighting. We set α to 5, which provided a good balance between including weights where similarity scores are only slightly worse than the best match, and significantly underweight instances where similarity scores are relatively poor.

The final output yielded a one-to-many weighted ANZSCO-SOC concordance. Task time shares for each ANZSCO ($AUshare_{i,n}$) was estimated by combining (1) and (2):

$$AUshare_{i,n} = \left(share_{m',n}\right)^{T} w^{i} \tag{3}$$

Where w^i is the vector of corresponding weights for all SOC occupations m' that map to ANZSCO i

3. Classifying task exposure to AI

We use detailed data classifications of O*NET tasks by Eloundou, et al. 2023[39] which provided a forward looking estimate of task exposure to AI in 2023, with three categories of tasks exposure:

1. E0: No potential for AI
2. E1: potential for LLMs to save up to 50% of time taken to perform task
3. E2: With further development of supporting technology, image models or LLMs could save up to 50% of time taken to perform task

We attempted to validate whether there was evidence that AI was being used to assist performance of these tasks by cross checking classifications with analysis of millions of Claude conversations[40]. Overall, E1 and E2 tasks were as significantly more likely to be tagged by Anthropic, meaning users of Anthropic are much more likely to be observed either automating or augmenting the performance of E1 and E2 tasks (Table 2). This provided external validation for the (Eloundou, et al. 2023) classification. For our purposes we included all E1 and E2 tasks as potentially exposed to AI.

Table 2. Logistic regression output results predicting whether a task appears in Claude conversations or not

Dep. Variable:	ai_dummy	No. Observations:	19265
Model:	Logit	Df Residuals:	19258
Method:	MLE	Df Model:	6
Date:	Mon, 13 Oct 2025	Pseudo R-squ:	0.1248
Time:	11:47:20	Log-Likelihood:	-8013.0
converged:	True	LL-Null:	-9155.7
Covariance Type:	nonrobust	LLR p-value:	0.000

	coef	std err	z	P>|z|	[0.025	0.975]
Intercept	-3.8041	0.090	-42.374	0.000	-3.980	-3.628
C(gpt4_exposure)[T.E1]	0.5219	0.079	6.630	0.000	0.368	0.676
C(gpt4_exposure)[T.E2]	0.4397	0.064	6.833	0.000	0.314	0.566
C(gpt4_automation)[T.T1]	2.0031	0.103	19.484	0.000	1.802	2.205
C(gpt4_automation)[T.T2]	2.6552	0.115	23.113	0.000	2.430	2.880
C(gpt4_automation)[T.T3]	2.5177	0.115	21.957	0.000	2.293	2.742
C(gpt4_automation)[T.T4]	1.7871	0.258	6.935	0.000	1.282	2.292

Anthropic's research also found that users were slightly more likely to automate or augment their tasks. (Eloundou, et al. 2023)task exposure ratings (E0/E1/E2) and automatability (T1: Most automatable – T4: Least automatable) tended to align with whether the nature of user interactions in Claude to automate vs. augment their tasks. We use the output of the regression in Table 3 to assign a share of task augmentation/automation to all tasks in the (Eloundou, et al. 2023) dataset.

Table 3. Logistic regression output results predicting whether users automate or augment work in Claude conversations

Dep. Variable:	aug_dummy	No. Observations:	2479
Model:	Logit	Df Residuals:	2472
Method:	MLE	Df Model:	6
Date:	Mon, 13 Oct 2025	Pseudo R-squ:	0.06098
Time:	11:47:20	Log-Likelihood:	-1612.9
converged:	True	LL-Null:	-1717.6
Covariance Type:	nonrobust	LLR p-value:	1.818e-42

	coef	std err	z	P>|z|	[0.025	0.975]
Intercept	0.8442	0.267	3.164	0.002	0.321	1.367
C(gpt4_exposure)[T.E1]	0.7660	0.186	4.109	0.000	0.401	1.131
C(gpt4_exposure)[T.E2]	0.9245	0.160	5.791	0.000	0.612	1.237
gpt4_automation[T.T1]	-0.7802	0.293	-2.663	0.008	-1.354	-0.206
gpt4_automation[T.T2]	-1.5313	0.317	-4.834	0.000	-2.152	-0.910
gpt4_automation[T.T3]	-2.3008	0.318	-7.226	0.000	-2.925	-1.677
gpt4_automation[T.T4]	-2.8395	0.731	-3.883	0.000	-4.273	-1.406

4. Estimating the AI token requirements to augment and automate tasks

For every E1/E2 task, we estimate several different types of tokens required to automate/augment parts of the relevant tasks. To do this, we used Open Router, and the following instructions with three different lightweight models, gemini-flash-1.5-8b, qwen-2.5-7b-instruct, and mistral-7b-instruct. For each task, we used the following prompt in python:

Figure 1. Prompt for task token requirements assessment

Assess the expected unit/token requirements to automate or perform specific tasks for an equivalent of one hour of a professional's work.

For each task consider the different types of tokens required in the AI workflow, using the following definitions:

– **structure_tokens:** Text (or tokenized control strings) that set up how the model should behave but are not part of the user's task content. Includes system prompts, tool specs, few-shot scaffolding, routing instructions, and formatting boilerplate.

– **text_input**: Tokens created when user/task text is ingested (instructions, source docs, notes, transcripts after ASR, etc.). Counted against context length and often billed as "input tokens."

– **audio_input:** Discrete units representing audio provided to the system (e.g., acoustic frames or model-specific audio tokens) prior to transcription or direct audio understanding.

– **image_input:** Discrete visual units (e.g., VLM patches/embeddings or latent tokens) produced when images are ingested for analysis or grounding.

– **video_input:** Spatio-temporal tokens (e.g., frame/patch sequences or latent video tokens) representing video inputs used for understanding or grounding.

- **contextual_tokens:** Tokens (or vectorized equivalents) produced/used for retrieval and context building: embedding computation, index lookups, query reformulations, and the re-chunked snippets inserted into context. May be billed separately (embeddings) even if not visible as "tokens."
- **reasoning_tokens:** Tokens generated for intermediate computation steps (planning, tool selection, hidden chain-of-thought, scratchpads). May be suppressed from the final answer but still drive latency/cost in "reasoning" modes.
- **text_output:** Tokens in the user-visible textual answer (summaries, code, explanations). Typically billed as "output tokens."
- **audio_output:** Discrete synthesis units used by TTS or audio-generation models to produce speech or other audio as the final output.
- **image_output:** Visual latent tokens/patches produced by image-generation or image-editing models to render the final picture(s).
- **video_output:** Temporal visual tokens produced by video-generation/editing models to render the final clip(s).
- **special_tokens:** (role delimiters, routing markers) Non-semantic control markers inserted by the API/runtime or prompt format (role tags, section delimiters, tool call markers, stop tokens). Usually small in number but necessary for correct parsing/routing.

Consider what the combination of AI-technologies is required for the task (Large Language Models (LLMs), Image Processing/generating Systems, video processing/generating systems, Agentic workflows, Reasoning models) and assess the relevant unit requirements for each of the above categories.

You should only consider the unit requirements for the relevant type of tokens, as opposed to their text token equivalent.

For high-cost tokens such as image and video output, the output should be zero unless the task explicitly requires producing videos or images.

For each task, consider:

- What types of input tokens listed above are required
- How much of each token are typically required for an equivalent of a human hour of task time
- For each evaluation:
- Spend some time thinking through each requirement and start by estimating likely ranges for each token required
- Evaluate your reasoning and make any necessary adjustments
- Determine a point estimate for units required for each of the above

Once you have completed your reasoning, provide your point estimates at the end of your response in the following format:

```
{"structure_tokens": units per hour,
  "text_input": units per hour,
  "audio_input": units per hour,
  "image_input": units per hour,
  "video_input": units per hour,
  "contextual_tokens": units per hour,
  "reasoning_tokens": units per hour,
  "text_output": units per hour,
  "audio_output": units per hour,
  "image_output": units per hour,
  "video_output": units per hour,
  "special_tokens": units per hour
}
"""+
f"Given the profession: {row['Title']}, and the specific task: '{row['Task']}' evaluate the token requirements for a human working iteratively with AI for {row['augment']}% of an hour performing this task, and to automate the remaining {row['automate']}% of an hour."
```

We store the token requirements for each type of token alongside the task classification, for all three models as well as minimum, median, mean and max values for each token estimate for each task.

5. Aggregating tasks to occupations

We then aggregate time shares, and token requirements per hour of work for each ANZSCO occupation into one of five categories

Table 4. Task categories

	Category	Definition
T0	Not exposed to AI	All E0
T1	Exposed to direct AI automation	All E1 tasks x predicted automation share
T2	Exposed to indirect AI automation	All E2 tasks x predicted automation share
T3	Exposed to direct AI augmentation	All E1 tasks x predicted augmentation share
T4	Exposed to indirection AI augmentation	All E2 tasks x predicted augmentation share

There are two outputs of this process:

a m×5 matrix of estimated of AI exposure types by occupations, where m is the number of unique 4-digit ANZSCO codes.

$$\mathcal{O}_{m,5} \tag{4}$$

And 12 m×5 matrices estimating the weighted average token requirements to integrate AI into each of the exposed tasks hours of work, to produce several versions of the following matrix:

$$\mathcal{K}_{m,5}^{token} \tag{5}$$

Where superscript $token$ indicates the type of token. For all tokens except image and video input requirements, the mean of three models was used for each entry in the relevant K matrix. Due to extreme results for some tasks with respect to image/video inputs in qwen/mistral models, gemini outputs were used for image/video inputs estimates.

6. Aggregating task hours and tokens across the economy

To estimate the overall potential for AI impact we aggregated task hours across the entire economy and industries. ABS data was used[41] to estimate total hours for 2025, and average hours by occupation spent on each task, by multiplying equation (4) by the respective hours worked in each occupation (t), yielding the total time spend on each of the five task types in Australia:

$$\mathcal{t} = \mathcal{O}'t \tag{6}$$

We carried out the same exercise for each industry by using Census data on occupation distributions by 2 digit ANZSIC codes[42], and assumed that the average time spent between occupations did not differ across industries. The share of time spent on five-task categories in industry i is given by:

$$\mathcal{t}(\mathcal{i}) = \mathcal{O}'(t \otimes \mathcal{w}_i) \tag{7}$$

Where w_i is a m length vector of the % share of 4 digit ANZSCO codes in industry 'i'. Similarly we do the same for each of the 12 token types, recalling that each of these represents the tokens required to integrate AI into one hour of work for the relevant tasks.

$$\mathcal{k}^{token} = \mathcal{K}_{m,}^{token'} t$$

$$\mathcal{k}^{token}(i) = \mathcal{K}_{m,}^{token'}(t \otimes w_i)$$

Lastly we aggregate the tokens into output-Text-Equivalent-Tokens (TTEs) based on a table of estimated equivalent compute requirements (see Table 5 for definitions of v)

$$tte(i) = \mathcal{k}(i) \cdot v, \qquad tte = \mathcal{k} \cdot v \tag{8}$$

The resulting tte vectors contain estimates of the total amount of tokens required per task type, by industry. These can also easily be converted back into typical hourly token requirements by dividing the token totals by the total hours of work in the relevant task type/industry which we denote as.

$$\widehat{tte(i)} = \frac{tte(i)}{t(i)}, \qquad \widehat{tte} = \frac{tte}{t} \tag{9}$$

These token requirements form the building blocks for estimating the cost of applying al to work models based on

7. Modelling impacts of AI – approach to estimating productivity gains

We assume that the economy produces goods within a Cobb-Douglas framework incorporating intermediate goods. Final outputs are either consumed or used as intermediate goods in production. We also assume that each task category in table 4 has its own production function. Modelling the productivity benefit of AI for each of the 4 impacted categories (E0 tasks are assumed to not be exposed) proceeds as follows:

Assume that an hour of work performing some task in the economy produces outputs with constant returns to scale ($\alpha+\beta+\gamma=1$), and no AI inputs.

$$Y = AL^{\alpha}K^{\beta}M^{\gamma} \tag{10}$$

A new constant-returns-to-scale production function is introduced, in which AI substitutes proportionately for other inputs.

$$Y_{AI} = \left(AL(AI)^{\alpha}K^{\beta}M^{\gamma}\right)^{\delta} AI^{\epsilon} \tag{11}$$

Where $\epsilon=1-\delta, L(AI)=\frac{L}{1-c}$ and c reflects a reduction in labour time required to produce an output.

Assume all markets clear:

$$p_Y Y_{AI} = w_L L + r_k K + p_m M + p_{ai} AI$$

Which converting into real prices yields

$$Y_{AI} = p_L^* L + p_k^* K + p_m^* M + p_{ai}^* AI$$

Where $p_X{}^* = \frac{Px}{py}$

Given the market is competitive we have prices equal to marginal product for units of production:

$$\frac{\partial Y_{AI}}{\partial AI} = \epsilon\left(AL(AI)^{\alpha}K^{\beta}M^{\gamma}\right)^{\delta} AI^{\epsilon-1} \equiv \frac{\epsilon Y_{AI}}{AI} = p_{AI}^{*} \tag{12}$$

$$\frac{\partial Y_{AI}}{\partial M} = \gamma\delta\left(AL(AI)^{\alpha}K^{\beta}\right)^{\delta} M^{\gamma\delta-1}AI^{\epsilon} \equiv \frac{\gamma\delta Y_{AI}}{M} = p_{M}^{*} \tag{13}$$

substituting (12) and (13) and $L(AI)= \frac{L}{1\text{-}c}$ into (11) yields:

$$Y_{AI} = (1-c)^{\frac{-\alpha}{1-\gamma}} AL^{\frac{\alpha}{1-\gamma}} K^{\frac{\beta}{1-\gamma}} \left(\frac{\gamma\delta}{p_M^*}\right)^{\frac{\gamma}{(1-\gamma)}} \left(\frac{\epsilon}{p_{AI}^*}\right)^{\frac{\epsilon}{\delta(1-\gamma)}} \tag{14}$$

Similarly from (10)

$$Y = AL^{\frac{\alpha}{1-\gamma}} K^{\frac{\beta}{1-\gamma}} \left(\frac{\gamma}{p_M^*}\right)^{\frac{\gamma}{(1-\gamma)}} \tag{15}$$

And dividing (14) by (15) yields a formula for expected productivity change due to AI

$$\frac{Y_{AI}}{Y} = (1-c)^{\frac{-\alpha}{1-\gamma}} (1-\epsilon\,)^{\frac{\gamma}{(1-\gamma)}} \left(\frac{\epsilon}{p_{AI}^*}\right)^{\frac{\epsilon}{\delta(1-\gamma)}} \tag{16}$$

The first term captures increased labour productivity, which reflects both the time savings to produce outputs, as well as labour's significance in the production function – the labour productivity effects are higher if the production function is more labour intensive (higher α).

The second term reflects the impact of reduced productivity of other production factors because of introducing AI. One rationale for this effect is that effective introduction of AI may require diversion of intermediate inputs from direct production to support AI implementation, e.g. introducing additional power redundancies to prevent catastrophic failure of a critical AI system.

Lastly the third term captures the impact associated with the price of AI itself as a factor of production. The higher the value of p_{AI}^*, the less efficient the AI production function is compared to the original production function. In the extreme case, AI could be so expensive to completely offset the labour productivity benefits from adoption, meaning firms opt not to use AI as a production factor.

Our baseline unit for production factors is defined as the total amount of that factor required to support one hour's worth of output. base units of AI and Y are equal to 1, substituting from[12]:

$$\epsilon = p_{AI}^* \frac{AI}{Y_{AI}} \equiv p_{AI}^* \tag{17}$$

While this assumption is limiting as it sets an arbitrary shadow price for AI, and assumes no price change in intermediate goods due to AI, it keeps analysis tractable. Overall, this approach allows us to introduce a cost to adding AI as a production factor, which other work often abstracts from. Our final productivity change from AI is thus given by:

$$\textit{Productivity potential} = (1-c)^{\frac{-\alpha}{1-\gamma}} (1-\epsilon)^{\frac{\gamma}{(1-\gamma)}} \tag{18}$$

Taking logarithms shows that our final estimate for productivity impact aligns with Hulten's theorem[43]:

$$\ln\left(\frac{Y_{AI}}{Y}\right) = \ln(1-c) * -\frac{\alpha}{1-\gamma} + \ln(1-\epsilon)\frac{\gamma}{1-\gamma} \approx \frac{\alpha}{1-\gamma} \cdot c - \epsilon \cdot \frac{\gamma}{1-\gamma}$$

AI's positive shock on labour generates efficiency gains proportional to its share of GDP, and negative shocks from disruptions in the supply chain from introducing AI, proportional to intermediate goods as a share of GVA.

We also assume that capital per worker remains constant after AI adoption, meaning that the aggregate impact on total factor productivity is equal to the impact on labour productivity.

Key limitations:

1. The approach abstracts from input-output dynamics
2. AI cost dynamics are assumed to primarily flow through the supply chain
3. The framework is a partial equilibrium approach, abstracting away, price impacts of AI, and critically the impact of AI technology on capital accumulation. Future work could attempt to endogenize price dynamics, and input-output mechanics to examine general equilibrium impacts of AI adoption.

8. Estimating productivity gains by industry/aggregate

We use ABS national accounts data[44], data on expenditure shares by subdivision[45], and Input-Output tables[46] to calibrate our estimates for relevant parameters (α,γ).

Our estimates of the other relevant parameters was informed by desktop research combined with data from ABS national accounts.

Parameter	subfield	Formula/value	Rationale
GVA/GVA_i	GVA per hour among all impacted industries/ industry i	N/A	N/A
γ/γ_i	intermediate share of income across economy/ within industry i	N/A	Stylised fact: Cobb Douglas income shares will equal parameter values
α/α_i	Labour share of income across economy/ within industry i	N/A	Stylised fact: Cobb Douglas income shares will equal parameter values
$\epsilon(T1,T3)$ $/\epsilon_i\,(T1/T3)$	Cost of compute output share of income	$\frac{\widehat{tte(\iota)}_T \times \text{Cost per Token}}{\left(\frac{GVA}{\gamma}\right) + cost\ of\ compute}$	Assumed AI costs are additive to current production function + CD stylised fact
$\epsilon(T2/T4)$ $/\epsilon_i\,(T2/T4)$	Cost of compute output share of income	$\left(\frac{\widehat{tte(\iota)}_T \times \text{Cost per Token}}{\left(\frac{GVA}{\gamma}\right) + cost\ of\ compute}\right) \times \frac{1}{A.x}$	E2 tasks in require additional technology to realise benefits (Eloundou, et al. 2023), therefore it is assumed that compute cost will represent an input into production of 'AI applications' for this class of tasks
$c(T1,T2)$	Productivity uplift for automation tasks	39%	Minimum savings achievable (50%) to be classified in (Eloundou, et al. 2023)[39] adjusted for the need to introduce quality assurance work (based on desktop research)
$c(T3,T4)$	Productivity uplift for augmentation tasks	17%	Empirical average productivity uplift over several studies for humans working with AI: (Bick, Blandin and Deming 2025)[1] (Brynjolfsson, Li and Raymond 2023)[14] (Dell'Acqua, et al. n.d.)[47] (Cui, et al. 2025)[48]

The overall uplift productivity uplift for the economy/industry is given by:

$$p'u \times (A.4)$$

Where $u_j = \frac{Tj}{\sum_{j=0}^{4} Tj}$ and $p_j = \left(1 - c(Tj)\right)^{\frac{-\alpha}{1-\gamma}}\left(1 - \epsilon(Tj)\right)^{\frac{\gamma}{(1-\gamma)}}$, i.e. the average of productivity uplifts weighted by time shares on task types.

From these estimates all other estimates of GVA growth are derived.

9. Additional constructed estimates

9.1. Estimating domestic share of AI applications market

The ABS publishes data on the following metrics:

- Software imports (Australian Bureau of Statistics 2025)[49]
- Software exports (Australian Bureau of Statistics 2025)[50]
- Software contribution to Australian GVA (Australian Bureau of Statistics 2024)[51]

Combined with the Input-Output table's[46] estimate of computer services GVA, we construct an estimate of Australia's software industry share of local delivery:

$$a = \left(\frac{GVA_{2023}^{software}}{\gamma_{2023}^{computer\ design\ services}}\right), \qquad b = Exports_{2023}^{software}, \qquad c = Imports_{2023}^{software} \tag{19}$$

$$domestic\ software\ share = \frac{a-b}{a+c}$$

For our modelling we assumed that the domestic AI application market will have a similar market structure, which is consistent with various stylised facts:

- Australian SaaS companies suchas Canva are leading AI integration into products
- Australia is developing new AI SaaS businesses e.g. Lorikeet

The total value of AI applications produced domestically was estimated as (See equation 8 for definition of $tte_{T\#}$, Table 6 for definition of CPT and Table 7 for A.24):

$$(tte_{T2} + tte_{T4}) \times CPT \times \left(\frac{1 - A.24}{A.24}\right) \times domestic\ software\ share$$

Which is the value adding production on top of compute tasks

9.2. Estimating data centre energy consumption

Data centre energy consumption was estimated by inferring the total GPU hours required to deliver AI workloads for the Australian economy (See equation 8 for definition of tte, Table 6 for definition if TTH and Table 7 for definition of A.19):

$$energy\ consumption = \frac{\sum tte}{TTH} \times A.19$$

9.3. Estimating AI compute capacity needs

Capacity needs were calculated by applying a data centre capacity utilisation ratio to peak capacity needs (See table 7 for definitions of $A.17$,$A.21$ and $A.22$):

$$capacity = \left(\frac{energy\ consumption}{365 \times 24}\right)\frac{1}{A.17 \times \left(\frac{A.21}{A.22}\right)}$$

The chosen ratio was based on combining public estimates of Global AI compute demand by 2030 (Goldman Sachs 2025) with public estimates of AI compute capacity required by 2030 (McKinsey 2025)

9.4. Estimating AI applications exports

Assumed to follow the same ratio of as software market (See Equation 8 for definitions of $tte_{T\#}$, equation 19 for defitions of a and b, and table 7 for $A.23$:

$$AI\ app\ exports = \frac{b}{a}(tte_{T2} + tte_{T4}) \times CPT \times \left(\frac{1 - A.24}{A.24}\right) \times domestic\ software\ share$$

9.5. Estimating AI compute exports

Australia targets 2.5% of global training demand and 5% of selected Asia pacific region demand (11% of world GDP), this yields an estimated compute exports share of global compute (See Table 7 for definitions of $A.15$,$A.26$ *and* $A.27$):

$$Compute\ exports = A.26 \times (A.15) \times 11\% + A.27 \times (1 - A.15)$$

The value of global compute is estimated by modelled compute costs/values to Goldman Sachs (2025) demand estimates (See Table 6 for definitions of TTH and CPT, and Table 7 for definition of $A.19$ and $A.23$):

$$Value\ of\ global\ compute = \frac{A.23}{A.19} \times 1{,}000{,}000{,}000 \times \frac{TTH}{CPT}$$

9.6. Estimating AI education exports

AI export potential was taken by estimating the per student GVA from overall education enrolments (See Table 7 for definitions of $A.31$, $A.34$, $A.35$, $A.36$ and $A.37$):

$$Ed\ Export\ GVA = \frac{A.36 + A.37}{A.31}$$

And multiplying this value by the projected number of international students enrolled in AI specific courses in 2030, which was taken as the midpoint of continuing exponential growth and continuing linear growth

$$\#\ of\ AI\ enrolments = \sum_{y=2028}^{2030} AI\ commencements_y$$

$$a_y = AI\ comencements_y$$

$$a_y = \frac{A.34(1 + A.35)^{y-2025} + a_{2025} + (a_{2025} - a_{2024}) \times (y - 2025)}{2}$$

Table 5. Characteristics of different types of tokens – developed through iterated conversation with ChatGPT 5

Token Type	Description	computational load (multiple of output tokens) (v)	Multiple rationale
Structural / Overhead tokens	Text (or tokenized control strings) that set up how the model should behave but are not part of the user's task content. Includes system prompts, tool specs, few-shot scaffolding, routing instructions, and formatting boilerplate.	0.08	Setup/scaffold; not really "per token". Amortize over the batch/task.
Text tokens (input)	Tokens created when user/task text is ingested (instructions, source docs, notes, transcripts after ASR, etc.). Counted against context length and often billed as "input tokens."	0.028285714	Prefill can be highly parallel → faster than decode per token. Longer contexts push toward 0.5×.
Audio tokens (input)	Discrete units representing audio provided to the system (e.g., acoustic frames or model-specific audio tokens) prior to transcription or direct audio understanding.	0.6	ASR/AV front-ends; depends on model size & frame rate. If you later transcribe to text, avoid double counting.
Image tokens (input)	Discrete visual units (e.g., VLM patches/ embeddings or latent tokens) produced when images are ingested for analysis or grounding.	1	Vision encoder on patches/latents; cost depends on resolution & patching scheme.
Video tokens (input)	Spatio-temporal tokens (e.g., frame/patch sequences or latent video tokens) representing video inputs used for understanding or grounding.	3.5	Spatio-temporal stacks are heavy; scales with fps·resolution·seconds.
Contextual tokens (Retrieval/ search tokens/ embedding vectors)	Tokens (or vectorized equivalents) produced/used for retrieval and context building: embedding computation, index lookups, query reformulations, and the re-chunked snippets inserted into context. May be billed separately (embeddings) even if not visible as "tokens."	0.35	If using a small embedding model: ~0.1–0.2×; if LLM-as-embedder or heavy re-ranking: up to ~0.6×. Retrieval itself (index lookups) is mostly CPU/IO.
Reasoning tokens (output)	Tokens generated for intermediate computation steps (planning, tool selection, hidden chain-of-thought, scratchpads). May be suppressed from the final answer but still drive latency/cost in "reasoning" modes.	3.5	"Thinking" modes (multiple draft passes, tool planning, scratchpads) inflate per-token compute. Use higher end for very deep reasoning/tool use loops.
Text tokens (output)	Tokens in the user-visible textual answer (summaries, code, explanations). Typically billed as "output tokens."	1	Autoregressive decode bottleneck. Batch/kv-cache/quantization can shift this materially.
Audio tokens (output)	Discrete synthesis units used by TTS or audio-generation models to produce speech or other audio as the final output.	0.35	TTS vocoders/flow models; depends on quality (hi-fi vs fast).
Image tokens (output)	Visual latent tokens/patches produced by image-generation or image-editing models to render the final picture(s).	37.5	Diffusion/rectified-flow with 20–50+ steps and up samplers. (Token-eq mapping matters; this captures the heaviness relative to text.)
Video tokens (output)	Temporal visual tokens produced by video-generation/editing models to render the final clip(s).	850	Multi-frame diffusion/transformers; duration·fps·resolution dominate. Very model-dependent.
Special/ metadata tokens (role delimiters, routing markers)	Non-semantic control markers inserted by the API/runtime or prompt format (role tags, section delimiters, tool call markers, stop tokens). Usually small in number but necessary for correct parsing/routing.	0.02	Role delimiters, routing markers; negligible but non-zero. Often amortized inside "structural".

Table 6. 2030 Compute requirements input constructions

Driver	Value	Source/Formula
KWh per GPU-hour (with data centre overhead) (Forecast) (KWh)	1.042	$A.19$
Tokens per GPU hour (weighted mix of Heavy and Lightweight model use for inference) (TTH)	86,174.59	Weighted harmonic average of throughputs for light and heavy weight models in 2030: $HeavyTTH = \frac{\left(\frac{3600}{A.8} \times 1000\right) \times A.13}{A.11}$ $LightTTH = \frac{\left(\frac{3600}{A.7} \times 1000\right) \times A.13}{A.12}$ $WeightLight = \frac{LightTTH \times A.10}{LightTTH \times A.10 + HeavyTTH \times (1 - A.10)}$ $TTH = LgihtTTH \times WeightLight + HeavyTTH \times (1 - WeightLight)$
Cost per Token (CPT)	$\frac{10.02 \times 10^{-6}}{0.66}$	$A.5 \times A.10 \times \left(\frac{A.12}{A.13}\right) + A.6 \times (1 - A.10) \times \left(\frac{A.11}{A.13}\right)$

Table 7. Key modelling inputs

Driver	Unit	Value	Source/ Rationale	
Economic variables				
Exchange rate	US$ per AUD	0.66	Current exchange rate as at September 30th 2025	A.1
Employment growth	% growth p.a.	N/A	Occupation projections sourced from Jobs and Skills Australia to estimate occupation numbers for 2030[52]	A.2
Australia real GDP growth	% growth p.a.	2%	Average annual rate in RBA Statement on Monetary Policy[53]	A.3
Share of AI potential reached by 2030	% of in-scope work hours utilising AI	56%	This is based on: 1. Estimated $TTEs$ produced globally by AI by 2030 based on applying our modelling (Table 6) to (Goldman Sachs 2025)[54] estimate for AI workload demands. 2. Multiplied by Australia's global GDP share (1.7%) 3. Multiplied by global share of inference (A.15) 4. Divided by the estimated number of tokens to fully integrate AI in Australian work hours (See equation 8 for definition of tte)	A.4
Compute inputs				
Lightweight Model price (2025)	$ per M tokens	$0.19	Data from using Gemini 2.5 Flash Lite	A.5
Heavy Model price (2025)	$ per M tokens	$10.00	Based on Desktop research on Openrouter - Large models can vary from $5-$15 per million tokens - some heavy reasoning models can be significantly higher	A.6
Leightweight model speed 2025	GPU seconds / 1000 text tokens output - single GPU	2.60	Empirical Blend from multiple models used on OpenRouter	A.7
Heavyweight model speed 2025	GPU seconds / 1000 text tokens output - single GPU	37.31	The implicit outcome of NVIDIA's estimate of a 72B parameter model on a H100 GPU[55] - also common in large model stacks. Note, that compute is significantly faster now, but so is the definition of a heavyweight model.	A.8
% of tokens generated by lightweight models -2025	%	50%	State of the Art models offer significant benefits regarding accuracy. For many tasks, 99.5% accuracy is significantly more valuable than 95% accuracy as precision is critical (e.g. writing production ready code)	A.9

% of tokens generated by lightweight models - 2030	%	75%	As lightweight models become more powerful, they will be appropriate for a wider range of tasks due to improved accuracy	A.10
Heavyweight model complexity 2030	X multiple of 2025	17.37	This blends complexity growth with conservative but well-evidenced efficiency gains:	A.11
Lightweight model complexirty 2030	X multiple of 2025	14.18	**Complexity increases of 80% p.a. for lightweight models and 50% p.a. at the frontier:** Longer contexts and multi-sample reasoning are expected to drive up the computational load for inference. Longer contexts are driven by multi-modality and additional data requirements for accurate inference generation, increasing computational and memory requirements. Multi-sample reasoning can improve model consistency but scales linearly with additional forward passes in generating outputs. Some of this growth will be offset by other architectural changes, e.g. sparse Mixture of Experts (MoE) architectures keep only a fraction of model parameters active per token. For example Mixtral-8×7B, routes 2 of 8 experts per token (~12.9B active params vs 46–47B total). Overall, we expect longer contexts and multi-sample reasoning to raise per-token computational cost unless aggressively compressed. Estimates used here are based on observed growth in model parameters between 2020-2023.	A.12
Compute efficiency: Koomey's law 2030	X multiple of 2025	4.54	Improving computational efficiency: Koomey's law measures the reduction in energy required per compute. Historically through the 20th century this has doubled every 1.56 years, and more recent evidence suggests this has slowed to doubling every 2.29 years.	A.13
Current industry share of inference demand	% share of global AI computation carried out for inference	70%	Difficult to quantify - case for Return on Investment is better for business users. We estimate that consumers are numerous but low touch users, where as business applications (including consumers using AI informally for business purposes) likely make up the bulk of demand	A.14
2030 Share of inference workload	% share of global AI computation carried out for inference	90%	As demand grows, expect compute to shift towards user applications and away from training. Training will still be required for fine-tuning and building newer models, but inference will make up bulk of demand	A.15
Data centre inputs				
Australia Data Centre power demand 2030 - Step Change scenario	TWh p.a.	11.79	Australian Energy Market Operator (AEMO)[56]	A.16
Hyperscale load factor	Avg. consumption Peak consumption	75%	Oxford Economics 2025 report for AEMO estimates hyperscale Load factor (peak demand / average draw) of 75%[57]	A.17
AI share of data Centre workload - Australia	% of consumption use for AI workloads 2024	19%	Implicit	A.18
GPU power draw	KW	1.042	(Goldman Sachs 2025)[54]	A.19
Global 2027 Demand	GW	25.76	(Goldman Sachs 2025)[54]	A.20
Global 2027 AI capacity	GW	62	(McKinsey 2025)[58]	A.21
Global 2030 AI capacity	GW	156	(McKinsey 2025)	A.22
Global 2030 AI power consumption	TWh	317	(Goldman Sachs 2025)	A.23

AI application inputs				
AI application company - compute as share of output	%	20%	Calibrated over numerous conversations with Gemeni 2.5Pro. Based on modelling for typical compute/cloud costs for a few use cases. Validated against estimate for DuoLingo, where Cost of Goods is approximately $200,000,000 on $750,000,000 worth of Sales. Gemeni estimated AI compute and Hosting costs of ~ $100,000,000 - which equates to 15% Duo is not a pure AI company, the estimated $100,000,000 would also not entail only AI compute expenses, but much of the revenue is also not tied to use of AI - as such the 15% estimate was considered reasonable for a pure AI company Kruze Consulting finds that AI startups are spending 50% of revenue on Compute, compared to 18% for traditional SaaS - suggests the AI compute component is as high as 32% of revenue. AI searches suggests AI companies have gross margins of ~60% vs. traditional SaaS companies margins of 80% - further supporting the notion of high compute costs. Based on this data, 20% compute cost was selected as a reasonable midpoint estimate	A.24
AI application GVA (computer	%	55%	Computer systems design and related services GVA share used as proxy	A.25
AI share of data Centre workload - Australia	%	34%	based on Software ratios	A.26
Compute Export inputs				
Australia share of Asia neighbours compute	%	5%	Latency requirements mean minimal opportunitiy to export inference - 5% seen as potentially optimistic	A.27
Australia share of Global training	%	5%	Training requires specialised equipment, meaning potential may be muted	A.28
A.29 Education export inputs				
Tertiary education export value add	$m	14499	IO Table 5	A.30
Total Enrollments -2025	#	808,793	(Department of Education (Australia) 2025)[59]	A.31
Total Commencements -2025	#	282,235	(Department of Education (Australia) 2025)[59]	A.32
AI Enrollments - 2025	#	3,374	(Department of Education (Australia) 2025)[59]	A.33
AI Commencements -2025	#	1,614	(Department of Education (Australia) 2025)[59]	A.34
Commencement growth past two years	%p.a.	69%	(Department of Education (Australia) 2025)[59]	A.35
Education export income from tuition FY24	$bn	20.6	This figure broadly reconciles with I-O tables, which for one year earlier had GVA for tertiary education at $14bn - however the 20.6bn is a broader capture of the education sector. (Department of Education (Australia) 2025)[59]	A.36
Education export income from goods and services expenditure FY24	$bn	30.2	(Department of Education (Australia) 2025)[59]	A.37

(Department of Education (Australia) 2025)

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