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Australia's AI Imperative

The economic impact of artificial intelligence and what's needed to further its growth

By John Mangan

Australia's AI Imperative: The economic impact of artificial intelligence and what's needed to further its growth

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Executive Summary

Artificial intelligence (AI) has become a topic of profound interest worldwide due to its transformative impact on the economy and society, across industries and sectors.

The implications of AI's overall significance are subject to widely differing predictions. Some view the AI revolution as another chapter in a long chain of technical progress. Other analysts depict AI as a new and unique phenomenon that may address the long-term productivity slowdown observed in Western economies and emphasise that AI will also present significant challenges that require novel solutions from both the government and the private sector.

This paper focuses on the economic implications of AI development and distribution and the costs of not doing so for Australia in the short term, specifically from 2023 to 2030. It also examines AI's impact on both the Australian and global economy across three key points:

- The global and Australian impact of AI distribution
- The importance of early adoption of AI systems for the economies of countries
- AI as another technology shift or as transformational change

This report also analyses factors that constrict AI adoption; discusses the social challenges that AI poses globally and within Australia; and provides recommendations for ways that the Australian Government can improve Australia's current and future investment and outcomes in AI.

Impact of AI distribution

AI relates to the ability of machines or computer programs to perform tasks that normally require human intelligence, such as visual perception, speech recognition, decision-making, and language translation. Currently it consists of an array of techniques and infrastructure including machine learning, robotics, artificial neutral networks, and natural language processing. It is both a major driver of economic growth (micro and macro) and a source of economic disruption.

Artificial intelligence is widely used in Australia in self-driving trucks in mining, managing our environment and resources more efficiently, and working to solve significant national challenges like bushfires and health care. It is estimated that the AI global market in 2023 was worth approximately US$142.3 billion dollars, with major growth being fuelled by investment in AI startups. Some of the potential benefits of AI include:

- automation of repetitive and tedious tasks that can lead to increased productivity, creativity, and efficiency in many industries
- increased accuracy compared to humans, thereby reducing errors and maintenance costs and improving the quality of work
- reduced labour costs through automation and the optimisation of processes including waste reduction
- creation of new business opportunities by enabling new products and services, improving customer experience, and increasing innovation
- provision of end-to-end efficiency by eliminating friction and improving analytics and resource utilisation resulting in significant cost reductions.

The collective advantage of AI is that it reduces the cost of prediction and therefore reduces uncertainty.

Economic modelling in this report indicates that between 2023 and 2027, Australia could face an opportunity cost of 1.4% (or A$35.7 billion) of GDP per year if it fails to introduce AI systems to world standards in key industries, including technology, finance, healthcare, education, and government. Healthcare is commonly identified as offering the best fit for a quick uptake of AI due to the health industry's need for collecting accurate patient-specific data, and the collection and rapid recall of medical records and files.

This report's economic modelling suggests that greater utilisation of AI in key Australian industries will lead to a short-term boost in GDP of more than $200 billion per annum and the creation of an additional 150,000 jobs during the period 2023-2030. PwC predicts that the increased diffusion of AI technology will add US$15.7 trillion dollars to the global economy by 2030 with early adopting local economies securing a 26% increase in GDP by 2030.

Countries slow to adopt AI will suffer

More important than the total economic impact of AI is the distribution of its impact. While it is generally conceded that the development of AI is still in its early stages, it is also becoming apparent that countries that are slow to adopt AI technology will suffer significant economic costs, a potential loss of sovereignty of key infrastructure, and a resulting loss of economic self-determination. The results of this uneven distribution will have major impacts on equity, income distribution, and national sovereignty.

Research has identified that most benefits will initially flow to early adopters and be captured by already high-income countries. Data indicates that if present trends continue without substantial investment by other countries, 40% of the total GDP gains from AI will be shared by China (26.1% increases in GDP) and North America (14.7%). Other areas predicted to gain include Developed Asia (10.1%), Western Europe (9.9%), and Southern Europe (11.9%).

AI-related research spending by business has increased 43% over the period 2019-2023 and according to the WIPO, patent applications in the AI field have increased a 'staggering' 718% between 2016 and 2022. However, this patent activity is heavily concentrated among a small group of nations, with China, the US and Japan accounting for 78% of the total increase.

China, Europe, and North America show the greatest enthusiasm for using AI investment to create a competitive advantage. Australian companies, though early adopters, are also planning to make AI investment a cornerstone in creating competitive advantage.

AI as another tech shift or transformational change

Economists are divided as to whether the AI revolution is just another, albeit major, shift in technology or if it represents transformational change for which there is no direct precedent.

The growth of AI technology and its impact is believed to be non-linear, perhaps exponential, with the latest estimates predicting a doubling in analytical capacity every 2-3 months, in comparison with Moore's Law of computing power which observes that computing power doubles every two years. AI differs substantially from earlier periods of technical change, both in the generality of its usages and the linking effects it has on all parts of the economy.

Research from economists show that 60% of today's workers are employed in occupations that did not exist in 1940, and more than 85% of employment growth over the last 80 years has resulted from the technology-driven creation of new positions. These economists do not see the AI revolution creating mass unemployment but rather see it (through its innovation process) as the only way to avoid it. Goldman Sachs, using data on occupational tasks in both the US and Europe, found that approximately two-thirds of current jobs in the United States are exposed to some degree of AI automation.

Challenges and recommendations

Challenge: Businesses have consistently identified that the main constraints to increased AI development and usage are inadequate datasets, the lack of skilled labour, cost of installation, and in Western countries, resistance by concerned groups such as labour unions. The IBM Global Adoption Index 2022 identified the top five barriers to greater adoption of AI at the enterprise level:

- limited AI skills at enterprise level/staff hiring issues (34% of enterprises)
- the price is too high (29%)
- lack of tools or platforms to develop models (25%)
- projects are too complex or difficult to scale (24%)
- too much data complexity (24%).

Recommendation: Australia needs to urgently address these issues with:

- a significant increase in funding by federal and state governments to universities to undertake research into AI development and implementation, coupled with the development of integrated AI undergraduate and postgraduate courses

- development by universities of integrated technical, analytical, and commercial (hard and soft skill) programs that address all areas of AI development and include the creation of funded chairs in science, engineering, computing, and business faculties
- creation of programs for re-orientation and adaptive skills, particularly for those whose occupations will disappear or be transformed
- fostering of greater industry/university partnerships, particularly for R&D, and for workplace placements for students.

In addition, government must play a key role in the areas of direct financial support, funding of research infrastructure, freeing up of data sources, reducing public concern, and providing regulatory frameworks through patent protection and market legislation that create the eco-system needed for AI to grow and flourish in Australia.

Challenge: Australia is an importer of AI technology rather than a developer or innovator which leaves Australia vulnerable to becoming a low-skilled economy, compromising its national sovereignty, and leaving itself open to security problems in crucial areas such as defence and telecommunications.

The Australian economy, despite being the 12th largest economy in the world and 9th in terms of per capita income, is dominated by services, mining, and agriculture. The Harvard Index of Economic Complexity (ECI) ranks Australia 91st in a world ranking of 133 nations in terms of economic diversity and complexity.

In terms of current deployment of AI technology, Australia (24% of companies deploying AI) ranks well below China (58%), India (57%), Germany (38%), and France (32%), but is comparable to the UK (28%), Canada (28%), and the US (25%).

Recommendation: Successive Australian Governments have stated their intention to accelerate AI diffusion and have undertaken a number of actions to do so including:

- establishing in 2020 the Centre for Augmented Reasoning within the Australian Institute for Machine Learning (AIML) at the University of Adelaide
- creating the National AI Centre within CSIRO's Data61 unit in 2021 to help Australian businesses navigate the AI ecosystem and adopt responsible AI practices
- developing Australia's Artificial Intelligence Action Plan in June 2021 which sought to spend:
    - $53.8 million over four years to create a National AI Centre and four AI and Digital Capability Centres
    - $33.7 million over four years to support Australian businesses to partner with government to pilot AI projects
    - $24.7 million over six years to establish the Next Generation AI Graduates Program
    - $12.0 million over five years to catalyse the AI Opportunity in our Regions program.

Though several of these projects were sidelined and an overall reduction in AI funding was proposed after the ascension of the Albanese government in 2022, others have progressed such as the creation of the National AI Centre. As part of the 2023-24 budget, the Albanese government announced $75.7 million of funding for AI initiatives that includes:

- $17 million for the AI Adopt program which will create new centres to support and train SMEs to make more informed decisions about using AI to improve their business
- $21.6 million to expand the remit of the National AI Centre, building on the existing funding of $8 million from the 2021–22 Budget ($2.6 million in 2023–24)
- $34.5 million of continued funding for the Next Generation Artificial Intelligence and Emerging Technologies Graduates programs to attract and train the next generation of job-ready AI specialists.

But the full AI funding package represents a decrease of the Morrison government's $124.1 million AI Action Plan and several elements of the plan were paused as the Albanese government took power in 2022.

Australia's current under-preparedness in terms of AI innovation and use suggests some common sense goals should be:

- immediate concentration of AI development in current areas of strength such as mining and agriculture, and services such as education, health, and banking
- the formation of regional partnerships for AI testing and development

- public awareness campaigns to address community concerns
- increased support for AI related higher education programs
- greater focus on the role of small and medium sized enterprises (SMEs) in the integration of AI into the production function, including financial support for research and development (R&D)
- identification of vulnerable industries for preserving national sovereignty in key infrastructure of defence, finance, communications, and health.

To ensure that Australia's AI journey becomes and remains sustainable for years to come, the government, in cooperation with private enterprise, should:

- identify new industries created and/or most affected by AI
- secure Australian ownership and technical control of key infrastructure
- use AI to rekindle growth in labour productivity
- utilise AI in implementing longer term goals such as reducing hazardous working environments
- use AI to improve transport systems with resultant reduction in travel time, traffic congestion, and accidents
- increase cybersecurity.

Challenge: AI has the potential to bring significant benefits to society, but there are also several social dangers associated with its development and deployment. These include:

- Affecting jobs: job displacement and unemployment for some workers, particularly those who are lower skilled or involved in repetitive work
- Bias and discrimination: amplifying societal biases which may lead to discrimination against certain groups of people
- Privacy violations: AI technologies can collect and analyse vast amounts of data about individuals, raising concerns about privacy violations and the misuse of personal information
- Security risks: AI systems can be vulnerable to attacks and hacking, which could have serious consequences for individuals and organisations
- Misuse of AI: developing autonomous weapons or using AI to manipulate public opinion or election outcomes
- Ethical concerns: such as whether machines should be granted legal rights, or whether AI should be used to make life-or-death decisions.

Recommendation: The societal concerns around AI are best addressed through legislation and regulation designed to minimise if not eradicate AI's ability to exacerbate societal issues, privacy violations, and security concerns. In a 2018 research report produced by the Brookings Institute, the organisation identified nine key points designed to get the most out of AI while still protecting human rights and values. They were:

- encouraging greater data access for researchers without compromising users' personal privacy
- investing more government funding in unclassified AI research
- promoting new models of digital education and AI workforce development so employees have the skills needed in the 21st century economy
- creating a federal advisory committee to make policy recommendations
- engaging with state and local officials to promote effective policies
- regulating specific objectives rather than specific algorithms
- taking bias complaints seriously so AI does not replicate historic injustice, unfairness, or discrimination in data or algorithms
- maintaining mechanisms for human control and oversight
- penalising unethical behaviour and promoting cybersecurity.

Foreword

Artificial intelligence (AI) has become a topic of profound interest worldwide due to its impact on the economy and society, with investment in AI platforms among the leading destinations for investible funds globally. Unlike previous periods of technical change, AI is not limited to specific sectors but is seen as a pervasive technology across all sectors.

The implications of AI's overall significance are subject to widely differing predictions. Some view the AI revolution as another chapter in a long chain of technical progress. As such, it will cause some short-term dislocation and re-adjustment in the economy, but the impact will be co-integrating (that is, the economy will settle back into a period of higher but long-term stable growth). However, even this conservative perspective acknowledges that the impact of AI will be more pronounced and pervasive than previous forms of technical change. Economists refer to this as the 'technical change model of AI.'

Other analysts depict AI as a new and unique phenomenon that may address the long-term productivity slowdown observed in Western economies. However, they emphasise that AI will also present significant challenges such as labour market dislocation and social adjustments, requiring novel solutions from both the government and the private sector. Additionally, a pessimistic scenario envisions an unpredictable surge in AI development leading to singularity, where AI systems surpass human capability to control them.

Determining which of these views is more accurate remains unknown at this stage. However, this report focuses on the implications of AI development and the costs of not doing so for Australia in the short term, specifically from 2023 to 2030. Economic modelling, while successful in the short term, has limited accuracy in long-run predictions, particularly for a fast-moving and dynamic process like AI. Therefore, this report concentrates on these crucial years for Australia's future in AI recognising that if Australia falls too far behind the rest of the world, especially its trade competitors, it is unlikely to ever recover.

Unfortunately, evidence suggests that Australia is currently underperforming in AI development and adoption. In 2022-23, the Australian Government's research and development (R&D) expenditure was forecast to be 0.49% of GDP. In contrast, countries like South Korea and Germany allocate a larger share of their GDP to R&D, and absolute R&D spending in Australia is dwarfed by China and the United States. This disparity would be less concerning if Australia were directing more of its total R&D spending toward AI. For instance, Canada spends approximately 5 times more on AI research compared to Australia, with the University of Toronto emerging as a global leader in AI development.

At the same time Australia is failing to invest in the transformational technology of the age, the country's economic complexity, as measured by Harvard's Atlas of Economic Complexity (ECI), has declined from 55th in 1995 to a current ranking of 91st.

Australian business adoption of AI is a complex story. According to the IBM Global Absorption Index for 2022, 44% of Australian companies are exploring increased use of AI. This compares well to Canada, the leading nation from the 37 surveyed, with 48% of Canadian companies exploring further AI uses. However, the same survey also highlights that Australia lags other developed economies in AI deployment due to lower confidence levels, skill shortages, and higher levels of anxiety surrounding ethical, legal, and security challenges. Australian companies' approach to adopting AI is portrayed as reluctant, perhaps due to the inevitable catch-up effort required.

Most notably, 41% of Australian respondents in a 2019 Deloitte report on how countries are pursuing an AI advantage, indicated that their organisations lack or have poorly developed AI strategies, surpassing the international average of 30%. This apparent disconnect between company ambitions and the current level of investment and government support in Australia suggests a market failure in the AI sector. Market failure refers to the inefficient supply of goods or services in a market, typically resulting from the inability of the market to convey accurate price signals to inform supply and demand decisions.

In the case of AI provision and development in Australia, this market failure is compounded by information asymmetry regarding AI's implications for Australia's competitive advantage, as well as a potential labour market dislocation and its impact on core infrastructure such as health, transport, and communications. Consequently, inertia from the government and complacency from the private sector prevail, bolstered by Australia's status as a wealthy country and its apparent ability to weather the global financial crisis and the COVID-19 pandemic, thanks to agricultural exports, mining, and education.

Despite the slow uptake of AI in Australia, the AI revolution is accelerating worldwide. According to the World Intellectual Property Organization (WIPO), the number of patents in AI technologies has more than doubled to 140,000 in the last 3 years and increased tenfold in the last 10 years. However, patent activity is concentrated among a small group of nations, namely the United States, China, and Japan, which collectively hold 78% of these patents. This concentration raises concerns about future AI development and applications, including the creation of super firms with monopolistic power over AI technology potentially misaligning their interests with host countries.

The economic benefits of early technology adoption, net of pioneer costs, are well-known, as are the costs associated with technical obsolescence and dependency. Economic modelling in this report indicates that between 2023 and 2027, Australia could face an opportunity cost of 1.4% (or AU$35.7 billion) of GDP per year if it fails to introduce AI systems to world standards in key industries. Additionally, there would be an absolute loss of A$318 billion per annum and over 350,000 jobs. These estimates, which do not account for the potential loss of competitive advantage or the dangers to Australian sovereignty resulting from a loss of control over vital infrastructure, are conservative and will expand in the future due to the non-linear nature of AI benefits.

These scenarios are not inevitable. Australia possesses the necessary human capital and investible funds to embark on an accelerated program of AI expansion. With Australian universities ranked among the top 100 globally and the Commonwealth Scientific and Industrial Research Organisation (CSIRO) operating as a world-class applied research centre, Australia has demonstrated its capacity for technical innovation and invention. While Australia does not possess the resources of the United States or China, research partnerships with other countries could enable Australia to become an important player in worldwide AI development and application. Several constraints currently exist, such as market failure, a lack of skilled resources, and the need for a regulatory framework to establish community trust in the machine-human relationship. Chapter Six of this report discusses these constraints in detail and outlines a program for accelerated AI development in Australia.

In conclusion, this report highlights the critical importance of AI development for Australia's future. Failing to keep up with global AI advancements would result in significant economic costs, job losses, and missed opportunities for Australia. However, the potential for Australia to become a key player in AI development and application remains within reach. By addressing existing constraints and fostering an environment conducive to AI innovation, Australia can position itself as a leader in the AI-driven economy of the future.

John Mangan
March 2024

Introduction

Artificial intelligence (AI) relates to the ability of machines or computer programs to perform tasks that normally require human intelligence, such as visual perception, speech recognition, decision-making, and language translation.[1] Currently it consists of an array of techniques and infrastructure including machine learning, robotics, artificial neutral networks, and natural language processing.[2] It is both a major driver of economic growth (micro and macro) and a source of economic disruption.[3]

It is estimated that the AI global market in 2023 is worth approximately US$142.3 billion[4] with major growth being fuelled by investment in AI startups. This is approximately double 2020's AI investment of US$72 billion. The major determinant of this growth is investment in machine learning and chatbot companies, with the main constraint in maintaining this rate of growth being the shortage of skilled labour.[5]

Initially most studies of AI sought to formalise it as automation, and as such, capital augmenting and labour replacing.[6] It is now seen as a completely new factor of production and as a capital-labour hybrid, with a greater focus on data than on finances. AI is not industry specific, and while it has an immediate impact on capital and labour requirements, it also has the ability to learn from data and generate new commercial decisions and production possibilities.[7]

The scope of these potential uses makes the modelling of the economic impacts of AI complex. There have been a number of studies that have attempted to estimate the future impact of AI on economic structures and socio-economic life, however these have been concentrated on a relatively small number of industries, notably technology, finance, and health. Although the projected path and speed of transmission is debated, it is nevertheless widely agreed that the impact of AI will be generalised across the economy.

This poses unique problems for economists in the analysis of AI, especially in the navigation between the conservative ('it's just another form of technical change, albeit more rapid and widespread') and the futurist viewpoints (that AI is a 'transformational change unlike any before'),[8] with the latter approach being almost impossible to model or to set up confidence intervals around the estimates. The former view, while comforting for the traditional economist, is too narrow and would greatly undersell the potential impacts of increased AI diffusion. An initial port of departure is therefore needed for analysis, one that uses standard techniques of economic analysis but is flexible enough to incorporate the more generalised spread of economic impacts across the economy.

1. Joiner, I. (2018). Artificial Intelligence. *Emerging Library Technologies: It's Not Just for Geeks.* Available at https://www.sciencedirect.com/topics/social-sciences/artificial-intelligence

2. Newhauser, M. (2023). Five Diagrams to Understand AI. GP Tech blog. Available at https://www.gptechblog.com/5-diagrams-to-help-you-understand-generative-ai/

3. McKinsey and Company (2018). AI adoption advances, but foundational barrier remain. Available at https://www.mckinsey.com/featured-insights/artificial-intelligence/ai-adoption-advances-but-foundational-barriers-remain

4. Statista. Artificial Intelligence (AI) worldwide – statistics and facts. Available at https://www.statista.com/topics/3104/artificial-intelligence-ai-worldwide/

5. See Agrawal, A, Gans, J. and Goldfarb, A. (2018). *Prediction Machines: The Simple Economics of AI*. Harvard Business Review Press.

6. Abrardi, L, Cambini, C and Rondi, L. (2019). The Economics of Artificial Intelligence: A Survey. European University Institute. Available at https://cadmus.eui.eu/bitstream/handle/1814/63684/RSCAS%202019_58.pdf?sequence=1&isAllowed=y

7. Aicadium (2023). The cost of not adopting AI into your workplace. Available at https://aicadium.ai/the-cost-of-not-adopting-ai-into-your-workplace/

8. Leavy, B., 2023. Understanding the fundamental economics of AI. *Strategy & Leadership*, *51*(2), pp.17-23.

Finally, if AI diffusion is to grow exponentially – as many believe it will – it will be necessary to impose time constraints on any quantification of its effects. Current standard economic models, even the more optimistic, generally do not extend beyond 20 years. Studies of the impacts of AI, with a reasonable expectation of accuracy, should be even less.[9]

More important than the precise estimate of the total economic impact of AI is the distribution of its impact. More than any other form of technical change, most advantages are likely to flow to early adopters, both within and across countries, and the results of this uneven distribution will have major impacts on equity, income distribution and, in the case of major public infrastructure, national sovereignty.[10]

This report examines the economics of AI and its potential value to the Australian economy. In doing so, it attempts to navigate the hyperbole and speculation that surrounds AI and present a plausible view of the likely short to medium term impacts of the accelerated diffusion of AI on the Australian economy.

As previously mentioned, this may not be easy. In evaluating the 'economics of AI,' economists are divided as to whether the AI revolution is just another, albeit major, shift in technology or if it represents transformational change for which there is no direct precedent. If it is the latter, then the standard 'economics of technical change' approach will underestimate its economic and social impacts. This report, via the literature review, investigates the current thinking on the evaluation of the economic impact of AI, and uses this collective knowledge as a guide to estimate the economic benefits of increased AI diffusion in the Australian economy.

While it is generally conceded that the development of AI is in its early stages, it is also becoming apparent that countries that are slow to adopt AI technology will suffer significant economic cost, a potential loss of sovereignty of key infrastructure, and the resulting loss of economic self-determination.[11] It is also important to acknowledge that the rapid introduction of AI technology has the potential to disrupt the labour market, generate greater social inequality, and lead to significant social issues. These aspects are considered in this report, but emphasis is placed on determining the economic advantages to Australia in joining the leading nations in the diffusion of AI and the opportunity costs of not doing so.

The remainder of this report serves as a general introduction to the topic by way of describing the current environment in which to study AI. Chapter 2 examines the potential importance of AI development for economic growth and future innovation. Chapter 3 covers the current spread of AI technology internationally as well as identifies early AI adopters and the competitive advantages they have already gained. Chapter 4 looks at Australia's capacity to develop a strong AI industry within its existing industrial structure, and Chapter 5 discusses the costs of not following this path for the Australian economy, using traditional metrics such as a loss of employment and wealth but also looking at the loss of national economic sovereignty in key industries. The report concludes by examining general and Australia-specific policies for accelerating the diffusion of AI.

9. Currently most forward projections on the growth in AI stop at around 2030.

10. See Larsen, B. (2022). The geopolitics of AI and the rise of digital sovereignty. Brookings Institute. Available at https://www.brookings.edu/research/the-geopolitics-of-ai-and-the-rise-of-digital-sovereignty/

11. Ibid. pp 1-12

1. The Current Environment for AI Diffusion

The increased development of AI can be traced back to the mid-20th century and the development of computer games such as chess that were designed to imitate human thought. Chronologically, other cornerstone advancements in AI include:[12]

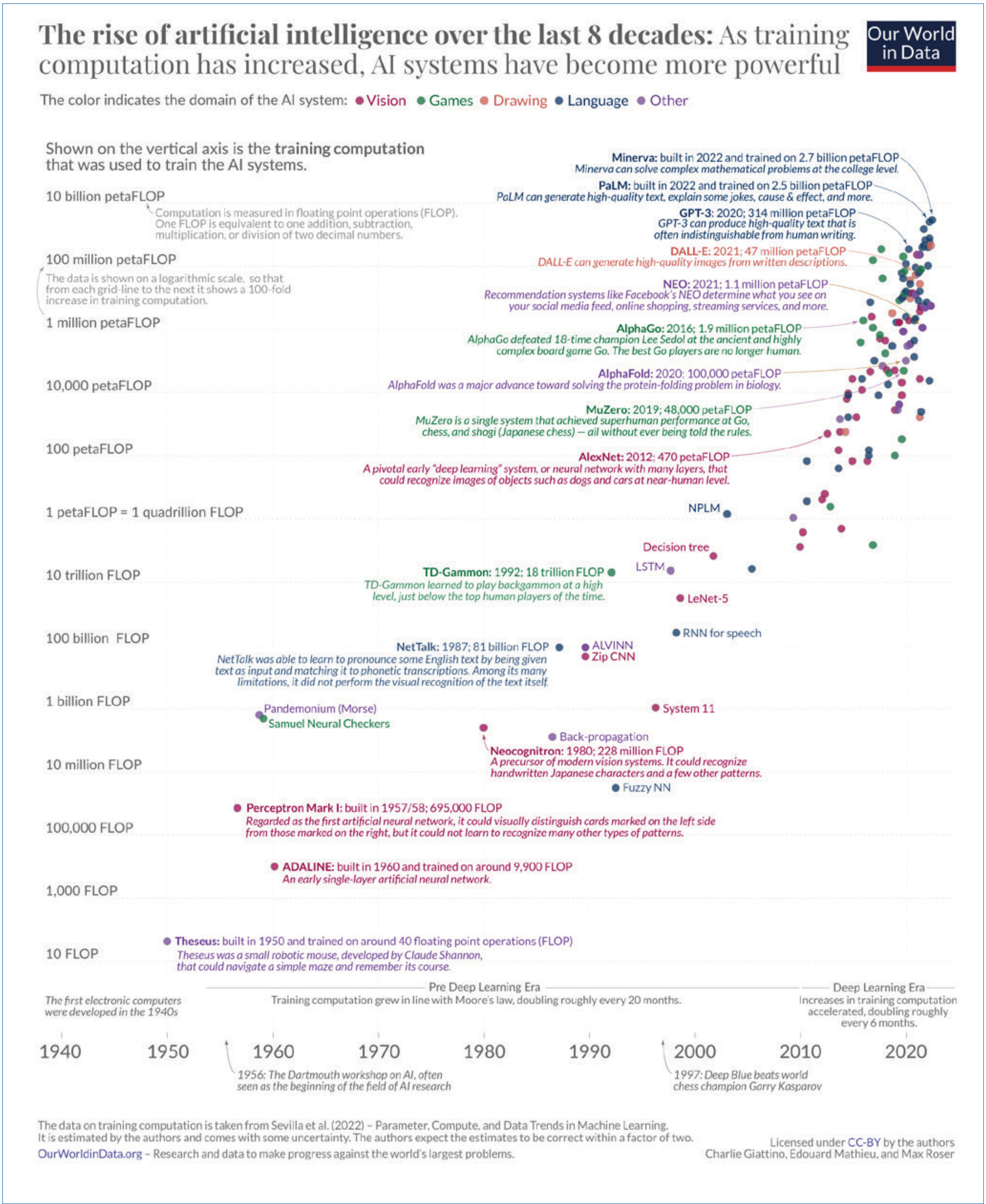
- **1950s and 1960s** – Development of programs for playing games like chess and basic problem-solving programs
- **1970s and 1980s** – Development of expert systems where programs could simulate the decision-making processes of humans in areas such as medicine and finance
- **1980s and 1990s** – Development of machine learning, where researchers create algorithms that enable computers to learn from data and improve their performance over time
- **1990s** – Neural networks, which were modelled after the structure and function of the human brain, became a popular approach to developing AI systems
- **2000s and 2010s** – Big data and deep learning, where the increased availability of computing power enabled the development of deep learning algorithms that can process large amounts of data and achieve state-of-the-art performance in tasks like image and speech recognition.

Some trace the development of AI even further back. Figure 1.1, drawn from research from the Stanford Artificial Intelligence Laboratory (SAIL), follows the growth of AI since the 1940s across vision, gaming, drawing, language, and other areas. It shows the strong influence of leisure and entertainment uses in the development of AI before the current emphasis on industrial uses.[13]

12. Gathered from multiple sources including Open AI on the question 'trace the history of AI.'

13. Lynch, S. (2022). The State of AI in 9 Charts Stanford University Human Centred Artificial Intelligence Unit – Available at https://hai.stanford.edu/news/state-ai-9-charts

Figure 1.1: The rise of artificial intelligence over the last eight decades



(Source – Roser, 2022) [14]

14. Roser, M. (2022). The brief history of artificial intelligence: The world has changed fast – what might be next? OurWorldInData.org Available at https://ourworldindata.org/brief-history-of-ai

1.1. Artificial intelligence and robotics

The terms AI and robotics are often used synonymously to indicate improvements in automation and machine learning. The two are related but refer to distinct areas of technology; the key difference is the extent to which each attempt to predict or mimic human activity. For example, a robot is a machine that can perform tasks autonomously or semi-autonomously. The term robotics refers to the design, construction, operation, and use of robots. It involves the integration of many different technologies, including mechanical engineering, electrical engineering, and computer science.

AI, however, refers not only to this integration of many technologies. It also refers to the ability of machines to perform tasks that typically require human intelligence, such as learning, problem-solving, perception, and decision-making. AI involves the development of algorithms and models that enable machines to learn from data, recognise patterns, and make decisions. Agrawal, Gans and Goldfarb have recognised this distinction suggesting that the fundamental distinguishing contribution of AI is its ability to predict.[15] 'Autonomous vehicles could not function outside of highly predictable and controlled environments until engineers recognised that they could focus instead on a single prediction problem, 'what would a human do?'

So, allowing for overlaps, robotics is the field of designing and building robots, while AI is the field of enabling machines to perform tasks that require human-like reasoning and prediction.[16] Nevertheless, robotics often incorporates AI technologies, with the embedded AI determining the complexity and sophistication of the robot. Not all robots are equipped with AI, with many performing their tasks based on pre-programmed instructions rather than learning from data.

AI is typically used in a wider range of applications than robotics, including speech recognition, image recognition, and natural language processing. These features make AI development particularly important for economic growth and future innovation. Some of the potential benefits of AI include:[17]

- automation of repetitive and tedious tasks that can lead to increased productivity, creativity, and efficiency in many industries
- increased accuracy compared to humans, thereby reducing errors and maintenance costs, and improving the quality of work
- reduced labour costs through automation and the optimisation of processes including waste reduction
- creation of new business opportunities by enabling new products and services, improving customer experience, and increasing innovation
- heightened end-to-end efficiency by eliminating friction and improving analytics and resource utilisation resulting in significant cost reductions
- greatly improved market analysis.

The collective advantage of AI is that it reduces the cost of prediction and therefore reduces uncertainty. In this sense, the use of AI recasts the cost of initial input decisions for business and personal activity.[18]

AI technology, in one sense, is just another form of technical change with resultant outcomes of reduced costs for the adopter and an eventual reduction in competitiveness for non or slow adopters. This in turn has spin off benefits for complementary goods and creates difficulties for substitute goods. These are outcomes from the application of fundamental economic theory, however the impacts from an analysis of AI differs from standard technical change because the effects of AI are not confined to specific activities but are applicable to all aspects of economic activity that benefit from reduced uncertainty and improved market analysis. These attributes change the production function of most products and services by increasing the efficiency of inputs and the elasticity of substitution among factors of production.

For these reasons, AI is the world's fastest growing technology sector.[19] Estimates of the potential economic benefits of AI, like all projections, differ both in extent and amount. The most aggressive estimates come from

15. See Agrawal et al (2018). *Prediction Machines*.

16. International Federation of Robotics (2023). Traditional robot programming vs AI & machine vision. Available at https://ifr.org/post/traditional-robot-programming-vs-ai-machine-vision

17. See Accenture. What is Artificial Intelligence? for further discussion on these points Available at https://www.accenture.com/us-en/insights/artificial-intelligence-summary-index

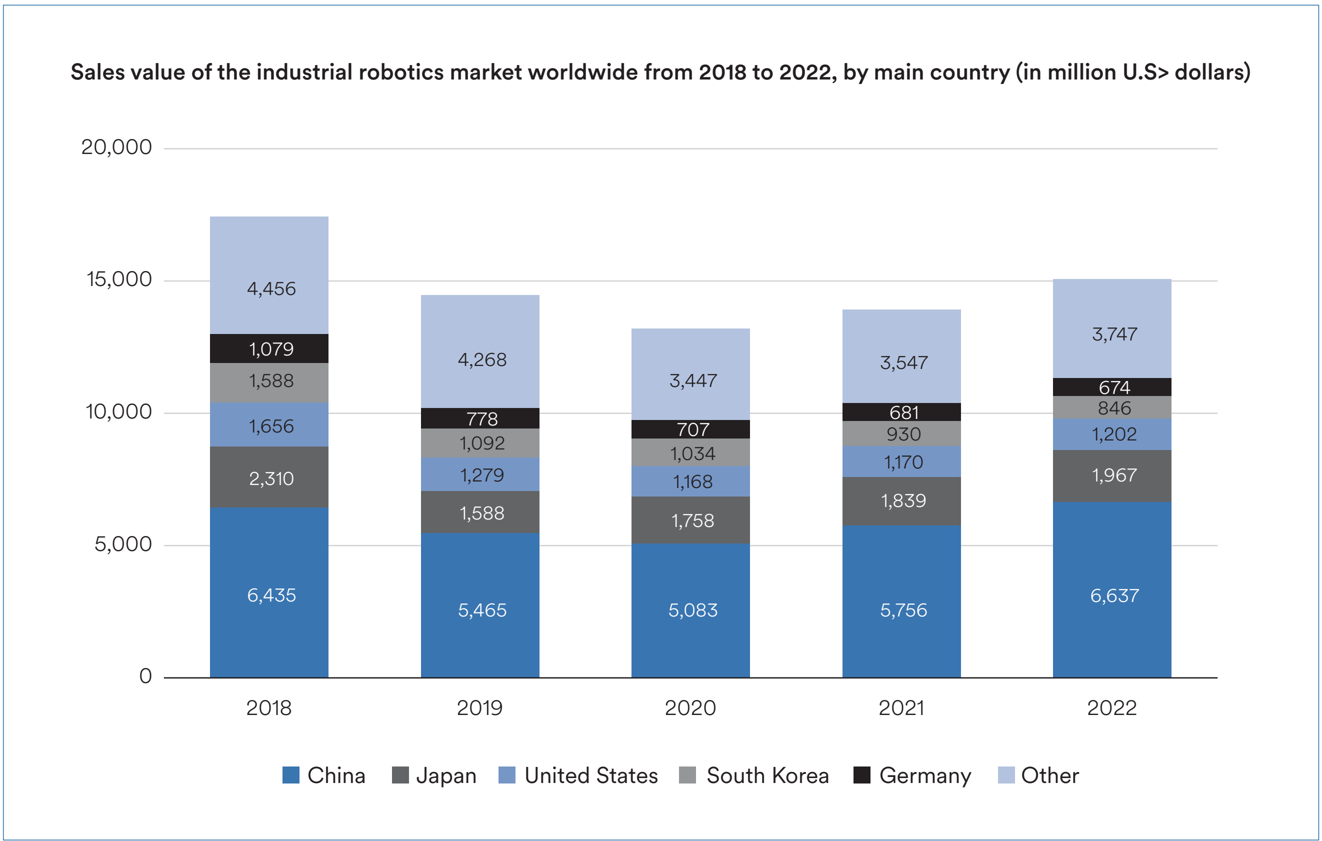
18. See McKinsey Quarterly (2018): The economics of artificial intelligence. Available at https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-economics-of-artificial-intelligence

19. See Lehman, M (2023). Are we ready for the robots? *The Weekend Australian Magazine* pp. 20-24

PricewaterhouseCoopers (PwC) which predicts that the increased diffusion of AI technology will add US$15.7 trillion dollars to the global economy by 2030 with early adopting economies securing a 26% increase in GDP by 2030.[20]

While economists differ over the extent and time frame of major economic benefits from AI, they all agree that AI-driven economic growth will not be shared equally across the globe and that most gains will flow to early adopters. This is certainly the pattern of the distribution of industrial robots. As can be seen in Figure 1.2, Asia dominates the global market for industrial robots, with China the largest consumer and producer of industrial robots in the world. Other countries such as Japan, South Korea, and Taiwan also have significant robot densities. Europe is the second-largest market for industrial robots, with Germany, Italy, and France the largest consumers of industrial robots in the region. North America is another significant market, with the United States the largest consumer of industrial robots there.[21]

Figure 1.2: Distribution of industrial robots 2018-2022



(Source – Statista, 2023) [22]

As seen in Figure 1.2, the distribution and use of industrial robots is already well advanced across the world. Latecomers trying to compete with the existing players in the industrial robot space face large entry costs. The same is likely to be true for AI. Moreover, the time frame for successful adoption is narrowing. In 2018, PwC reported that only about 9% of companies worldwide have already implemented AI applications to improve operational decision making.[23] By 2022, an IBM report on AI found that 35% of companies reported using AI in

20. See PwC (2020) PwC's Global Artificial Intelligence Study: Exploiting the AI Revolution. Available at https://www.pwc.com/gx/en/issues/data-and-analytics/publications/artificial-intelligence-study.html

21. International Federation of Robotics. (2021). Record 310,700 Robots in United States' Factories – IFR reports. Available at https://ifr.org/downloads/press2018/USA-NAFTA-2021-OCT-IFR_press_release_industrial_robots.pdf

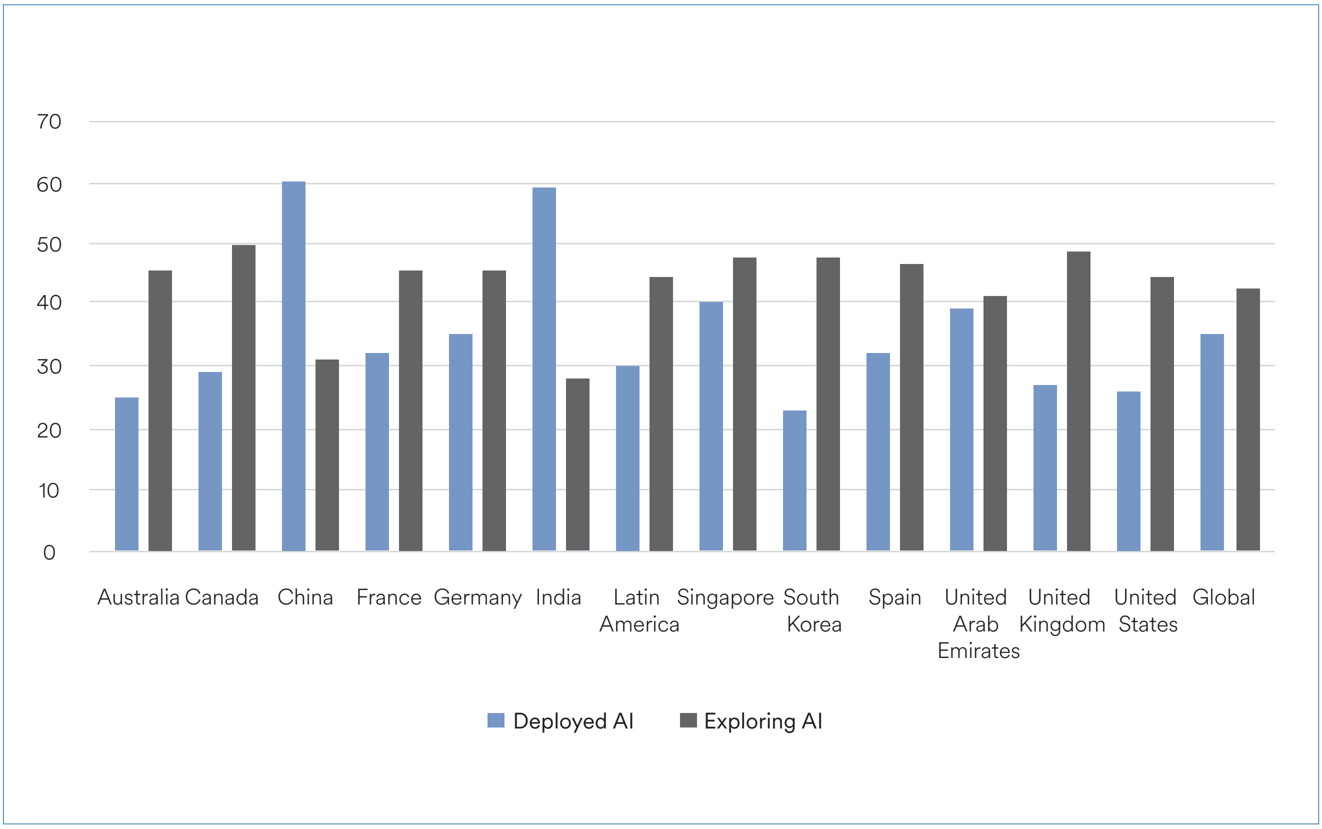
22. Statista (2023). Sales value of the industrial robotics market worldwide from 2018 to 2022, by main country. Available at https://www.statista.com/statistics/1018634/industrial-robotics-sales-value-by-country/

23. PwC. (2018). Global Digital Operations Study 2018: Digital Champions. Available at https://www.strategyand.pwc.com/gx/en/insights/industry4-0/global-digital-operations-study-digital-champions.pdf

their business, and an additional 42% reported they are exploring the use of AI, up four points from 2021. Another 13% of companies were preparing to adopt AI within their businesses.[24] This growth is shown in Figure 1.3:

Figure 1.3: AI adoption and intentions

(Source – IBM Global AI Adoption Index, 2022) [25]



Yet despite this impressive growth, take-up costs for AI are still manageable for countries with the will and foresight to embark on a sustained path of development. This is particularly important for countries such as Australia that have the infrastructure and human resource capabilities to embark on an accelerated program of AI development.

The implications of the research from PwC (2020) and McKinsey (2022) are that most benefits will initially flow to early adopters and be captured by already high-income countries. PwC provides estimates of the global distribution of these benefits, shown in Figure 1.4 that indicate that, if present trends continue without substantial investment by other countries, 40% of the total GDP gains will be shared by China (26.1% increases in GDP) and North America (14.7%). Other areas predicted to gain include Developed Asia (10.1%), Western Europe (9.9%), and Southern Europe (11.9%).

A recent McKinsey report (2022) stressed the growing competitive advantage for early adopters of AI and showed that AI adoption in these countries has doubled since 2017.[26]

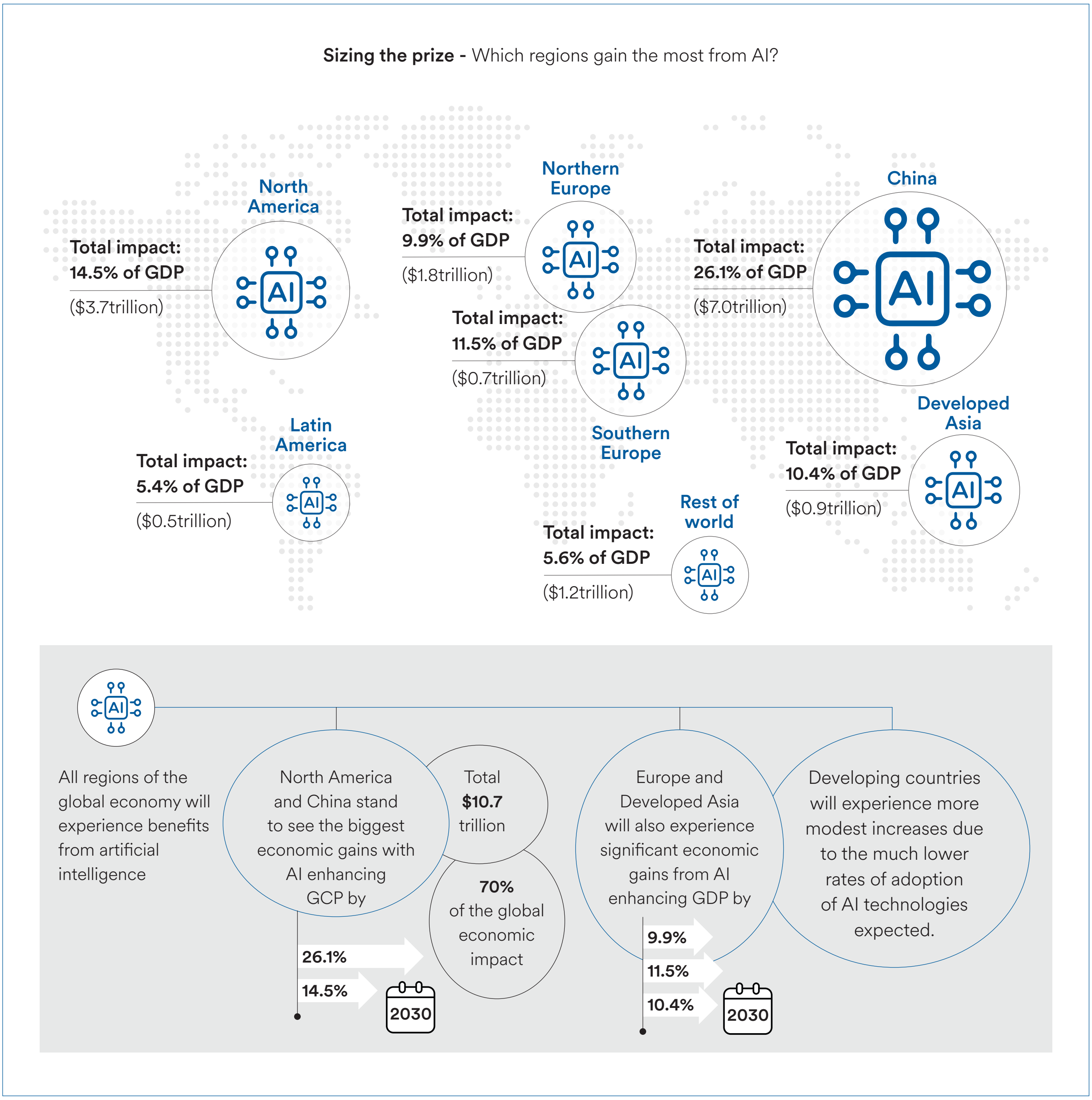
Though the proportion of organisations using AI has plateaued between 50 and 60% for the past few years, companies seeing the highest financial returns from AI continue to pull ahead of competitors. The results show that these leaders are making larger investments in AI, engaging in increasingly advanced practices known to enable scale and faster AI development, and showing signs of faring better in the tight market for AI talent.

24. See IBM Global AI Adoption Index 2022. Available at https://www.ibm.com/downloads/cas/GVAGA3JP

25. IBM Global AI Adoption Index 2022 Available at https://www.ibm.com/downloads/cas/GVAGA3JP

26. McKinsey Global Survey on AI. (2022). The state of AI in 2022—and a half decade in review/. Available at https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai-in-2022-and-a-half-decade-in-review

Figure 1.4: Regions that will gain the most from AI



(Source – PwC, 2017) [27]

27. PwC. (2017). Sizing the prize: What's the real value of AI for your business and how can you capitalise? Available at https://www.pwc.com/gx/en/issues/data-and-analytics/publications/artificial-intelligence-study.html

1.2. Which industries are most likely to adopt AI?

Currently, the distribution of AI adoption by industries is centred on several key sectors, including technology, finance, healthcare, education, and government. Comparable data on which industries are in the forefront of adopting AI technology are shown in Table 1.1:

Table 1.1: Per cent use of AI as inputs by industry 2020-2021

Industry	Use of AI (percentage)
Technology	17%
Financial Services	15%
Healthcare	9%
Transport	9%
Education	8%
Government/Public Sector	6%
Telecomm	5%
Manufacturing	4%
Retail	4%
Media	3%
Energy	2%
Defence	N/A

(Source – CompTIA, 2023) [28]

These findings are partially supported by other publications that have identified healthcare; customer service and experience; banking, financial services and insurance; logistics; retail; cybersecurity; transportation; marketing; defence; and lifestyle as the ten industries most likely to be impacted by AI by 2030.[29]

A comparison of the sources shows that healthcare is commonly identified as offering the best fit for a quick uptake of AI. There is a need within healthcare to collect accurate, patient-specific data and to rapidly recall medical records and files.

Just as importantly, AI brings the promise of greatly improved predictive health when compared to the current reactive care and diagnostics approach. For example, Internet of Things (IoT)-enabled, embedded devices can be used to remotely monitor the health of patients and AI offers the opportunity for much faster and more accurate scanning. The increased use of health chatbots will also enable health professionals to collect primary data on patient symptoms.[30]

Other identified industries, such as retail and transport, have a common set of features that lend themselves well to AI adoption, including the need for:

- improved accuracy and efficiency through machine learning
- reduced operating costs, particularly in labour costs
- increased predictive power, meaning the ability to correctly forecast future needs and values.

28. Watters, A. (2023). 30+ Artificial Intelligence Statistics and Facts for 2023. CompTIA. Available at https://connect.comptia.org/blog/artificial-intelligence-statistics-facts

29. V.K. A. (2022). 10 Industries AI Will Disrupt the Most by 2030. Spiceworks. Available at https://www.spiceworks.com/tech/artificial-intelligence/articles/industries-ai-will-disrupt

30. V.K. A. (2022). 10 Industries AI Will Disrupt the Most by 2030

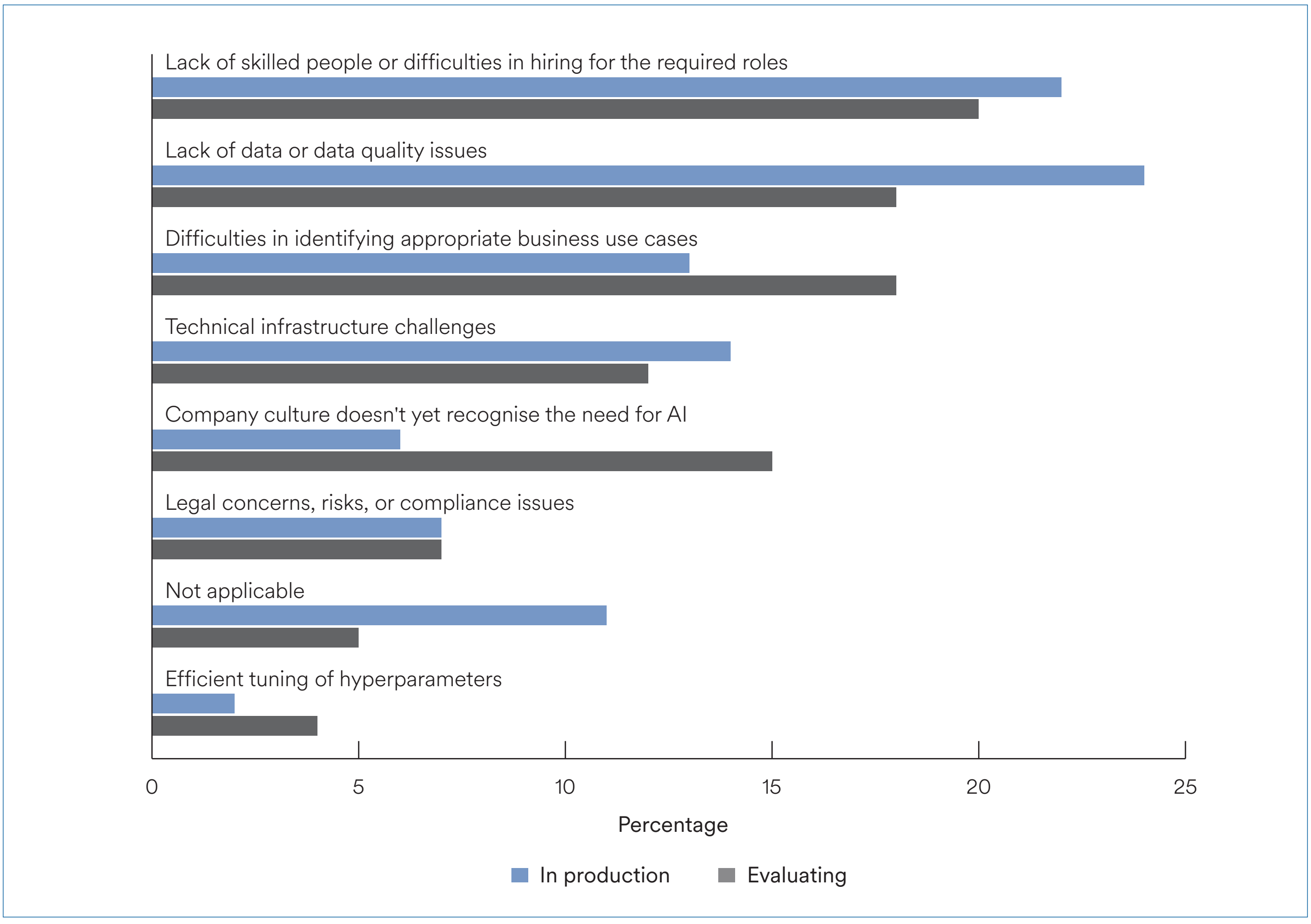
1.3. What is constraining the growth of AI?

Factors constraining the diffusion rate of AI include the availability of skilled talent, access to data, regulatory environments, and cultural attitudes towards AI. The IBM Global Adoption Index 2022 identified the top five barriers to greater adoption of AI at the enterprise level.[31] They were:

- limited AI skills at the enterprise level/staff hiring issues (34% of enterprises)
- the price is too high (29%)
- lack of tools or platforms to develop models (25%)
- projects are too complex or difficult to scale (24%)
- too much data complexity (24%).

Similar findings from O'Reilly are shown in Figure 1.5. Once again, skilled labour shortages and lack of data availability and quality were seen as the major constraints.

Figure 1.5: Constraints on the absorption of AI at the enterprise level



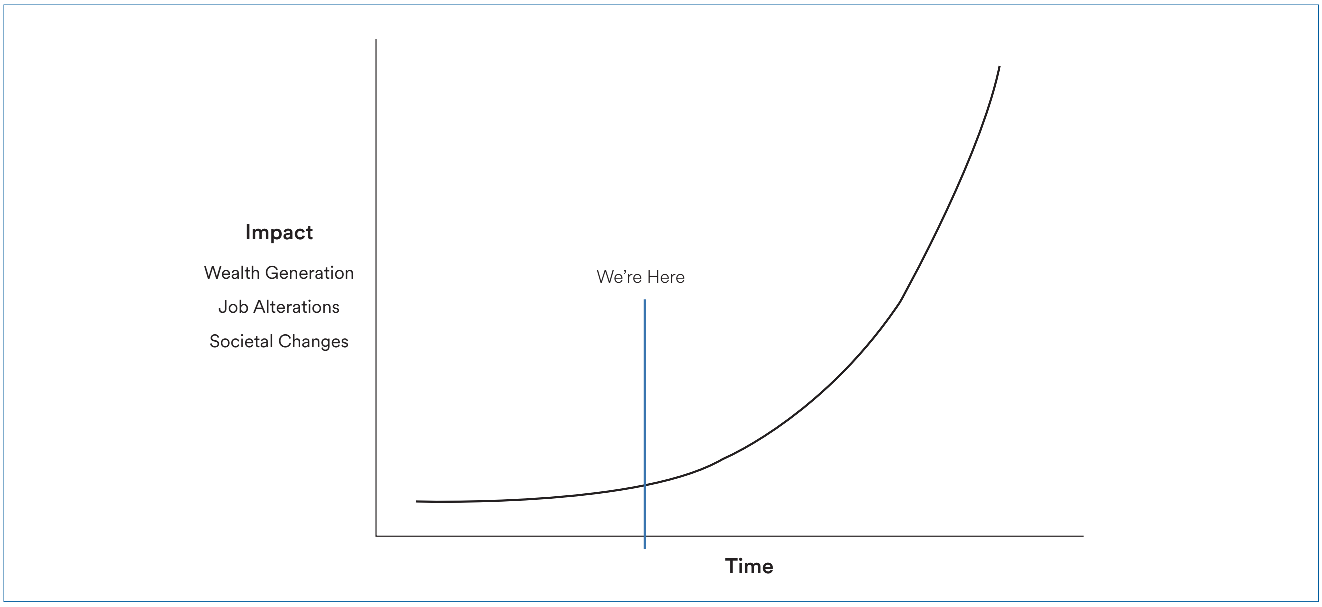
(Source – O'Reilly Media, 2022) [32]

Nevertheless, the United States and China seem to be finding ways to overcome these constraints. Data from Stanford University's Institute for Human-Centered AI (HAI) show a marked increase in AI-related job postings in 2022-2023, and an increase in AI budgets at the federal level in the US due to a significant investment in AI research and development which has helped to accelerate the adoption of AI in those regions. [33]

31. See IBM Global AI Adoption Index 2022 https://www.ibm.com/watson/resources/ai-adoption
32. Loukides. 2022. AI Adoption in the Enterprise.
33. Lynch S. (2023). The State of AI in 14 charts. Stanford University, Human-Centered Artificial Intelligence. Available at https://hai.stanford.edu/news/2023-state-ai-14-charts

It is widely (but not universally) thought that the growth in AI diffusion will be non-linear, bringing increasingly disproportionate benefits to companies and countries already leading in AI adoption.[34] This belief is based upon data that shows that AI's computing power doubles every three to four months, which exceeds the prediction of Moore's Law of every two years.[35]

Figure 1.6: Predicted exponential impact of AI



(Source – The Science of Machine Learning, 2020) [36]

1.4. Is the AI technology phase different from earlier periods?

Allowing for periods of overlap, historically technical shocks are often grouped into four industry stages:[37]

- **Industry 1.0** – The period of the industrial revolution. Machines were developed to assist workers and raise productivity. Due to issues in income distribution, wage increases lagged technical progress
- **Industry 2.0** – Machines were programmed and controlled by workers to increase efficiency, productivity, and quality. To some extent, machines started to replace certain functions of labour
- **Industry 3.0** – Closely associated with the invention of computers, followed by information and communication technology (ICT), which changed the production function and the labour skills required. There was both substitution (job loss) and income (job producing) effects, and education and skills became the chief screeners for employment. However, human control was still needed in Industry 3.0 for programming and operating the technology, although the substitution of capital for labour in lower skilled jobs was taking place. During the latter part of this period, income distribution became more uneven in developed countries. Instead of playing technology's traditional role of raising the incomes of low skilled workers, most wage benefits were captured by higher income groups and wages for low skilled workers became stagnant or fell
- **Industry 4.0** – The current age and the age of AI. Although in its early stages, this age seems to be significantly different from other stages of technical change in that it may change the roles of and interaction between human beings and machines in production as well as in society. AI technology could give machines new roles in the production process, including control of production planning and operation.

34. McKinsey Global Institute. (2018). Notes from the AI Frontier: Insights from Hundreds of Cases. Available at https://www.mckinsey.com/~/media/mckinsey/featured%20insights/artificial%20intelligence/notes%20from%20the%20ai%20frontier%20applications%20and%20value%20of%20deep%20learning/notes-from-the-ai-frontier-insights-from-hundreds-of-use-cases-discussion-paper.pdf

35. The Science of Machine Learning. (2020). Exponential Growth. Available at https://www.ml-science.com/exponential-growth Moore's Law refers to the growth of transistors in integrated circuit chips.

36. The Science of Machine Learning. Exponential Growth.

37. See Institute of Entrepreneurship Development (2019). The 4 industrial Revolutions. Available at https://ied.eu/project-updates/the-4-industrial-revolutions/

Although each industry stage shown above is distinct, there is a detectable trend. At each stage, capital became more significant in the production process, corresponding with a reduction in the significance of labour's role. For the most part, this trend worked in favour of labour, with gains from productivity distributed throughout the economy, raising the wages and living standards of the low skilled. This started to change at the end of Industry 2.0 and accelerated throughout Industry 3.0.

Technological change did not appear to bring the promised productivity gains, leading to the famous Solow Paradox[38] where an increase in capital deepening does not produce the expected increases in productivity gains. Those gains that did eventuate were distributed upwards to higher skilled/higher income groups. During this time, the labour market managed to cope with large increases in female employment, but alongside this trend, casual employment and under employment levels rose substantially, as did income inequality.

It was in this period that the AI era arrived, with questions raised about its potential impact on employment, income distribution, and social equity. No one is sure what Industry 4.0 will bring.

The benign view is that, given the experiences of the IT-driven Industry 3.0 period, Industry 4.0 will return the economy to a long run equilibrium. There may be labour market dislocation, but the net outcome will be more jobs, and the income effect will continue to dominate the substitution effect.[39] Productivity gains may not be distributed downwards to the lower paid, but interventionist governments could counteract this by introducing guaranteed income legislation, and aggregate standards of living will continue to rise.[40] Bill Gates and others have argued for taxing robotics and AI if they replace workers.[41]

Early signs suggest this may not be happening.[42] Although positioned near the beginning of the AI revolution, advanced economies such as the US are still facing low productivity growth. This offers further support for the Solow Paradox, where productivity gains were only experienced in technology *producing* sectors (especially IT) and not in technology *using* sectors.

This finding was reinforced by Acemoglu in his study of IT-using firms in US manufacturing.[43] He argued that any productivity gains in IT-using sectors were not associated with increasing output because of IT-induced cost reduction but rather were driven by declining output and a rapid decline of employment. In the short run, job losses can often cause an increase in the productivity of those remaining in employment.

Michaels and Graetz studied the introduction of industrial robots across a panel of industries in 17 countries.[44] They found the introduction of industrial robots had small positive impacts on employment and wages in contrast to the widespread use of IT technology, which tended to be labour shedding. In a later study, the authors found that the wage and employment benefits from the introduction of industrial robots in the US fell as the intensity of use of robots increased, suggesting, for these aspects, diminishing returns on robot technology. [45]

Counter to these arguments, Brynjolfsson et al. suggest that apparent falls in productivity in the US and elsewhere are explained by lags in diffusion of upfront AI technologies. They argue that 'the current Solow Paradox is just a lag in technology take-off.'[46]

McKibbin and Triggs used computable generalised equilibrium (CGE) modelling across four distinct, predicted, productivity outcomes from the large-scale diffusion of artificial intelligence. They find that even under the best-case scenario in terms of productivity growth, most benefits would flow to first movers and the resultant pressure on inflation and interest rates would need strong macro-economic policy to address. [47]

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38. Dreyfuss, E., Gadson, A., Riding T. and Wang, A. The IT Productivity Paradox. Available at https://cs.stanford.edu/people/eroberts/cs201/projects/productivity-paradox/background.html#:~:text=The%20productivity%20paradox%20(also%20the,go%20down%20instead%20of%20up.

39. Mangan, J. (2019). The Robotics and Automation Advantage for Queensland. Synergies Economics. Available at https://www.synergies.com.au/reports/the-robotics-and-automation-advantage-for-queensland/

40. Brynjolfsson, E., Rock, C and Syverson, C. (2004). Artificial Intelligence and the Modern Productivity Paradox. NBER Working Paper 24001. Available at https://www.nber.org/papers/w24001

41. *Quartz* (2017). The robot that takes your job should pay taxes, says Bill Gates. Available at https://qz.com/911968/bill-gates-the-robot-that-takes-your-job-should-pay-taxes

42. Aggregate labour productivity growth in the US averaged only 1.3% per year from 2005 to 2016, less than half of the 2.8% annual growth rate sustained from 1995 to 2004. Cited in Brynjolfsson et al (2004). Artificial Intelligence and the Modern Productivity Paradox

43. Acemoglu, D., Autor, D., Dorn, D., Hanson, G., & Price, B. (2014) Return of the Solow Paradox? IT, Productivity, and Employment in US manufacturing. *American Economic Review*,104(5), 394–399.

44. Graetz, G. and Michaels, G. (2018). Robots at work. *Review of Economics and Statistics*, *100*(5), pp.753-768.

45. Presidente, G., Cali, M. (2022). Robots for economic development. Centre for Economic Policy Research. Available at https://cepr.org/voxeu/columns/robots-economic-development

46. Brynjolfsson, E., Rock, D. and Syverson, C., 2017. Artificial intelligence and the modern productivity paradox: A clash of expectations and statistics. *The economics of artificial intelligence: An agenda* (pp. 23-57). University of Chicago Press.

47. McKibbin, W., Triggs, A. (2018). Modelling the G20: CAMA Working Paper No. 17/2018. Available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3167666

Lu and Zhou argue that the Solow Paradox has not yet been resolved and so the longer term distributional and productivity outcomes of AI are still unknown. However, they concede that Industry 4.0 is different from earlier periods of economic change because it will have more widespread implications even though the outcomes for growth and distribution are uncertain. However, they do suggest that 'AI will use data to develop computational models, and the availability of cloud services can enable the technology to be adopted with a much lower capital investment than during the IT period. This difference could potentially make AI's adoption pathway different from that of previous technologies.'[48]

1.5. Is AI innovation only for big nations?

AI development is currently concentrated in a relatively small number of countries. This is partly based upon a heritage of technological innovation and a strong innovation infrastructure culture based on venture capital and responsive governments, such as those found in the US, Japan, Germany, and more recently China. The US has been a global leader in innovation for decades, with an innovative technology sector and world-renowned universities driving research and development in a range of fields. Similarly, Japan has a long history of innovation and is known for its advanced technology from robotics to electronics, and Germany houses some of the world's leading engineering and technology companies and emphasises research and development.

Yet alongside these leading groups, smaller nations have developed an enduring reputation for innovation. South Korea has become a global leader in innovation and technology, with a highly educated population and a strong focus on research and development. Similarly, Switzerland is known for its innovation in the fields of pharmaceuticals and biotechnology, as well as its high-tech manufacturing industries.

The size of the home market and the derived benefits of scale and size determine what happens to production or costs when the size of a company changes (increases). For example, scale economies implies that business costs reduce when a company's production of goods increases and becomes more efficient. This equation is spelled out formally as:

$$Y = f(x_1, x_2, x_p) \qquad (1)$$

If all p inputs are increased by multiplying all inputs by a factor ***t (t >1)***

$$t\,(f\,(x1, x2, xp) = f\,(tx1, tx2, txp) \qquad (2)$$

increasing returns to scale imply.

$$tn\; f\,(x1, x2, xp) = f\,(tx1, tx2, txp)\;(n > 1) \qquad (3)$$

Economies of size are not limited to production costs. The term is also used to describe when the total cost per unit of output decreases as the firm expands its output due to a variety of reasons not confined to production, such as marketing and distribution costs.

Empirical observations show that larger companies are often more productive than smaller companies, and that large companies therefore produce at lower unit costs. This advantage drives the structural development of industries through time, so that companies typically become larger and larger.

There are several other reasons for a company to gain economies of size. These include:

- better utilisation of existing capacity
- increased capacity, which allows for the distribution of fixed costs to more productive units, thereby achieving lower unit costs
- a pricing advantage caused by producing large volumes which may also lead to lower input prices due to quantity discounts
- continuous technical development. Empirically there is a tendency for new technologies to favour large-scale production as that is where new technology is most cost beneficial. Additionally, smaller economies lack access to local and international venture capital, which tends to make them risk averse.[49]

48. Lu, Y. and Zhou,Y. (2021). A review on the Economics of Artificial Intelligence. *Journal of Economic Surveys*. Available at https://onlinelibrary.wiley.com/doi/10.1111/joes.12422

49. Jeng, L.A. and Wells, P.C., 2000. The determinants of venture capital funding: evidence across countries. *Journal of corporate Finance*, *6*(3), pp.241-289. Available at https://www.sciencedirect.com/science/article/pii/S0929119900000031

For these reasons, it is often thought that smaller economies operate under severe disadvantage in trying to compete technologically with larger economies. This often explains why smaller economies are urged to acquire technology by importation rather than internal innovation.

This strategy is not only risk averse, it confines the importing nation to secondary status, removing their chance to profit from home-produced technology and increasing their dependence on foreign interests. In the case of a pervasive technology such as AI, this is a serious threat to the national sovereignty of nations urged to import.

Importantly, as economists Leng and Wells (2000) show in their study of investment in 21 countries, size of GDP and market capitalisation are not the major determinants of venture capital flows.[50] The authors found these variables to be less significant than previously thought. Their findings stress the key role of strong regulatory systems and government policies that favour initial public offerings (IPO), or the process where private companies sell their shares to the public to raise equity capital from the public investors. An IPO transforms a privately held company into a public company. The authors find from their sample that IPOs are the strongest driver of venture capital investment. Government policy and regulation favouring investment and the presence of stable labour markets are also seen as strong drivers of the flow of venture capital.

These are important findings because they argue against the inevitability of large firm dominance in AI investment and R&D, and demonstrate that smaller economies, with the right government policy settings, can compete in capturing venture capital to be used for AI innovation. There are a number of relatively recent examples where a combination of private equity and government backing have led to major technical development in smaller economies. Examples include:

Table 1.2 Technical developments caused by private equity and government funding

Technology	Country developed in
Skype	Estonia
Bluetooth	Sweden
Wi-Fi	Australia [51]
Java programming language	Canada
Zendesk (customer support software)	Denmark
MySQL (open-source database software)	Sweden and Finland
Nginx (web server software)	Russia
QR code	Japan
Unity (game engine)	Denmark
SoundCloud (music streaming service)	Sweden

The development of all these products involved a combination of private equity, government policy, and venture capital. For example, in the case of Skype, the following sequence took place:

1. The initial development was funded through private capital by entrepreneurs Zennström and Friis, with the assistance of crowd sourced seed funding
2. The second stage was financed by venture capital. In 2004, Skype raised $18.8 million in funding from a group of investors, including Index Ventures, Andreessen Horowitz, and Mangrove Capital Partners
3. In the third stage, eBay acquired Skype for $2.6 billion. eBay believed that integrating Skype's communication capabilities into its e-commerce platform would enhance the overall user experience
4. In 2011, Microsoft acquired Skype from eBay for approximately $8.5 billion. The aim was to strengthen Microsoft's presence in the communication and video chat market. The financing for this acquisition was entirely internal.

50. Ibid.

51. The Commonwealth Scientific and Industrial Research Organisation (CSIRO) developed orthogonal frequency division multiplexing (OFDM), a key step in the final development of Wi-Fi. See Who Invented Wifi? Secure A Com. Available at https://secureacom.com.au/who-invented-wifi/

The success of the ventures listed above, and many others, shows that innovation is not just the preserve of the big economies, but they do have the advantage. The key ingredients needed for smaller economies to compete in research and development include:

- investment-conducive government policy and regulatory systems
- active government industry policy
- domestic sources of investment funds such as superannuation or private pension funds
- efficient stock and capital markets.

1.6. Social concerns of AI

AI has the potential to bring significant benefits to society, but there are also several social concerns associated with its development and deployment. These include:

Job displacement: As AI becomes more advanced, it has the potential to replace many jobs, leading to job displacement and unemployment for some workers, particularly those who are lower skilled or involved in repetitive work

Bias and discrimination: AI algorithms can reflect the value systems of their creators and amplify societal bias which may lead to discrimination against certain groups of people

Privacy violations: AI technologies can collect and analyse vast amounts of data about individuals, raising concerns about privacy violations and misuse of personal information

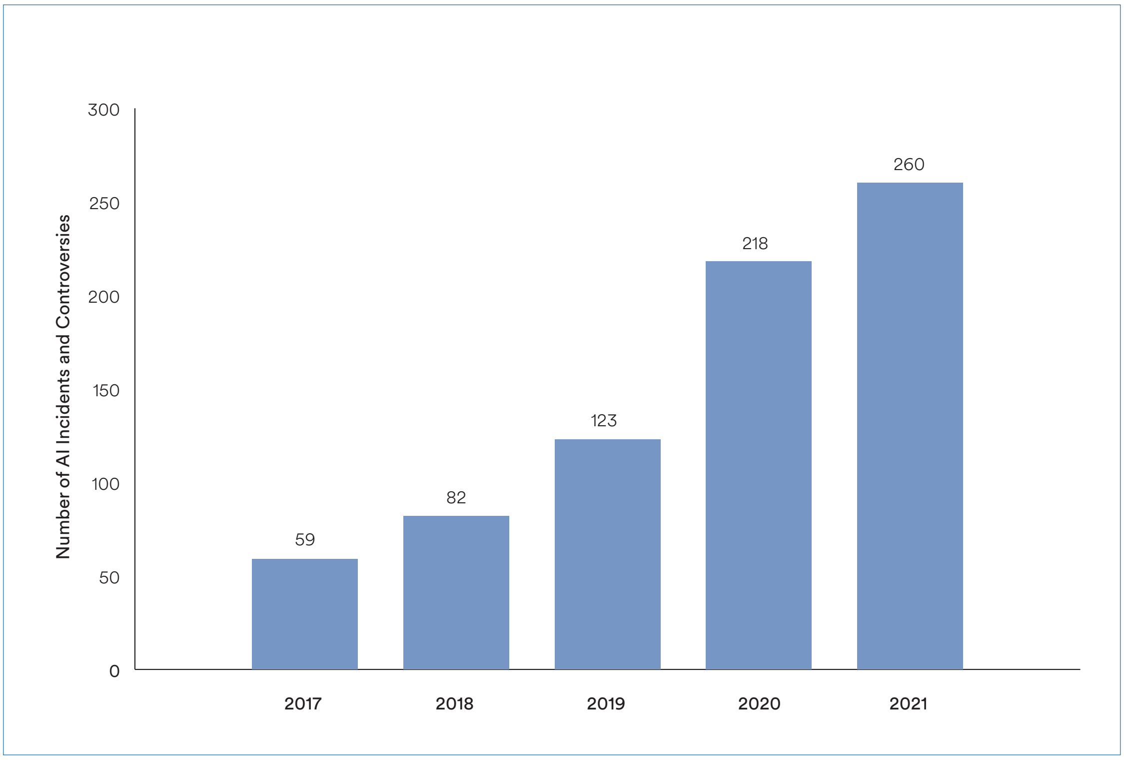
Security risks: AI systems can be vulnerable to attacks and hacking, which could have serious consequences for individuals and organisations

Misuse of AI: There is a risk that AI could be used for harmful purposes, such as developing autonomous weapons or manipulating public opinion or election outcomes

Ethical concerns: The development and deployment of AI raises complex ethical questions, such as whether machines should be granted legal rights, or whether AI should be used to make life-or-death decisions.

Based on these considerations, regulators and social commentators are increasingly concerned about the unrestricted growth of AI. This is highlighted in Figure 1.7 which notes the increase in AI controversies as noted by the Stanford HAI.

Figure 1.7: Uptick in AI controversies



(Source – Stanford HAI 2023) [52]

Figure 1.7 tracks the growth of reported AI controversies in the US between 2017 and 2021. These will grow over time and reducing public concerns over AI use will become a major determinant of the successful use of AI. It's important to address these social concerns to ensure that AI is developed and deployed in a way that benefits society as a whole. This can be done through responsible AI development practices, transparency in AI decision-making, and regulation to address potential harms.[53]

To further address the social challenges of AI, on 3 November 2023, Australia, along with 27 other countries and the EU, signed the Bletchley Declaration following the AI Safety Summit held in the UK. Though non-binding, the Bletchley Declaration seeks to ensure that AI 'be designed, developed, deployed, and used, in a manner that is safe, in such a way as to be human-centric, trustworthy and responsible' due to the potential for 'serious, even catastrophic, harm, either deliberate or unintentional, stemming from the most significant capabilities of these AI models.' [54] The declaration aspires to bring all of AI's major stakeholders – including governments, industry, academia, and civil society – together to foster public trust and confidence in AI by ensuring the safety and transparency of AI systems.

Australia's signing of the Bletchley Declaration was a major step in ensuring the responsible development and use of AI in-country. The government is also considering the creation of mandatory guardrails for AI and is working with industry to:

- develop a voluntary AI safety standard
- develop options for voluntary labelling and watermarking of AI-generated materials
- establish an expert advisory body to support the development of options for further AI guardrails. [55]

52. Lynch, State of AI in 14 Charts

53. Cavalcante L., et al, 2023. Meaningful human control: actionable properties for AI system development. *AI and Ethics*, *3*(1), pp.241-255. Available at https://link.springer.com/article/10.1007/s43681-022-00167-3

54. Australian Government, Department of Industry, Science, and Resources. (2023). The Bletchley Declaration by Countries Attending the AI Safety Summit, 1–2 November 2023. Available at https://www.industry.gov.au/publications/bletchley-declaration-countries-attending-ai-safety-summit-1-2-november-2023

55. Australian Government, Department of Industry, Science and Resources. (2024). Safe and responsible AI in Australia consultation: Australian Government's interim response. Available at https://storage.googleapis.com/converlens-au-industry/industry/p/prj2452c8e24d7a400c72429/public_assets/safe-and-responsible-ai-in-australia-governments-interim-response.pdf

2. AI Development and Economic Growth

Many see the increased diffusion of AI as the best chance to reverse the trend of declining productivity that has characterised developed nations since the mid-1990s and developing countries since the early 2000s.[56] For example, Furman (2019) reports that 36 of 37 advanced economies had slower productivity growth in 2006–2016 compared to 1996–2006. Across these economies, growth has slowed from a 2.7% average growth rate in the earlier decade to a 1% average annual growth rate in the past decade. This stagnation in economic growth and productivity has occurred despite rapid technological change, especially in ICT, leading some economists to revisit the Solow or productivity paradox, where low productivity coexists with accelerating technological progress.[57]

There are many competing explanations for technology's inability to spur economic growth. However, a consensus appears to be forming that the growth and productivity impacts from AI will be stronger with much more tangible results based on the generalised nature of AI. The reasons many believe that AI will improve productivity include:

Productivity increases: AI-powered automation can perform tasks faster and more accurately than humans, leading to increased productivity and competitiveness, and more output and profits for businesses.

Innovation: AI can help businesses innovate by identifying patterns and trends in consumer behaviour or market trends, enabling them to develop new products or services to meet changing demands. This can lead to new revenue streams and economic growth.

Cost savings: AI can improve productivity by helping businesses reduce costs by automating repetitive tasks and reducing the need for human labour. This can lead to lower prices for consumers and improved profitability for businesses.[58]

New industries and jobs: AI can create new industries and job opportunities, such as those related to the development and deployment of AI technologies, leading to increased economic growth and job creation.

Offsetting these benefits, the European Parliament warns:

> AI may also have a highly disruptive effect on the economy and society. Some warn that it could lead to the creation of super firms – hubs of wealth and knowledge – that could have detrimental effects on the wider economy.[59]

These destabilising impacts are likely to impact heavily on traditional labour markets. Goldman Sachs, using data on occupational tasks in both the US and Europe, found that approximately two thirds of current jobs in the United States are exposed to some degree of AI automation, and that generative AI could substitute up to one quarter

56 Lu and Zhou. (2019). A Short Review on the Economics of Artificial Intelligence

57. Szczepański, M. (2019). Economic impacts of artificial intelligence (AI). European Parliamentary Research Service. Available at https://www.europarl.europa.eu/RegData/etudes/BRIE/2019/637967/EPRS_BRI(2019)637967_EN.pdf

58. McKinsey. (2023). The state of AI in 2023: Generative AI's breakout year. Available at https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai-in-2023-generative-ais-breakout-year

59. Szczepański. (2019). Economic impacts of artificial intelligence

of the current workforce.[60] Goldman Sachs tempers this view by pointing out that historically the job producing aspects of technological change (the income effect) have outweighed job loss (the substitution effect).[61]

The potential labour market and social impacts of AI are discussed later in this report. This section concentrates on analysing the impacts of increased AI use on economic growth and productivity.

On this, there are differing opinions. Generally, business analysts and consulting firms have an optimistic view of the impacts of AI and differ only in the extent and timing of benefits. Economists take a more subdued outlook, looking to discover the transmission mechanisms by which AI diffusion will translate into growth and remain mindful of the well-known technology paradox.[62]

However, in the case of AI, these concerns seem to be easing. For example, Brynjolfsson (2017) argues that the Solow Paradox is 'just a lag in technology trade-offs' caused by lags in complementary technology diffusion.[63] Similarly, Saniee et al (2017) predict that there will be a 'second productivity jump in the United States that will occur in the 2028-2033 timeframe, driven by AI'.[64]

Within this generally agreed upon view of the positive growth of AI are differences over how an AI-augmented production function works. Most agree that AI augmented production will take place within some form of constant elasticity of substitution (CES) production, displaying increasing returns to scale.[65] Some of the major studies in this area and their predictions are shown in Table 2.1 below:

Table 2.1: Estimates of the impact of AI on economic growth

Study	Prediction	Causal factors
Goldman Sachs (2023) [66]	Generative AI could raise global GDP by 7% and productivity by 10% over a 10- year period	Mainly labour market driven; two-thirds of occupations will be automated although innovation creates increased job growth
Accenture (2016)	Doubling of global economic growth rates by 2035 [67]	Mainly labour market and innovation driven. A 40% increase in labour productivity, creation of virtual workforce, and increased innovation
PwC (2018)	Increased global revenue by US$16.7 trillion by 2030 [68]	Data driven including Internet of Things data, productivity gains via worker augmentation, increased innovation, and better decision making
McKinsey Global Institute (2017) [69]	Global GDP increased by 1.2% annually and US$13.0 trillion by 2030	Labour productivity, increased automation particularly in manufacturing and transport, and increased innovation
Analysis Group (2016)	US$1.49 to US$2.95 trillion increases in global economic impact by 2030[70]	Direct effects will be generated by increased revenues and employment in firms and sectors that develop or manufacture AI technologies. Indirect effects will come from a broader increase of productivity.

60. Goldman Sachs. (2023) Generative AI could raise global GDP by 7%. Available at https://www.goldmansachs.com/intelligence/pages/generative-ai-could-raise-global-gdp-by-7-percent.html

61. See Borjas, G. (2019). *Labor Economics.* 8th edition, McGraw Hill for a discussion pf the historical behaviour of these effects.

62. See Ernst, E et al (2019). The Economics of Artificial Intelligence: Implications for the Future of Work. *Journal of labour Mobility;* Mihet, R. and Philippon, T. (2019). The Economics of Big Data and Artificial Intelligence. *International Finance Review*, Volume 20, 29–43; and Acemoglu, D., Autor, D., Dorn, D., Hanson, G. and Price, B. (2014). Return of the Solow Paradox? IT, Productivity and Employment in US Manufacturing. *American Economic Review* 104(5) 394-99

63. Brynjolfsson et al (2017). Artificial Intelligence and the Modern Productivity Paradox

64. Saniee, I., Kamat, S., Prakash, S., Weldon, M. (2017). Will productivity growth return in the new digital era? An analysis of the potential impact on productivity of the fourth industrial revolution. *Bell Labs Technical Journal*. Available at http://dx.doi.org/10.15325/BLTJ.2017.2714819

65. See CES Production Function. (2015) *Handbook of Regional and Urban Economics*. Available at https://www.sciencedirect.com/topics/economics-econometrics-and-finance/ces-production-function

66. Goldman Sachs. (2023) Generative AI could raise global GDP by 7%

67. Accenture. (2016). Artificial Intelligence Poised to Double Annual Economic Growth Rate in 12 Developed Economies and Boost Labor Productivity by up to 40 Percent by 2035, According to New Research by Accenture. Available at https://newsroom.accenture.com/news/2016/artificial-intelligence-poised-to-double-annual-economic-growth-rate-in-12-developed-economies-and-boost-labor-productivity-by-up-to-40-percent-by-2035-according-to-new-research-by-accenture

68. PwC (2018). The macroeconomic impact of artificial intelligence. Available at https://www.pwc.co.uk/economic-services/assets/macroeconomic-impact-of-ai-technical-report-feb-18.pdf

69. McKinsey Global Institute (2018). Notes from the AI Frontier: Modeling the Impact of AI on the World Economy. Available at https://www.mckinsey.com/featured-insights/artificial-intelligence/notes-from-the-ai-frontier-modeling-the-impact-of-ai-on-the-world-economy

70. Chen et al (2016). Global Economic Impacts Associated with Artificial Intelligence. Analysis Group. Available at https://www.analysisgroup.com/globalassets/content/insights/publishing/ag_full_report_economic_impact_of_ai.pdf

For Australia, the CSIRO's Data61 unit forecasts that AI benefits will be worth A$22.17 trillion to the global economy by 2030.[71] It predicts that Australia could boost its economy by A$315 billion by 2028 using digital technologies.

While these forecasts are over slightly different time periods and cite different causal factors, it is possible to devise a consensus view from these estimates that predicts: 1) annual global growth rates from the increased diffusion of between 1.95% and 2.4% over the period 2022-2030 [72]; and 2) annual labour productivity growth exceeding 3% over the period 2022-2030.[73]

The Australian GDP at the time of the CSIRO predictions (2021-22) was US$1.7 trillion,[74] constituting 1.7% of the global GDP and making Australia the 12th largest economy in the world.[75] The CSIRO predictions of a A$315 billion increase to the Australian economy by 2028 would suggest an annual average growth rate of between 1.78% and 2.03%, estimates which are very similar to those shown in Table 2.1.

2.1. Growth rates in selected industries from AI

So far, the benefits of AI have been considered at the macro-level, but these benefits will vary across countries and industries and some early adopting industries will function as distributors of growth to the rest of the economy. While it is acknowledged that AI will exercise a general effect across the economy, it is believed that six industries will be at the forefront of AI absorption and AI induced growth, acting as distribution points for growth diffusion effects across the economy.[76] These industries are:

Healthcare: AI has the potential to revolutionise healthcare by enabling faster and more accurate diagnoses, personalised treatment plans, and improved patient outcomes. The global market for AI in healthcare is expected to grow at a compound annual growth rate (CAGR) of between 41.5% and 47.6% from 2021 to 2028.[77]

Finance and insurance: AI is being used to automate financial tasks, reduce fraud, and provide personalised financial advice. The global market for AI in finance is expected to reach $25.8 billion by 2028, rising at a market growth of 16.8% CAGR during the forecast period.[78]

Retail: AI is being used to improve customer experience, optimise supply chain operations, and enable personalised marketing. The global market for AI in retail is expected to grow at a CAGR of 23.9% from 2022 to 2030, according to a report by Grand View Research.[79]

Manufacturing: AI is being used to optimise production processes, reduce costs, and improve quality control. The global market for AI in manufacturing is expected to grow at a CAGR of 45.6% by 2028.[80]

Transportation: AI is being used to improve safety, optimise routes, and reduce fuel consumption in the transportation industry. The global market for AI in transportation is expected to grow at a CAGR of between 22.7% over the forecast period 2023 to 2032.[81]

Other studies have pointed to subgroups within these industries such as marketing, automotive, and advertising that will also have a disproportionate share of economic benefits of AI. [82]

71. Schubert, M. (2022) Why must Australia invest in AI research and development? Australian Institute of Machine Learning (AIML). Available at https://www.adelaide.edu.au/aiml/news/list/2022/08/03/why-must-australia-invest-in-ai-research-and-development

72. These results will depend on whether the low estimate of the Analysis group is included or not. In essence they represent an outlier compared to most other estimated.

73. Based on Goldman Sachs. (2023) Generative AI could raise global GDP by 7%; and McKinsey Global Institute (2018). Notes from the AI Frontier: Modeling the Impact of AI on the World Economy.

74. Statista. Australia: Gross domestic product (GDP) in current prices from 1987 to 2028. Available at https://www.statista.com/statistics/263573/gross-domestic-product-gdp-of-australia/

75. Australian Government. Australia is a top 20 Country for Economy. Available at https://www.dfat.gov.au/sites/default/files/australia-is-a-top-20-country-all-topics.pdf

76. Fain, J. (2019). Five Industries Being Transformed By Artificial Intelligence. Forbes. Available at https://www.forbes.com/sites/forbesagencycouncil/2019/04/15/five-industries-being-transformed-by-artificial-intelligence/?sh=497d172f4c7e

77. Markets and Markets. (2023). Artificial Intelligence in Health Care Market Size. Available at https://www.marketsandmarkets.com/Market-Reports/artificial-intelligence-healthcare-market-54679303.html

78. KBV Research. (2022). Global Artificial Intelligence In Fintech Market Size, Share & Industry Trends Analysis. Available at https://www.kbvresearch.com/artificial-intelligence-in-fintech-market/

79. Grand View Research. (2023). AI In Retail Market Size, Share & Trends Analysis Report. Available at https://www.grandviewresearch.com/industry-analysis/ai-retail-market-report

80. Markets and Markets. (2023) Artificial Intelligence in Manufacturing Market Size Share& Industry Growth Analysis Report. Available at https://www.marketsandmarkets.com/Market-Reports/artificial-intelligence-manufacturing-market-72679105.html

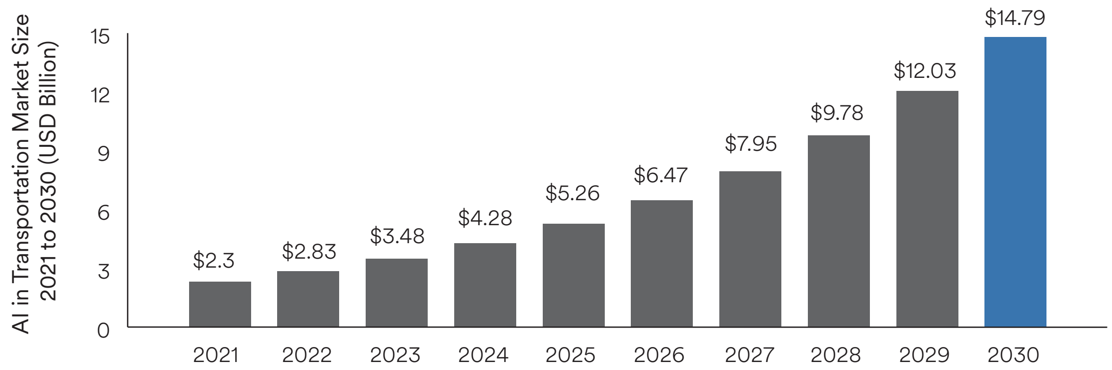
81. Precedence Research. (2023). Artificial Intelligence in Transportation Market. Available at https://www.precedenceresearch.com/artificial-intelligence-in-transportation-market

82. Fain, J. (2019) Five Industries being Transformed by Artificial Intelligence.

The impact of a 10% AI increase on total transport industry output will depend on a range of factors such as the current level of AI adoption in the industry, the specific applications of AI being used, and the overall state of the economy.

These estimates relate to the growth in the incidence of AI and not necessarily the impact on industry output. Figure 2.1 shows an almost 7-fold increase in the transport industry between 2021 and 2030 as provided by Precedence Research.[83]

Figure 2.1: The estimated growth of AI in transport



(Source: Precedence Research, 2022)

This data is important because it is one of the few studies at the industry level that have attempted to link AI (capital) deepening with the economic growth of the industry as a whole. Most studies of the incidence of AI refer to growth in the intensity of AI use rather than the impact it will have on the growth and outputs of a specific industry.

Education: AI in education offers personalised learning by analysing individual students' strengths, weaknesses, and learning styles. AI algorithms can customise educational content to meet each student's specific needs, which fosters better engagement and comprehension, ultimately improving learning outcomes. The global AI in education market is expected to grow at a CGAR of 40.70% during 2023-2028.[84]

Table 2.1 above takes the AI proportion increases and assigns average industry growth rates under two assumptions – constant returns to scale and increasing returns to scale.

These may be estimated within a standard production function:

$$Q_{it} = A_i L_{it}^{a} K_{it}^{b} e^{u}{}_{it}$$

where Q_{it} = output, L= labour supply, K= stock of physical capital, A is a time variant firm specific efficiency parameter, and a and b are exponents representing the marginal productivities of labour and capital, respectively. e is the residual.

Alternately. Damici, Van Roy and Vertesy (2021) use a knowledge-enhanced production function to incorporate AI within the production function.[85] Under this formulation:

$$Q_{it} = A_i L_{it}^{a} K_{it}^{b} AI_{it}^{\sigma} e^{u}{}_{it}$$

where AI is the augmentation effect of AI on labour and capital.

83. Precedence Research. (2022). AI in Transportation Market Size to Surpass USD $14.79 Bn by 2030. Global News Wire. Available at https://www.globenewswire.com/en/news-release/2022/08/24/2503979/0/en/AI-in-Transportation-Market-Size-to-Surpass-USD-14-79-Bn-by-2030.html

84. Thapar, A. (2023) AI in Education Market Size to Reach US$ 19.9 Billion, Globally, by 2028 at 40.70% CAGR. Available at https://www.linkedin.com/pulse/ai-education-market-size-reach-us-199-billion-globally-ayesha-thapar

85. Damioli, G., Van Roy, V. and Vertesy, D. (2021) The impact of artificial intelligence on labour productivity. *Eurasian Business Review*. Available at https://link.springer.com/article/10.1007/s40821-020-00172-8

Their work builds upon similar production function formulations by Fors (1996) and Belderbos *et al*. (2015).[86] Within both formulations, scale economies are measured as the sum of the natural logs of the productivity coefficients $\boldsymbol{a} + \boldsymbol{b}$ or $\boldsymbol{a} + \boldsymbol{b} + \bar{\boldsymbol{o}}$. In the case of the knowledge enhanced production function, where these sum to 1 it indicates constant returns to scale, and where these are > 1 there are increasing returns to scale.

Damici *et al* (2021) used a sample of 5,257 companies that have filed at least one AI related patent between 2000 and 2016. They took the inflow of patents as the measure for change in the stock of knowledge or AI capital, finding that AI improved both labour and capital productivity, but that the AI impact was labour replacing and capital inducing.[87] The coefficients on both the labour and capital variable were both highly significant and indicate scale effects on capital of 1.09 and on labour of 1.077.

These authors note that these are relatively modest impacts, a fact they attribute to the use of patents as an indicator of AI diffusion. There are a number of more robust estimates of the impacts of R&D on scale such as proportion of investment in machine learning.

Belderbos *et al* (2015) estimates scale returns to R&D are between 1.5 and 1.97.[88]

In attempting to derive average industry returns to AI dispersion and based on the studies by Damici *et al* (2021) and Belderbos *et al* (2015), this report adopts a conservative estimate of returns to scale and investigates two scenarios – constant returns to scale (scale coefficient of 1.0) where increases in AI stock lead to proportionate increases in industry output), and increasing returns to scale (scale coefficient of 1.2) where increases in AI stock led to a greater than proportionate response in output.

For example, if you have an investment that has a CAGR of 22.97% over five years (for example, finance and insurance), it means that on average, the investment has grown by 22.97% per year over that entire period. This rate considers the compounding of returns, so the actual growth may vary from year to year. Some assumptions are required to convert a CAGR into an annualised growth rate as shown in Table 2.2.

Table 2.2 uses the data from Table 2.1 and the two production function scenarios to estimate annual production growth in the key industries that are driven by AI expansion.

Table 2.2: Translating projected AI growth into output growth in key industries

Industry	Average annual growth rate of AI intensity	Average annual industrial growth rate – constant returns to scale	Average annual industrial growth rate – increasing returns to scale
Healthcare	6.07%	6.07%	7.28%
Transport	2.52%	2.52%	3.03%
Retail	2.99%	2.99%	3.59%
Manufacturing	7.58%	7.58%	9.1%
Finance	3.15%	3.15%	3.78%
Education	7.2%	7.2%	8.64%

(Source – Derived from data and articles cited in Table 2.1) [89]

These results will provide the underpinning of the potential first round, economy-wide impacts of accelerated AI in Australia. Both scale options will be used, and the six industries in Table 2.2 will be taken as distribution points (nodes) for the allocation of benefit across the economy.

The growth estimates shown above are based on the consensus views from a number of studies, except in the case of education. There are large amounts of commentary on AI's impact on the economics of education, but

86. Fors, G. (1996). Utilization of R&D Results in the Home and Foreign Plants of Multinationals. *Journal of Industrial Economics*. Available at https://www.econstor.eu/bitstream/10419/95125/1/wp459.pdf, and Belderbos, R. Lokshin,B, & Sadowski, B. (2015) The returns to foreign R&D. *Journal of International Business Studies*. Available at https://www.researchgate.net/publication/275414515

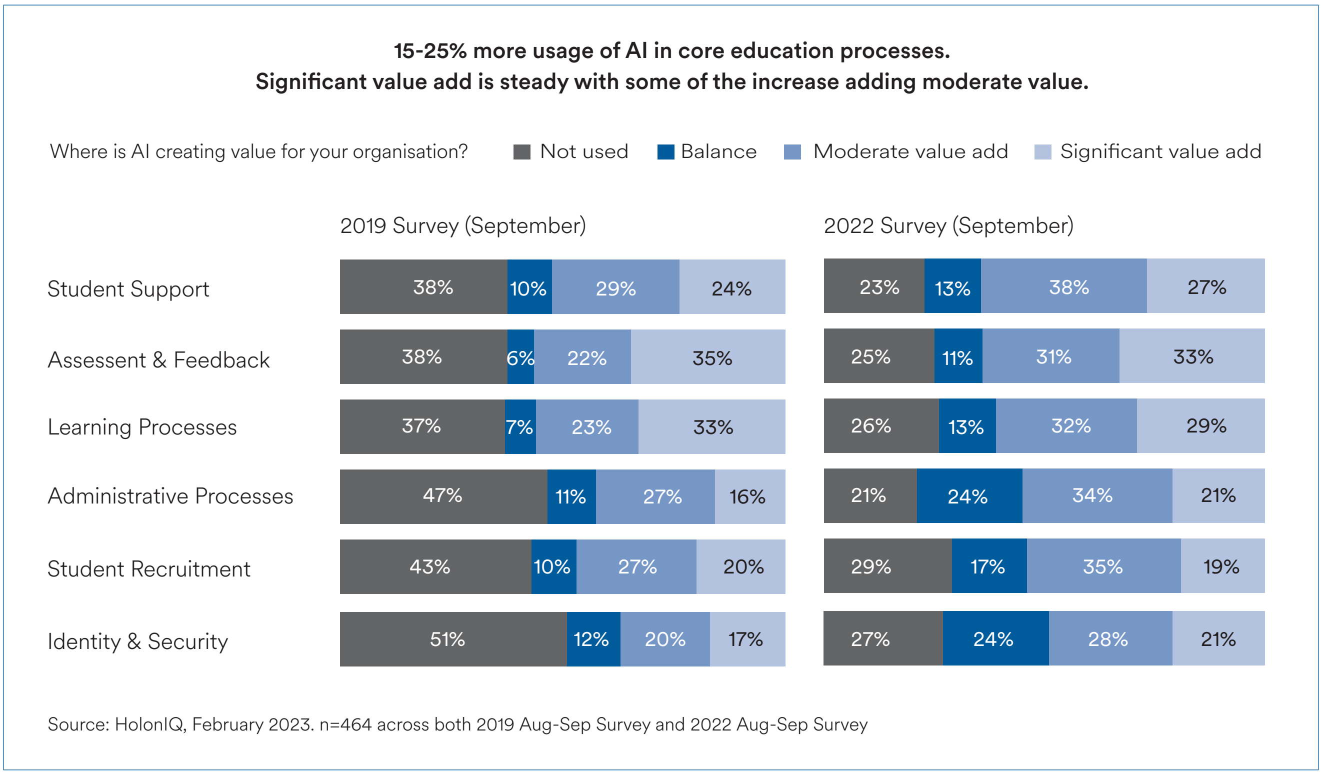
87. Damici et al (2021)

88. Belderbos et al (2015). The returns to foreign R&D was used to estimate these elasticities as was Frontier Economics. (2023). Rate of Return to Investment in R&D: A report for the Department for Science, Innovation and Technology. Available at https://www.frontier-economics.com/media/015adtpq/rate-of-return.pdf

89. Average growth rates were calculated based on constant returns to scale and then increasing returns to scale.

little in terms of its impact on the value of output.[90] Figure 2.2 reaffirms the belief that there will be considerable value-adding in education with an accelerated AI program.

Figure 2.2: Usage of AI in core education processes



(Source - HolonIQ, February 2023) [91]

In the absence of any empirical estimates on the extent of added and more efficient outputs in education, we adopt a modest growth rate of 3.5% annual productivity.

90. See for example, Holon IQ. (2023). Artificial Intelligence in Education. 2023 Survey Insights. Available at https://www.holoniq.com/notes/artificial-intelligence-in-education-2023-survey-insights; and Schiff, D. (2020). Out of the laboratory and into the class room: The future of artificial intelligence in education. *AI & Society: Journal of Knowledge, Culture and Communication* https://link.springer.com/article/10.1007/s00146-020-01033-8

91. HolonIQ. (2023) Artificial Intelligence in Education 2023 Survey Insights. Available at https://www.holoniq.com/notes/artificial-intelligence-in-education-2023-survey-insights

3. Early Adopters of AI and the Advantages Gained

In standard economic theory, early adopters of technology face what are called pioneer costs. These are defined as the additional costs associated with introducing and trialling innovative technology.[92] These costs can include research and development, testing, prototyping, and marketing among others.

Pioneer costs can be significant and may cause delays in the adoption and spread of new technologies. For example, pioneer costs have delayed the widespread uptake of technology such as electric cars, high speed trains, 5G technology, and solar power. Early AI also faced pioneer costs, but these seem to have dissipated towards the end of the 1990s.[93] Kushwaha and Kar (2020) argue that:

> Investments in AI across the world continue to grow at an astonishing rate. A report by Gartner in 2016 reported the adoption of AI by 9% of the organizations. By the end of 2019, AI adoption and use have increased by 25% in the business organizations and are set to double in the next five years. This shows the pace at which the organizations are embracing AI as part of business objectives.[94]

92. Boulding, W. and Christen, M. (2008). Disentangling Pioneering Cost Advantages and Disadvantages. *Marketing Science* 27 (2) 199-216. Available at https://www.jstor.org/stable/40057118

93. Ransbotham, S., Gerbert,P., Reeves, M., Kiron, D. and Spira, M. (2018). Artificial Intelligence in Business gets Real. MIT Sloan Management Review. Available at https://sloanreview.mit.edu/projects/artificial-intelligence-in-business-gets-real/

94. Kushwaha, A.& Kar A. (2020). Micro-foundations of Artificial Intelligence Adoption in Business: Making the Shift. International Working Conference on Transfer and Diffusion of IT(TDIT)

Countries and specific industries are now clearly engaged in a race to introduce AI capacity into their economies and gain competitive advantage. One way of tracing the speed of AI diffusion is to examine the number of patents lodged. According to the WIPO, patent applications in the AI field have increased a 'staggering' 718% between 2016 and 2022.[95]

However, this growth in AI technology has been heavily skewed towards a small number of countries. According to the WIPO, three countries have dominated patent applications – China, the US, and Japan – which collectively accounted for 78% of total AI-related filings, while between 2000 and 2015, almost one in five AI patent families featured a European country.[96]

Expenditure on AI-specific projects is a subset of total R&D expenditure, although distinguishing between the two can be difficult. Table 3.1 shows the intensity of R&D research (% of GDP spent) across the top 20 spenders.

Table 3.1: Top 20 highest spending countries on R&D as a percentage of GDP in 2022

Country	Ranking	Percentage of GDP
Israel	1	4.8
South Korea	2	4.5
Japan	3	3.4
Finland	4	3.2
Sweden	5	3.2
Austria	6	3.1
Denmark	7	3.1
Switzerland	8	3.0
Germany	9	2.9
Belgium	10	2.8
France	11	2.8
Norway	12	2.8
United States	13	2.8
Netherlands	14	2.7
Canada	15	2.6
Australia	16	2.4
UK	17	2.4
Italy	18	2.2
Spain	19	1.2
Portugal	20	1.1

(Source – OECD Data) [97]

95. WIPO (2022). WIPO Conversation on Intellectual Property (IP) and Frontier Technologies. Available at https://www.wipo.int/edocs/mdocs/mdocs/en/wipo_ip_conv_ge_2_22/wipo_ip_conv_ge_2_22_3.pdf

96. Szczepański. Economic impacts of artificial intelligence (AI). (2019)

97. OECD. Gross domestic spending on R&D. Available at https://data.oecd.org/rd/gross-domestic-spending-on-r-d.htm

The data listed in Table 3.1 shows South Korea occupying the second spot in percentage of GDP spent on research, however in terms of absolute spending South Korea (US$106 billion) ranks well below the United States (US$679 billion). The top 10 spenders on R&D are listed in Table 3.2 below:

Table 3.2: Highest expenditure on R&D 2022

Country	Expenditure in USD
United States	$679 billion
China	$551 billion
Japan	$182 billion
Germany	$143 billion
South Korea	$106 billion
France	$69 billion
United Kingdom	$55 billion
Russia	$52 billion
Brazil	$37 billion
Italy	$36 billion

(Source – Statista, 2022) [98]

In general, research into AI and AI-related applications is a subset of R&D expenditure and it is often difficult to separate AI-centred investment from total R&D expenditure. For example, South Korea has the world's highest intensity of industrial robots (measured as a % of GDP) but ranks eighth in the world in terms total expenditure on AI-related research.

The US and China are widely believed to be the biggest investors in AI research and development, with both countries dedicating significant resources to developing AI technologies and applications. The top five spenders on AI research are shown in Table 3.3 below:

Table 3.3: *Top 5 spenders on AI research 2023*

Country	Ranking based on investment, innovation & implementation (out of 100)
United States	**100**
China	62
Singapore	50
United Kingdom	42
Canada	41

(Source – The Global AI Index) [99]

98. Statista. (2022). Leading countries by gross research and development (R&D) expenditure worldwide in 2022. Available at https://www.statista.com/statistics/732247/worldwide-research-and-development-gross-expenditure-top-countries/

99. Tortoise Media. The Global AI Index. Available at https://www.tortoisemedia.com/intelligence/global-ai/

3.1. Benefits from early adoption

AI technology is still in a relatively early stage of its deployment and, as a result, empirical evidence on the relative economic performance between early and later adopters is scarce. However, a number of studies have warned of the consequences that will arise for slow or late adopting nations and industries. The European Parliament Research Services speak of the creation of super firms based on AI monopolies and warn of increased disparity between *have* nations (in terms of AI) and *have not* nations.

> Some warn that it could lead to the creation of super firms – hubs of wealth and knowledge – that could have detrimental effects on the wider economy. It may also widen the gap between developed and developing countries.[100]

As early as 2018, Meléndez was warning of a gap developing between early adopters (mainly referring to firms within the US) and the rest.[101] This theme is also carried in McKinsey (2017), PwC (2018), Accenture (2016), and Goldman Sachs (2023).

While few datasets currently exist to evaluate the impact of AI, the closest comparable test may be a study of the impact of industrial robots.

A study by London School of Economics and Political Science (LSE) economists Michaels and Graetz (2015) uses a dataset across 14 industries (mainly manufacturing industries, but also agriculture and utilities) in 17 developed countries (including Australia, European countries, South Korea, and the United States). The dataset includes a measure of the industrial robots employed in each industry within these countries, and how it has changed between 1993 and 2007. According to the authors:

> We conservatively calculate that on average, the increased use of robots contributed about 0.37 percentage points to annual GDP growth, which accounts for more than one tenth of total GDP growth over this period. The contribution to labour productivity growth was about 0.36 percentage points, accounting for one sixth of productivity growth.[102]

However, the authors were undecided about the job loss aspects of the diffusion of industrial robots.

Manyika *et al* (2017) estimated that, based on scenario modelling, automation could raise productivity growth globally by 0.8% to 1.4% annually.[103]

100. Szczepański, Economic impacts of artificial intelligence (AI) (2019)

101. Meléndez, C. (2018). Why It Pays To Be An Early Adopter Of AI. *Forbes*. Available at https://www.forbes.com/sites/forbestechcouncil/2018/05/09/why-it-pays-to-be-an-early-adopter-of-ai/?sh=5c312b3341fa

102. Michaels, G. & Graetz, G. (2015). Industrial robots have boosted productivity and growth, but their effect on jobs remains an open question. London School of Economics and Political Science blog. Available at https://blogs.lse.ac.uk/politicsandpolicy/robots-at-work-the-impact-on-productivity-and-jobs/

103. Manyika, J. et al (2017). A future that works: Automation, employment, and productivity. McKinsey & Co. Available at https://www.mckinsey.com/featured-insights/digital-disruption/harnessing-automation-for-a-future-that-works/de-DE

A report from The World Economic Forum (2015) concluded that:

> **...industrial robots increase labour productivity, total factor productivity and wages. At the same time, while industrial robots have no significant effect on total hours worked... there is some evidence that they reduce the employment of low-skilled workers and, to a lesser extent, middle-skilled workers.[104]**

The consensus of these reports is that industrial robots increase productivity and growth, while having a mixed impact on employment. Yet industrial robots, particularly early versions, are primitive compared to AI-enhanced technology and would not be expected to exercise the same transitional impact of AI. They are industry-specific, used in highly controlled environments, and require human supervision. AI promises to have much more pronounced impacts on productivity, although the job replacing potential of AI has so far had a diverse effect across various countries.

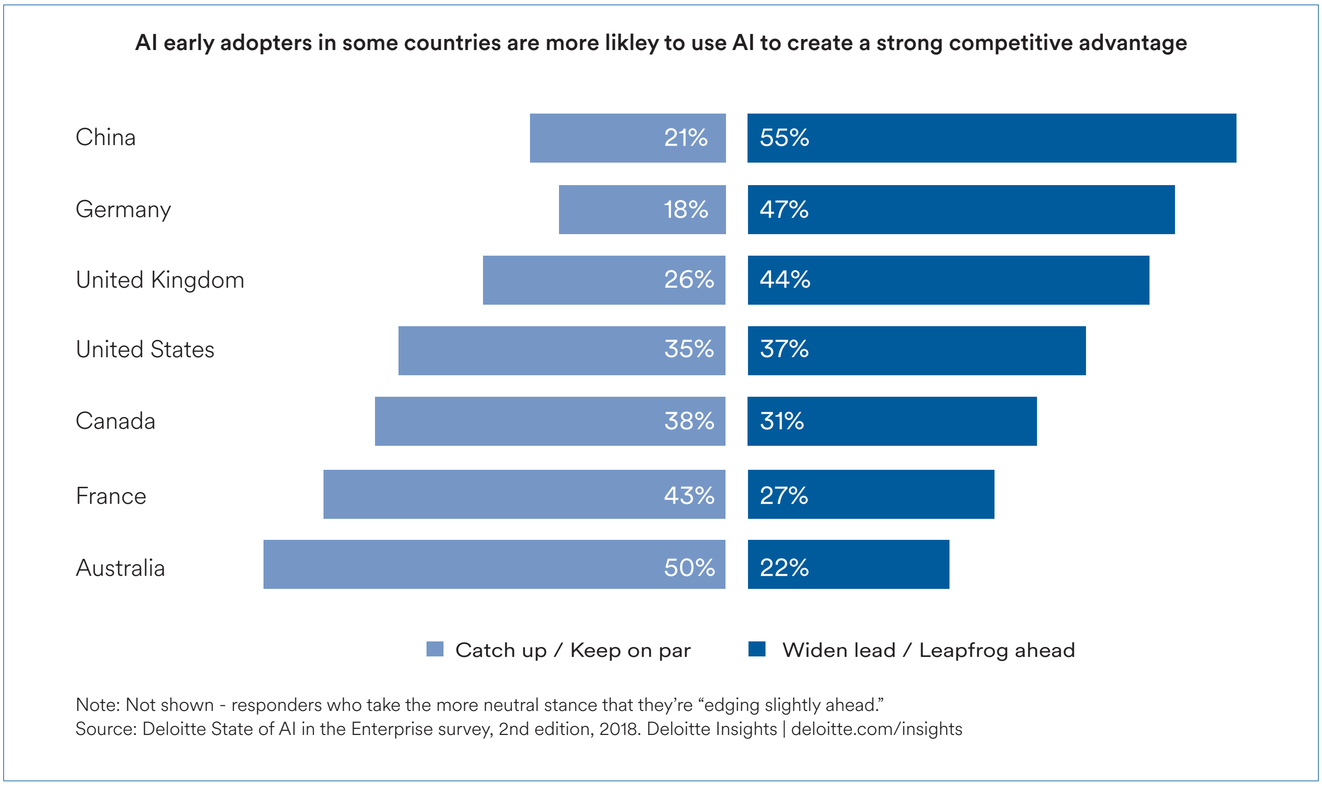
A recent study by David Autor (2021) reverses the traditional concern of job losses from AI expansion and highlights another advantage that comes from early and widespread adoption of innovation. His research shows that 60% of today's workers are employed in occupations that did not exist in 1940.[105] He argues that more than 85% of employment growth over the last 80 years is explained by the technology-driven creation of new positions. Economists such as Autor do not see the AI revolution creating mass unemployment but rather see it (through its innovation process) as the only way to avoid it.

While debate continues on the empirical estimates of AI induced economic gains, there is widespread agreement that late or slow adopters of AI, both at a national level and within countries, will suffer economic loss and loss of sovereignty. This was recognised early by Deloitte (2019) whose conclusions on early versus late adoption are shown in Figure 3.1.

104. Graetz, G. (2015). How much do robots affect jobs and productivity? World Economic Forum. Available at https://www.weforum.org/agenda/2015/03/how-much-do-robots-affect-jobs-and-productivity/

105. Autor, D. (2022). The Labor Market Impact of Technological Change: From Unbridled Enthusiasm to Qualified Optimism to Vast Uncertainty. National Bureau of Economic Research. Available at https://www.nber.org/system/files/working_papers/w30074/w30074.pdf

Figure 3.1: Early adopter advantage



(Source –Deloitte Insights 2019) [106]

This figure indicates that China, Europe, and North America show the greatest enthusiasm for using AI investment to create a competitive advantage. Australian companies, though early adopters, are also planning to make AI investment a cornerstone in creating competitive advantage.

106. Deloitte Insights. (2019). Future in the balance? How countries are pursuing an AI advantage. Available at https://www2.deloitte.com/content/dam/Deloitte/lu/Documents/public-sector/lu-global-ai-survey.pdf

4. AI Investment in Australia and the Underlying Economic Environment for AI Expansion

4.1. AI in Australia

Artificial intelligence is critical to multiple facets of the Australian economy. It's used to operate self-driving trucks in mining, support compliance management in finance, and administer clinical decisions in healthcare. Despite this, Australia is an importer of AI technology rather than a developer or innovator. It is now recognised that under-investment in AI leaves Australia vulnerable and blindly walking towards becoming a low-skilled economy.[107] Williams (2019) writing for the Royal Society of New South Wales, claims that:

> ...[as] a nation, Australia simply cannot afford to continue to be an AI adopter and follower, because our economy, our workforce, our national security, and our future opportunity is increasingly vulnerable to the influence of AI and the power of those who wield it.[108]

107. Raft, T. (2022). Low adoption of AI is hurting Australia in the global field. Australian Financial Review. Available at https://www.afr.com/technology/low-adoption-of-ai-is-hurting-australia-in-the-global-field-20220715-p5b1t7

108. Williams, M. (2019). The Artificial Intelligence race: will Australia lead or lose? *Journal & Proceedings of the Royal Society of New South Wales*. Available at https://www.royalsoc.org.au/images/pdf/journal/152-1-Williams.pdf

Others argue that in the absence of enough capability in AI:

> **...[we] won't have the depth of industry. We'll be locked out of global supply chains because we won't be digital, or smart enough. We won't have traceability. We won't have the efficiencies. So, we won't be able to compete for industry or all the skills in the marketplace, that is, an Australia that looks like a low-skilled economy.[109]**

These warnings are not new – the dangers of under-investment in AI were outlined more than six years ago in a 2017 PwC report. Figure 1.4 of this report shows that AI investment and innovation in Australia is currently not of a sufficient size to be measured separately and is included in estimates for the rest of the world, which collectively are expected to add 5.8% of GDP by 2030 due to the infusion of AI technology.

These estimates were completed in 2017, before the impact of COVID-19, and should be regarded as indicative rather than proscriptive. Nevertheless, they show the domination of large economies and early adopters and provide warning to companies that are slow to embrace new technology. This is reinforced by data gathered by Deloitte (2018) [110] and in Figure 3.1, Early adopter advantage, from this report.

The data confirms an under investment in AI from Australia, a country that in 2022 was ranked 12th in the world in terms of national GDP and ninth in the world for average per capita income.[111]

The IBM AI Adoption Index (2022) provides a different perspective of the current and likely future deployment of AI in Australia. In terms of current deployment of AI technology, Australia (24% of companies deploying AI) ranks well below China (58%), India (57%), Germany (38%), and France (32%), but is comparable to the UK (28%), Canada (28%), and the US (25%), while being slightly ahead of South Korea (23%). This latter figure is somewhat surprising for a country that is a leader in the diffusion of industrial robots. A potential explanation for the apparent slowness of Western countries to apply AI more widely is that they are more likely to face organised resistance from labour unions than either China or India. However, in terms of the percentage of firms planning to explore the diffusion of AI, Australia at 44% is surpassed only by the UK and Canada.

Despite this apparent enthusiasm for AI among Australian companies, Deloitte and others point out a lack of ambition and entrepreneurial spirit among local business. An article in *CIO* magazine uses the Deloitte survey data to argue that Australia is '...lagging other developed economies in the deployment of artificial intelligence technologies thanks to a perfect storm of lower confidence levels, skill shortages, and higher levels of general anxiety around ethical, legal, and security challenges.'[112]

Similarly, Deloitte (2019) found that early adopters of AI in Australia were less ambitious about the potential of AI usage and approached the task almost grudgingly, seeing such a move as inevitable because of the need to catch up.[113] This apparent lack of foresight was highlighted in a Deloitte report where only 22% of respondents from Australian companies saw the '...blue sky+ potential of AI compared with 55% for China, 47% for Germany and 44% and 37% respectively for the UK and Canada.'[114] Deloitte has put this down to the lack of AI fluency among Australian business, with '...44% of Australian respondents indicat[ing] that their organisations had no or poorly developed AI strategies...compared with an international average of 30%.'[115]

109. Raft (2022). Low adoption of AI is hurting Australia in the global field

110. Deloitte. (2018). State of AI in the Enterprise, 2nd Edition Early adopters combine bullish enthusiasm with strategic investments. Available at https://www2.deloitte.com/content/dam/insights/us/articles/4780_State-of-AI-in-the-enterprise/DI_State-of-AI-in-the-enterprise-2nd-ed.pdf

111. Australian Government. Australia is a top 20 Country for Economy

112. Binning, D. (2020). A CIO's guide to AI: Australian artificial intelligence suffering from arrested development. CIO. Available at https://www.cio.com/article/193216/a-cio-s-guide-to-ai-australian-artificial-intelligence-suffering-from-arrested-development.html

113. Deloitte Insights. (2019). Future in the balance? How countries are pursuing an AI advantage. Available at https://www2.deloitte.com/cn/en/pages/technology-media-and-telecommunications/articles/how-countries-are-pursuing-an-ai-advantage.html

114. Ibid

115. Ibid

Finally, Deloitte noted the widespread concern among Australian business of the availability of skilled AI staff:

> Skill gaps present another obstacle: a third of respondents from Australia, more than from any other country, called their AI skill gaps 'major' or 'extreme.' They indicated that their most acute needs are AI researchers, business leaders, and software developers.[116]

However, Australia may not be alone in being currently underprepared for the AI revolution. Tech entrepreneur Ben Lamm suggested low levels of AI maturity in a number of countries, finding that throughout 2021, '...75% of AI projects will remain at the prototype level as AI experts and organisational functions cannot engage in a productive dialogue.'[117] A report from Gartner (2021), which has developed an AI maturity index, suggests that it will take at least until 2025 for a minimum of 50% of organisations to reach AI maturity.[118]

While Australian companies and government agencies are users of imported AI technology, they are not, in large part, becoming developers and innovators. Part of the reason for this relates to the structure of the Australian economy with its under-developed advanced manufacturing industries, however these industries are the natural gestation point for AI technology.

116. Ibid

117. Lamm, B. (2020). What It Takes To Accomplish AI At Scale. Available at https://www.linkedin.com/pulse/what-takes-accomplish-ai-scale-ben-lamm

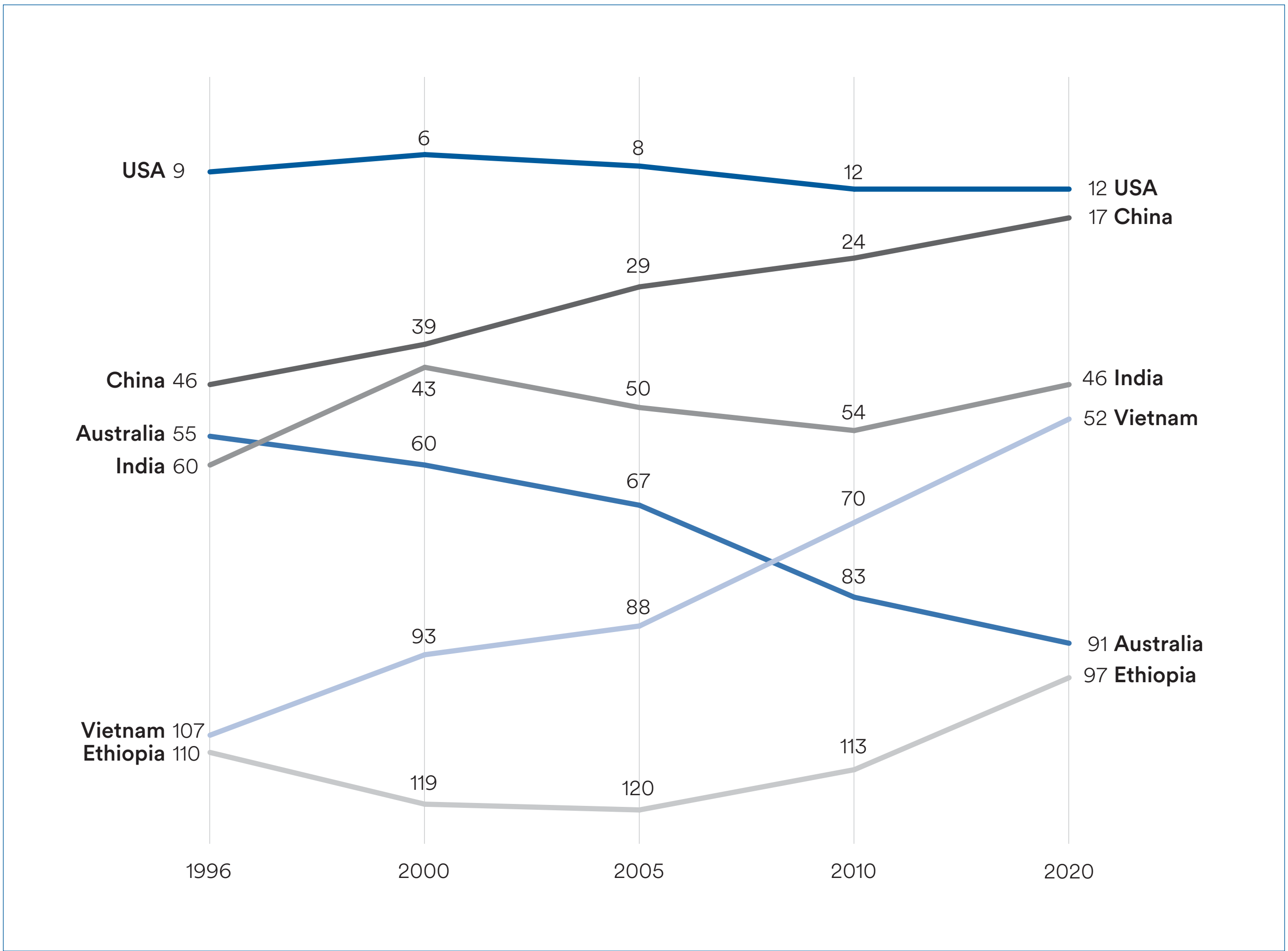
118. Gartner Forecasts Worldwide Artificial Intelligence Software Market to Reach $62 Billion in 2022. (2021) Available at https://www.gartner.com/en/newsroom/press-releases/2021-11-22-gartner-forecasts-worldwide-artificial-intelligence-software-market-to-reach-62-billion-in-2022

4.2. The current economic environment

Australia is currently the 12th largest economy in the world and ranks ninth in terms of per capita income. Under these circumstances it might be expected that Australia would try to stake a position on AI. However, the current strength of the Australian economy and its ability to match AI growth internationally and remain competitive in an AI dominated world may not be reflected in the headline data.

For example, the Australian economy and its industrial structure is based upon what might be termed 'old style' industrial organisation, dominated by services, mining, and agriculture. The Harvard Index of Economic Complexity (ECI) ranks Australia 91st in a world ranking of 133 nations in terms of economic diversity and complexity.[119]

Figure 4.1: Harvard Index of Economic Complexity (ECI) – Australia compared to other selected countries



(Source - Harvard Growth Lab's Country Rankings) [120]

The ECI is calculated using a network analysis approach, which considers the interdependence between products and the countries that export them. The index assigns a score to each country based on the diversity and ubiquity of products in its export basket, with lower scores indicating greater economic complexity.[121]

119. How, B. (2022) Australia slides further on Harvard's economic complexity index. InnovationAus.com. Available at https://www.innovationaus.com/australia-slides-further-on-harvards-economic-complexity-index/

120. Harvard Growth Lab's Country Rankings. Available at https://atlas.cid.harvard.edu/rankings

121. Ospina, E. & Beltekian D. (2018) How and why should we study 'economic complexity'? Our World in Data. Available at https://ourworldindata.org/how-and-why-econ-complexity

The ECI has been used to study the relationship between economic complexity and economic growth, and to identify potential avenues for economic development and diversification. Figure 4.1 shows that Australia's relative standing in industrial complexity declined from 55 in 1995 to 91 in 2020, with a slight recovery between 2005 and 2010. To reinforce this point, Table 4.1 traces the economic complexity index for Australia over the same period compared to selected countries.

Table 4.1: Australia's ECI ranking compared to selected countries

Year	Economic Complexity Index Australia	Economic Complexity Index Canada	Economic Complexity Index Japan	Economic Complexity Index New Zealand
1995	0.11	0.98	2.76	0.50
2000	0.04	1.07	2.82	0.42
2005	-0.14	0.88	2.65	0.47
2010	-0.48	0.63	2.44	0.17
2015	-0.48	0.58	2.43	0.17
2020	-0.52	0.57	2.37	0.17

(Source - Derived from ECI data country rankings 2022) [122]

Since the index was compiled, Japan has been identified as the most industrially complex nation.[123] There are a number of reasons for this, including that Japan:

- is at the forefront in adopting and producing advanced technology and innovation
- has a highly skilled and educated workforce, which complements the use of advanced technology
- possesses strong and flexible industrial structures, such as efficient transportation systems and power supply
- has an interventionist government with an active economic development program for supporting innovation.124

The combination of these factors has contributed to Japan's high industrial complexity index. However, ECI is not the only factor contributing to economic growth. As Chen *et al* (2021) note, Japan's high ranking has not translated into strong economic growth, a fact partly explained by the relative stagnation of the country's ECI over the last 10 years, the aging of its population, and its deflationary policies.[125]

Nevertheless, economic complexity is a measure of the flexibility of an economy and its capacity to absorb innovative technology. Table 4.1 shows that Australia's level of economic industrial complexity was lower in 2020 than in 1995 and has fallen consistently. This does not necessarily imply that Australia has performed worse in terms of economic growth, but it does confirm that Australia's economic base, in terms of diversification, is narrowing in a relative sense, making the country more vulnerable to economic shocks in key industries. In reviewing Australia's performance over time in the ECI, a correspondent at the *Australian Financial Review* described Australia as 'rich, dumb, and getting dumber.'[126]

122. ECI Country & Product Complexity Rankings. Available at https://atlas.cid.harvard.edu/rankings

123. Observatory of Economic Complexity. (2021). Japan profile. https://oec.world/en/profile/country/jpn

124. Compared to modest funding from the Australian government. See Federal budget 2023: Artificial intelligence ignored. Herald Sun. 10 May 2023. Available at https://www.heraldsun.com.au/news/national/federal-budget/federal-budget-2023-less-than-100m-for-artificial-intelligence/news-story/e062a5a2b590fd378dbfc8d9ac04fbeb

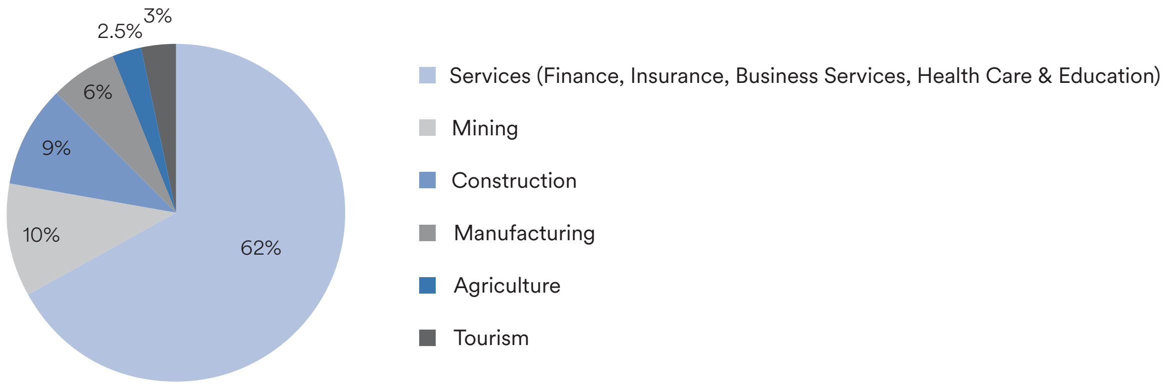
125. Chen, M. (2020). China–Japan development finance competition and the revival of mercantilism. Development Policy Review. Available at https://doi.org/10.1111/dpr.12526

126. Patrick, A. (2019). Australia is rich, dumb and getting dumber. *Australian Financial Review*. Available at https://www.afr.com/policy/economy/australia-is-rich-dumb-and-getting-dumber-20191007-p52y8i

4.3. Main contributions to the Australian economy

The main contributors to the Australian economy in 2022 are shown below in Figure 4.2:

Figure 4.2: Australian GDP 2022 by main sector



(Source – Australian economic model (Mangan 2022) using Australian National Accounts data)

In most countries, services make up the bulk of GDP but in Australia's case, very few of these services, except for education and services to tourism, are exportable. Table 4.2 shows the main exports from Australia by commodity to be:

Table 4.2: Australian exports by main product 2021

Product	% of total value of exports
Iron ore and concentrates	33.3%
Coal	8.5%
Natural gas	6.5%
Education-related travel services	6.0%
Gold	5.7%
Beef	1.8%
Aluminium ores and concentrates	1.8%
Copper ores and concentrates	1.5%
Crude petroleum	1.5%
Wheat	1.5%
Personal, cultural, and recreational services	1.3%
Professional Services	1.2%

(Source – DFAT) [127]

The data above show the heavy reliance placed on mineral exports in this country, with Australia's narrow economic base making it vulnerable to economic shocks and changes in technology. Historically, the lessons of Argentina come to mind. Argentina was one of the ten wealthiest countries per capita in the early 20th century, however its overreliance on commodity exports and unsustainable government spending fuelled frequent boom-bust cycles, resulting in political instability and economic decline in the decades that followed.

127. Australian Government, Department of Foreign Affairs and Trade. Australia's Top 25 Exports, Goods and Services. Available at https://www.dfat.gov.au/sites/default/files/australias-goods-services-by-top-25-exports-2020-21.pdf

4.4. Government policy and Australia's roadmap for AI

In common with most governments around the world, successive Australian governments have stated their intention to accelerate AI diffusion. They have undertaken a number of actions, including the:

- establishment in 2020 of the Centre for Augmented Reasoning within the Australian Institute for Machine Learning (AIML) at the University of Adelaide. The centre is a $20 million investment from the Department of Education in people and research to develop the high-calibre machine learning expertise Australia needs to be an active participant in the machine learning-enabled global economy[128]
- release of the AI Ethics Framework, which outlines principles and guidelines for the ethical development and use of AI in Australia, stressing transparency, accountability, and human-centric values in AI systems[129]
- autonomous government-funded agency, the CSIRO, stating in their Artificial Intelligence Roadmap that it recognised AI as a '...general purpose technology with the potential to be applied across almost every industry within the Australian and global economy.'[130]
- establishment in 2021 of the National AI Centre within CSIRO's Data61 unit to help Australian businesses navigate the AI ecosystem and adopt responsible AI practices.

The first major impetus occurred in June 2021 with the publication of Australia's Artificial Intelligence Action Plan under the then Morrison government.[131] The main focus of this plan was to:

- increase the development and adoption of AI to create jobs and boost productivity
- grow and attract world-class talent and expertise
- harness our world-leading AI capabilities to solve national challenges and benefit all Australians
- ensure AI technologies are responsible, inclusive, and reflect Australian values.

The key features of the plan in 2021 were:

- $53.8 million over four years to create the National AI Centre and four AI and Digital Capability Centres
- $33.7 million over four years to support Australian businesses who partner with government to pilot AI projects
- $24.7 million over six years to establish the Next Generation AI Graduates Program
- $12.0 million over five years to catalyse the AI Opportunity in our Regions program.

The plan was criticised for its slow rollout, with the government only administering a third of the $22 million it had budgeted in its first year (2021-2022). The Australian Information Industry Association (AIIA) said in February 2022 that the design and pace of the program was accelerating Australia's AI talent exodus.[132]

Unveiled in March 2022, nearly a year after it was announced, the $44 million Digital Capability Centre program received grant applications but did not establish any centres before it was eventually scrapped in 2023.

More recently, as part of the 2023-24 budget, the Albanese government announced $75.7 million of funding for AI initiatives that includes:

- $17 million for the AI Adopt program which will create new centres to support and train SMEs to make more informed decisions about using AI to improve their business
- $21.6 million to expand the remit of the National AI Centre
- $34.5 million of continued funding for the Next Generation Artificial Intelligence and Emerging Technologies Graduates programs to attract and train the next generation of job-ready AI specialists.[133]

128. Walker, T. (2020) $20M to Establish Centre for Augmented Reasoning at AIML. Australian Institute of Machine Learning. Available at https://www.adelaide.edu.au/aiml/news/list/2020/10/07/20m-to-establish-centre-for-augmented-reasoning-at-aiml

129. Australian Government. ((2019). Australia's Artificial Intelligence Ethics Framework. Available at https://www.industry.gov.au/publications/australias-artificial-intelligence-ethics-framework

130. CSIRO. Artificial Intelligence Roadmap. Available at https://www.csiro.au/en/research/technology-space/ai/artificial-intelligence-roadmap

131. Australian Government. (2021). Australia's Artificial Intelligence Action Plan. Available at https://www.industry.gov.au/publications/australias-artificial-intelligence-action-plan

132. Brookes, J. (2022). Govt's 'AI Action Plan' is lacking action. InnovationAus. Available at https://www.innovationaus.com/govts-ai-action-plan-is-lacking-action/

133. Australian Government, Department of Industry, Science and Resources. (2024). Safe and responsible AI in Australia consultation: Australian Government's interim response. Available at https://consult.industry.gov.au/supporting-responsible-ai

The $17 million in grants for the development of 'up to five' AI Adopt centres mimics the 2021 plan by the former government to create four AI and Digital Capability Centres that never materialised.[134] Some AI programs are continuing in full under the Albanese government, including the National AI Centre and graduate programs.[135] But the full AI funding package represents a cut of around $30 million from the Morrison government's $124 million AI Action Plan,[136] and several elements of the plan were paused as the Albanese government took power in 2022.

Many view this level of public support for AI as inadequate. Warren, Hunt, and Manantan (2023), writing for the Australian Institute for International Affairs,[137] note the funding pledged by the Morrison government and the creation of the AI Innovation Network, but cite a recent report by the Canadian International Development Research Centre, which classed the Australian budget for AI as very small.[138] At the time, the Canadian government was investing approximately 5 times more than the Australian government.

The Organisation for Economic Co-operation and Development (OECD) in 2020 noted that '...the public budgetary investment on AI varies radically across countries, ranging from over US$500 million [in] Japan, Korea and the United Kingdom to less than US$1 million [in] Australia, Estonia, Greece, Lithuania and Portugal.'[139] By comparison (and after adjusting based on economy size) current contributions to AI by the public sector in Australia look small.

AI investments in other countries

United States: The U.S. has been a major player in AI research and development. In September 2019, the White House announced a FY2020 non-defence AI R&D budget request of nearly $1 billion.[140] Additionally, private companies in the US, such as Google, Microsoft, and Amazon, have invested heavily in AI research.

China: China has also been making substantial investments in AI research. In 2017, the Chinese government outlined a plan to become the world leader in AI by 2030 and committed to investing over $150 billion in AI research and development.[141] Chinese tech companies, including Baidu, Alibaba, and Tencent, have been actively involved in AI research as well.

European Union: The European Union has been focusing on AI research and development to boost its competitiveness. In 2018, the European Commission announced plans to increase investments in AI to at least €20 billion by the end of 2020, with the aim of mobilising an additional €20 billion from private investment. [142]

Canada: Canada has been recognised for its AI research, particularly in the field of deep learning. The Canadian government has invested in AI research through initiatives like the Pan-Canadian Artificial Intelligence Strategy, which committed C$125 million in funding for AI research institutes in three major cities (Edmonton, Toronto, and Montreal) as phase one of its strategy,[143] followed by an additional C$433 million for the second phase commencing in 2022.

United Kingdom: In 2022 the UK Government published its National AI Strategy and Action Plan, outlining a package of over $1.3 billion of support for the sector. This support complements and leverages the $2.8 billion that the UK Government had previously invested in AI.[144]

South Korea: South Korea has shown significant interest in AI research and development. In 2019, the government announced plans to invest $2 billion in AI research and development by 2022, with a focus on human resources, technology, and infrastructure.[145]

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134. Brookes, J. (2023). Govt gets moving on $17m plan for AI uptake centres. InnovationAus. Available at https://www.innovationaus.com/govt-gets-moving-on-17m-plan-for-ai-uptake-centres/

135. Brookes, J. (2023). Australia's AI policy, programs on ice. InnovationAus. Available at https://www.innovationaus.com/australias-ai-policy-programs-on-ice/

136. Brookes, J. (2023) Govt backs quantum and AI industries with $101m. InnovationAus. Available at https://www.innovationaus.com/govt-backs-quantum-and-ai-industries-with-101m/

137. Warren, A., Hunt, C., and Manantan, M. (2023). Australia's Critical Test for Future Growth: Moving the National AI Strategy from Rhetoric to Reality. Australian Institute for International Affairs. Available at https://www.internationalaffairs.org.au/australianoutlook/australias-critical-test-for-future-growth-moving-the-national-ai-strategy-from-rhetoric-to-reality/

138. Canadian International Development Research Centre. (2019). Government Artificial Intelligence Readiness Index 2019. Available at https://africa.ai4d.ai/wp-content/uploads/2019/05/ai-gov-readiness-report_v08.pdf

139. OECD. National policies for Artificial Intelligence: What about diffusion? Available at https://www.oecd-ilibrary.org/sites/cc3a9728-en/index.html?itemId=/content/component/cc3a9728-en

140. Bipartisan Policy Center. (2020). Cementing American Artificial Intelligence Leadership: AI Research & Development. Available at https://bipartisanpolicy.org/report/ai-research-development/

141. Kharpal, A. (2017). China wants to be a $150 billion world leader in AI in less than 15 years. CNBC. Available at https://www.cnbc.com/2017/07/21/china-ai-world-leader-by-2030.html

142. European Commission (2018). Artificial intelligence: Commission outlines a European approach to boost investment and set ethical guidelines. Available at https://ec.europa.eu/commission/presscorner/detail/en/IP_18_3362

143. Holon IQ. (2019). The Global AI Strategy Landscape. Available at https://www.holoniq.com/notes/the-global-ai-strategy-landscape

144. US international Trade Administration. (2023). United Kingdom Artificial Intelligence Market 2023. Available at https://www.trade.gov/market-intelligence/united-kingdom-artificial-intelligence-market-2023

145. South Korea Aims High on AI, Pumps $2 Billion Into R&D. (2018). Available at https://medium.com/syncedreview/south-korea-aims-high-on-ai-pumps-2-billion-into-r-d-de8e5c0c8ac5

5. Economic Modelling of AI's Impacts

In examining the economics of AI, it is instructive to see how economists have treated AI in their modelling. To this point there have been several approaches, and AI has been seen as:

- part of the capital stock [146]
- automation in the production function which is labour replacing [147]
- a horizontally integrated technical progress
- human capital augmenting.

Lu and Zhou [148] provide a generalised production structure to investigate some of the issues around modelling AI and illustrate how AI could be modelled effectively:

AI Model Equation: Lu and Zhou

$$Y(t)=G(N(t), y_i(t)), \qquad (1)$$

$$yi(t)=A(t)*F(\alpha(t)Ki(t),ß(t)L_i(t)) \qquad (2)$$

Where ***Y*** is the final good(s) and is a function of a set of intermediate goods ***yi*** and the quantity or the quality of innovations ***N***.

The production function is determined by capital K_t and Labour L_i

t denotes time

A is the total factor productivity, and ***a*** *and* ***b*** are the corresponding factor-augmenting productivity.

Within this general framework, two competing models – the technical change model of Hémous and Olsen (2016) and the capital stock model by Aghion *et al* (2019) – have received the most support.

146. See Aghion, P., Jones, B., and Jones, C. (2017) Artificial Intelligence and Economic Growth. Available at https://scholar.harvard.edu/sites/scholar.harvard.edu/files/aghion/files/artificial_intelligence.pdf

147. Dechezlepretre, A., Hemous, D., Olsen, M., & Zanella, C. (2021). Induced Automation: Evidence form Firm-Level Patent Data. University of Zurich Working Paper. Available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3835089

148. Lu and Zhou. (2021). A review on the Economics of Artificial Intelligence

5.1. Technical change model

Hémous and Olsen (2016) use a technical change model to examine the impact of AI on horizontal innovation and income inequality.149 AI is collectively modelled under 'automation' which allows expansion of the tasks (expansion exponent) that can be performed by machines. In contrast to the Lu and Zhou model, the final goods become a constant elasticity of substitution (CES) nesting of intermediate goods:

AI Model Equation: Hémous and Olsen

$$Y(t) = G(N(t),\ y_l(t)) = \left(\int_0^{N(t)} y(t,i)^{\frac{\sigma-1}{\sigma}} di\right)^{\frac{\sigma}{\sigma-1}}$$

As N(t) increases, there is technological progress, that is, horizontal innovations that expand the range of products. There is a differential setting for intermediate production in that labour (L) is distinguished as either low skill (-) or high skill (h), and AI (or automation) can act as a perfect substitute for low-skilled workers. In the second equation the production of intermediate goods is modelled as:

$$y(i) = [l(i)^{\frac{\varepsilon-1}{\varepsilon}} + \alpha(i)(\widetilde{\phi} x(i))^{\frac{\varepsilon-1}{\varepsilon}}]^{\frac{\varepsilon-1}{\varepsilon}} h(i)^{1-\beta},$$

Where *x(I)* is the type I machine that is enabled by the automation technology. There is also an indicator function *α(i)* to differentiate between firms with and without access to AI technology, which is represented as types of machines or capital (*K*) in the Lu and Zhou equation (1). In addition, a part of the high-skilled worker group is hired as AI technology researchers, which are an investment from non-automated firms as well as the source of innovation.

Therefore, the real source of growth is the human capital that creates or controls the AI technology. Economic growth in this model goes through three phases:

1. In the first phase, low-skilled wages are low, there is little incentive for AI, and income inequality and the labour share of GDP are constant
2. The second is a transitional phase in which rising low-skilled wages induce further AI innovation, but this acts to reduce the share of labour and low-skilled wages
3. Finally, a state is achieved in the third phase, where low-skilled wages grow but at a lower rate than high-skilled wages.

The model allows for wage growth among low skill workers in the long run, a slower rate for high skill workers, and no growth at all if middle skill workers are in the model.

5.2. Capital stock model

The Aghion *et al* model has a simpler structure to the Lu and Zhou framework. AI is referred to as 'automation' and is defined as representing the entire capital stock. Capital stock is distinct from the Lu and Zhou model equation and is an integral of all the intermediate goods that have not been automated. The treatment of intermediate goods is simplified to be produced with either capital alone, or labour alone. The final good production then becomes a CES nesting of labour and capital, suggesting that AI can replace labour with constant elasticity of substitution. This last finding is empirically important. If the elasticity of substitution is greater than one, then automation is labour replacing and capital deepening. If the elasticity of substitution is less than one, automation is labour augmenting and capital depleting, which would be an unexpected result, like that of the Solow Paradox.[150]

The authors also argue that ongoing AI development may generate exponential growth if AI starts to replace the generation of ideas. Under this scenario, 'all tasks in idea production are automated and no human being is involved in idea production. In this case, if the growth rates of both capital and ideas rise sufficiently fast then it will deliver a singularity.'[151]

149. Hemous. D and Olsen, M. (2022). The Rise of the Machines: Automation, Horizontal Innovation, and Income Inequality. *American Economic Journal-Macroeconomics*. Available at https://www.aeaweb.org/articles?id=10.1257/mac.20160164

150. Aghion, P., Jones, B. and Jones, C. (2017). Artificial Intelligence and Economic Growth. Available at https://scholar.harvard.edu/sites/scholar.harvard.edu/files/aghion/files/artificial_intelligence.pdf

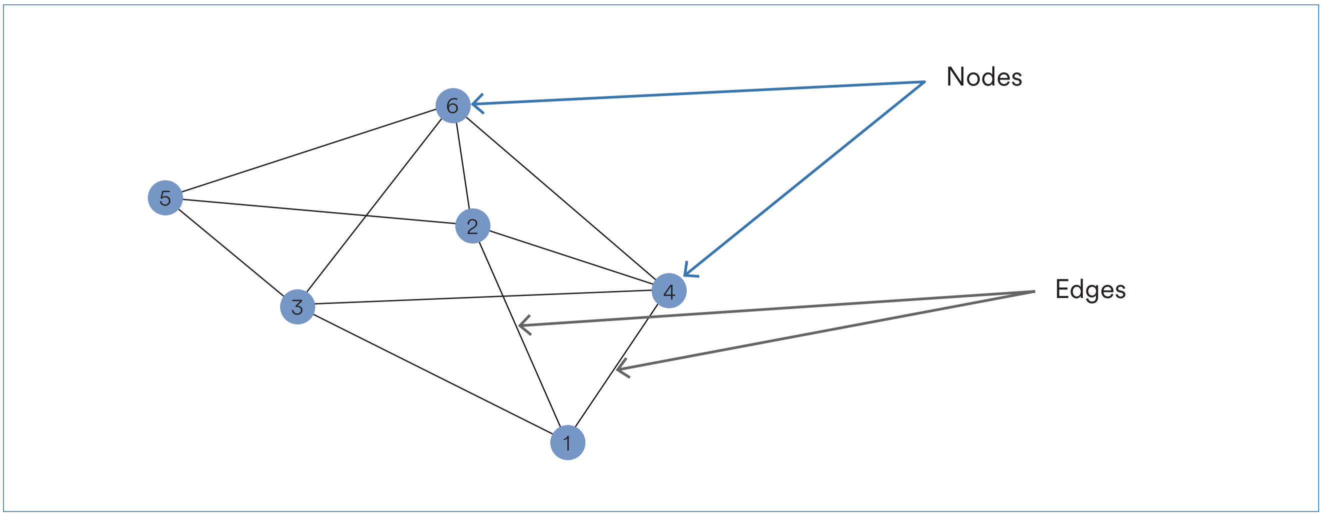
151. Lu and Zhou (2021). A review on the economics of artificial intelligence

In essence, economists are modelling AI as a combination of differentiated capital (arbitrarily divided into AI and non-AI) and technical change, nuanced by having different production functions for goods with AI input and those without. This is a problematic distinction as AI becomes involved in virtually all production into the future. In this case, economists will fall back on the technical change approach but with one major question: how different is AI technology from previous technical innovations?

5.3. A network approach using input-output (IO) modelling

A network refers to a structure representing a group of objects/people and relationships between them. It is also known as a graph in mathematics. A network structure consists of nodes and edges, where nodes represent objects that are analysed, and edges represent the relationships between those objects (see Figure 5.1)

Figure 5.1: Network analysis



(Source – Loem 2021) [152]

Network analysis is a method of studying the relationships between entities in a network. It involves analysing the connections, or links, between the entities as well as the characteristics of the entities themselves. Network analysis can be used to study a wide range of systems, including social networks, transportation networks, and biological networks.

In economic modelling, input-output (IO) and CGE analysis operates within a similar framework. The economy is the network, the nodes are the impacting sector(s), and the edges are the impacted sectors. IO tables provide information on the industrial structure of an economy in a specific period. They contain information on the flow of goods and services between industries and economic sectors. The backward and forward links are descriptive measures of the economic interdependence of sectors. Sectors with strong backwards and forward linkages are vital and play an essential role in a country's development strategy.[153]

In this section, network analysis via an IO table of the Australian economy is used to provide an estimate of the potential and initial impact of AI on the Australian economy. Those key sectors identified in Chapter 2, Section 2.1, will act as the impacting sectors (nodes) and the diffusion path and flow-on impacts will be estimated. In addition, given the general pervasive nature of AI, all non-node sectors will be given a general productivity increase in line with projections of economic growth shown in Chapter 2. In these circumstances the valuation mechanism works in two areas: (1) the exogenous impacts on the key sectors that will benefit most from AI in the initial stages and the associated flow-on from these, and (2) an economy-wide productivity boost as predicted from the early stages of AI.[154]

152. Loem, M. (2021). What is Network Analysis? Medium. Available at https://towardsdatascience.com/network-analysis-d734cd7270f8

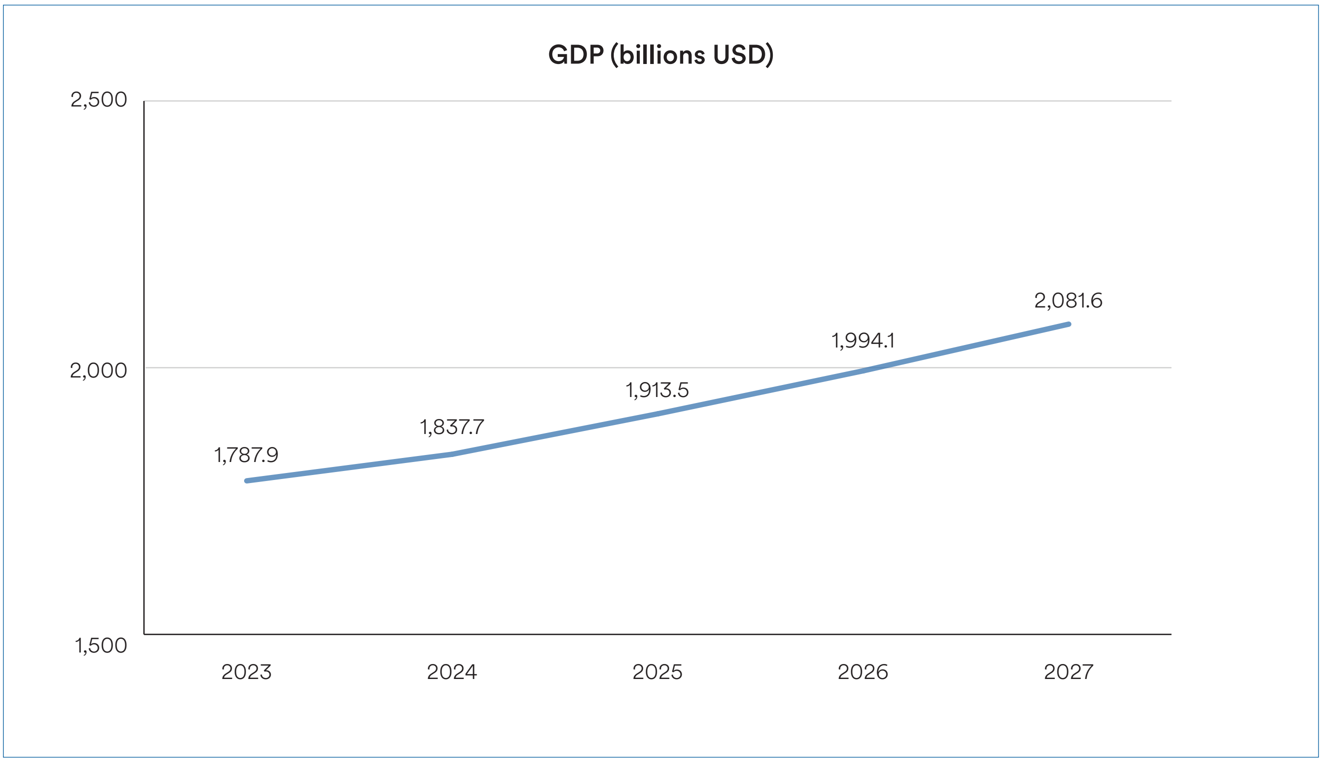
153. Ojaleye, D. (2022). Identification of Key Sectors in Nigeria – Evidence of Backward and Forward Linkages from Input-Output Analysis. Academic Research and Publishing. Available at https://armgpublishing.com/journals/sec/volume-6-issue-1/article-3

154. Tyson, J. (2023). AI boosts productivity 14%: NBER case study. Available at https://www.cfodive.com/news/ai-boosts-productivity-nber-case-study-generative-workforce/649110/. This is only applied to the non-nodal sectors as it is assumed that the key sectors already include this effect.

This analysis should be seen as short run effects of increased AI diffusion over the next five years. Given the exponential nature of returns to AI, it would be unwise and speculative to go beyond the standard forecasting range of IO analysis which is about 5-7 years.

The International Monetary Fund (IMF) has forecast Australia's GDP for 2023-2027. Their estimates are shown in Figure 5.2 and will be used as the default estimates for Australian GDP when comparing potential AI induced economic growth.

Figure 5.2: IMF Growth Estimates for the Australian Economy 2023-2027



(Source – IMF World Economic Outlook database 2022) [155]

Economic models are driven by what are called shifts in final demand. This means that additional expenditure on finished products or services represent a stimulus to economic activity. If this additional expenditure is exogenous (originates from outside the host economy), it is particularly valuable to the local economy because it represents new investment rather than displacement from other areas of past spending.

Overall, the main factors that govern how influential an industry will be in terms of economic impact are whether an activity is endogenous (originates from inside the local economy) or exogenous, and the amount of leakage – or money taken out of the economy – from the host economy. Leakage can be caused through imports in the production process or the repatriation of profits and dividends. The more leakage an activity has, the less impact it will have on the domestic economy.

155. IMF. (2022). World Economic and Financial Surveys: World Economic Outlook Database. Available at https://www.imf.org/en/Publications/WEO/weo-database/2022/October/weo-report?c=193,&s=NGDP_RPCH,NGDPD,PPPGDP,NGDPDPC,PPPPC,PCPIPCH,LUR,GGXWDG_NGDP,&sy=1980&ey=2027&ssm=0&scsm=1&scc=0&ssd=1&ssc=0&sic=0&sort=country&ds=.&br=1

5.4. Using the AIBE model to estimate total economic outcomes

The Australian Institute for Business and Economics (AIBE) model used is a 19 sector, 2020 Australian model based on digit 1 Australian and New Zealand Standard Industrial Classification (ANZSIC) classifications.[156] It has:

- 19 intermediate sectors[157]
- 4 final demand sectors[158]
- 6 primary input sectors[159]

The model is a marginal coefficients IO model, able to adopt both linear and non-linear properties within the IO8 input-output software developed by Guy West at the University of Queensland, Centre for Economic Policy Modelling.[160] Data in the model are taken from the Australian Bureau of Statistics (ABS) National Accounts survey for 2020 and updated in 2022 when more data became available.

Estimates are produced using a non-linear framework. The advantages of non-linear modelling are that it removes some of the issues related to fixed coefficient modelling, a feature of linear models, which includes the tendency to overestimate employment impacts.[161]

A full specification of the methodology used is shown in the appendix.

5.5. Economic impact measures

The primary economic impact measures are as follows:

Gross output (regional turnover): Refers to the gross value of increased production from an additional economic activity. Within this gross value is included the value of raw materials that, in most cases, have already been counted as part of gross output from earlier production. As a result, there is a tendency for gross output figures to include some double counting. Consequently, more concentration is placed upon incremental (additional output created), or value added. Nevertheless, the concept of gross output should not be discarded because it is a good indicator of the level of turnover in the economy and its capacity to accommodate increased economic activity. As a result, it is a useful measure of the total level of economic activity

Value added refers to added or net output. Value added is equivalent to the gross state/regional product as used by the ABS and is usually preferred when measuring economic impact. It measures the added value placed on products (raw materials) throughout the productive process. It is made-up of margins, wages, profits, and transfers

Factor income relates to the share of value added (and gross output) which is directly paid to individuals or firms in the form of wages and/or profits. It is calculated as a percentage of value added and cannot exceed value added

Jobs relates (usually) to the amount of labour required for the level of production. Depending upon the type of activity, job numbers measure either the use of existing labour (continuing jobs) or hiring new staff. Full time equivalent (FTE) employment is a measurement used to figure out the number of full-time hours worked by employees in a business, project, or service provision. Non-linear modelling is the best means of generating realistic employment generation data. Total job numbers were adjusted to FTE estimates to take into consideration the high (upwards of 30%) number of casual and part-time workers.

156. The model can be extended up to 114 sectors

157. The sectors are the 19 ANZSIC Digit 1 sectors, see ANZSIC 2006 https://www.abs.gov.au/statistics/classifications/australian-and-new-zealand-standard-industrial-classification-anzsic/latest-release

158. Household Consumption, Fixed Capital expenditure, Exports, Other Final Demand

159. Compensation of employees, gross operating surplus, taxes less subsidies, other taxes, competing imports, and other primary inputs

160. For recent examples of non-linear IO and why it is sometimes the preferred form of IO modelling, see Guerra, A. and Sancho, F. An Operational, Non-Linear Input-Output System. *Economic Modelling.* Available at https://econpapers.repec.org/article/eeeecmode/v_3a41_3ay_3a2014_3ai_3ac_3ap_3a99-108.htm

161. See Guerra, A. and Sancho, F. An Operational, Non-Linear Input-Output System

5.6. Estimating initial AI impacts using network analytics

Economic impact in this section comes though the 6 key sectors (nodes) growing at the annual average rates as shown in Chapter 2. In addition, the remaining sectors are assumed to be affected by a modest AI impact of 1.2% per annum as predicted by the McKinsey Global Institute.[162]

In both cases two scenarios are estimated: (1) where growth exhibits constant returns to scale (when an increase in inputs causes the same proportional increase in outputs) and (2) where growth exhibits increasing returns to scale (when outputs increase by a larger proportion than the increase in inputs during the production process). Given the nature of AI, the second scenario is the more likely.

On this basis, the added direct injections into the economy from nodal and non-nodal sources are shown in Table 5.1:

Table 5.1: Exogenous injections under constant and increasing returns (US dollars)

Constant returns to scale				Increasing returns to scale		
Year	**Nodal**	**Non-nodal**	**Total**	**Nodal**	**Non-nodal**	**Total**
2023	34.57	12.28	46.85	41.98	14.74	56.72
2024	36.34	12.76	49.09	44.47	15.31	59.77
2025	38.20	13.25	51.45	47.12	15.90	63.02
2026	40.16	13.80	53.96	49.93	16.56	66.49
2027	43.24	14.36	56.62	52.93	17.26	70.20
Total	**191.51**	**66.47**	**257.89**	**236.43**	**79.76**	**316.20**

(Data estimated by author based on 6 of 19 ANZSIC sectors)

These estimates were applied to the AIBE model of the Australian economy for both scenarios and for both nodal estimates and non-nodal estimates. The nodal estimates were applied across the six major impacting sectors and the non-nodal estimates applied in proportion of output size to the remaining 13 sectors in the economy. These produced the following total economic impact measures:

Table 5.2: Total economic impacts of increased AI 2023-2027 – Constant returns to scale (US dollars)

	Final demand	Industry effects	Consumption effects	Total	Flow-on
Gross output/ turnover ($ million)	257.89	212.43	395.14	865.46	607.57
Gross domestic product ($ million)	121.93	99.43	173.68	395.04	273.11
Factor income ($ million)	68.08	49.99	61.24	179.31	111.23

(Source - Standard economic modelling methods applied by the author)

162. McKinsey Global Institute (2018). Notes from the AI Frontier: Modeling the Impact of AI on the World Economy.

These results indicate:

- turnover or gross output increases of US$865.46 billion over the period 2023-2027
- additions to GDP of US$395.04 billion over the period 2023-2027
- increased factor income, including wages and profits of US$179.31 billion over the period.

No estimates of employment effects have been produced due to the uncertainty surrounding the impact of AI on the level and distribution of employment. However, assuming a net cost per job of $250,000, this level of GDP growth (on current levels) would fund an additional 288,000 jobs per year over the 5-year period.

Recognising the likely non-linear behaviour of AI, the model was re-run to allow for modest increases in scale output. The results were re-run using a scale coefficient of 1.2. The results appear in Table 5.3 below.

Table 5.3: Total economic impacts 2023-2027 – Increasing returns to scale (US dollars)

	Final Demand	Industry Effects	Consumption Effects	Total	Flow-on
Gross output/ turnover ($ billion)	316.20	263.07	483.21	1062.48	746.28
Gross domestic product ($ billion)	148.62	124.82	212.42	485.86	337.24
Factor income ($ billion)	82.88	61.55	99.04	243.47	160.59

(Numbers in table 5.3 are derived from AIBE non-linear model)

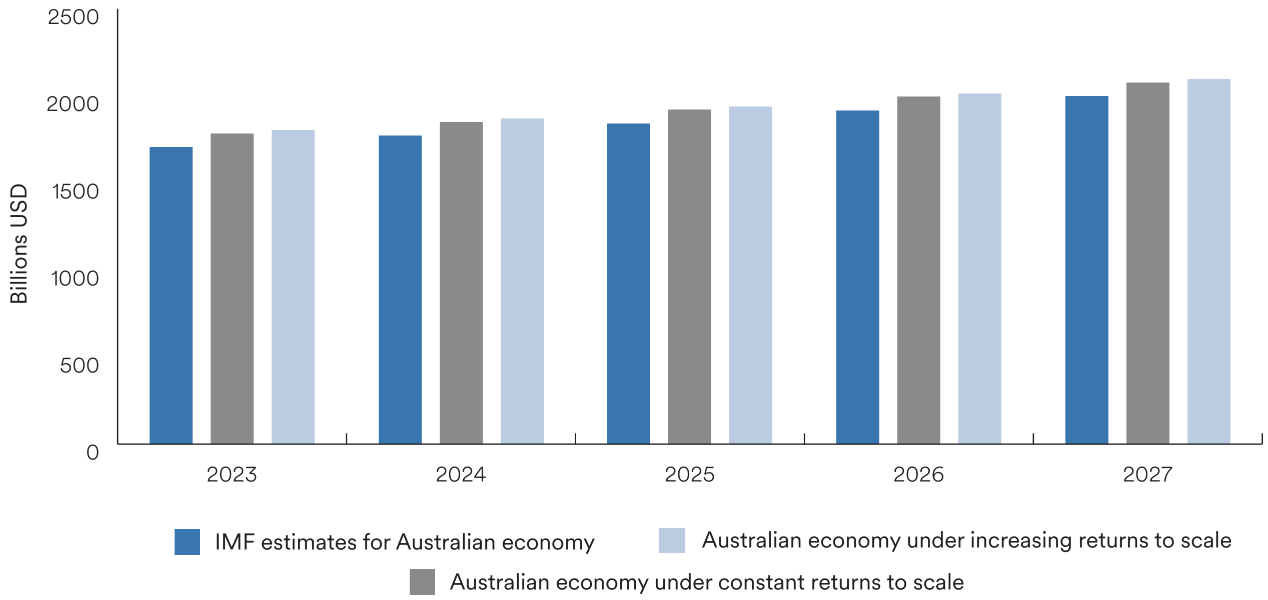
The results suggest that over the 5-year period, AI could provide:

- a total output/turnover impact of AUD $1.062 trillion
- additions to GDP of AUD $485.86 billion
- whole of period factor income generation of AUD $243.47 billion increase.

Using the same job/GDP ratio, this increase suggests the capacity to support approximately 380,000 jobs per year.

Turnover and output measures contain large amounts of double counting, but the important measure is additions to the GDP. On this basis, the estimates of GDP growth (both scenarios) were then apportioned annually, added to the default GDP estimates from the IMF, and graphed. The results appear in Figure 5.3:

Figure 5.3: Predicted growth of the Australian economy 2023-2027, IMF and AI Scenarios



(Source - IMF World Economic Outlook, 2022) [163]

The data show an increase in GDP from 2023-2027 due to expanded AI of between 22.5% (US $395 billion) and 28% (US $486 billion) which implies an average growth rate for the AI infused economy of 4.43% to 4.82%. This compares with the IMF predicted default rate of total period 17.1% growth at 3.4% average annual. The estimated GDP growth is in line (slightly higher) with international estimates shown in Chapter 2.

Economic impact analysis is not an exact science. This is particularly true involving predictions of the impact of AI on economic development. No one is sure of the impacts which are a function of the rate of diffusion. The estimates shown above are conservative and supportive of other (international) results reported earlier.

163. IMF World Economic Outlook database, 2022

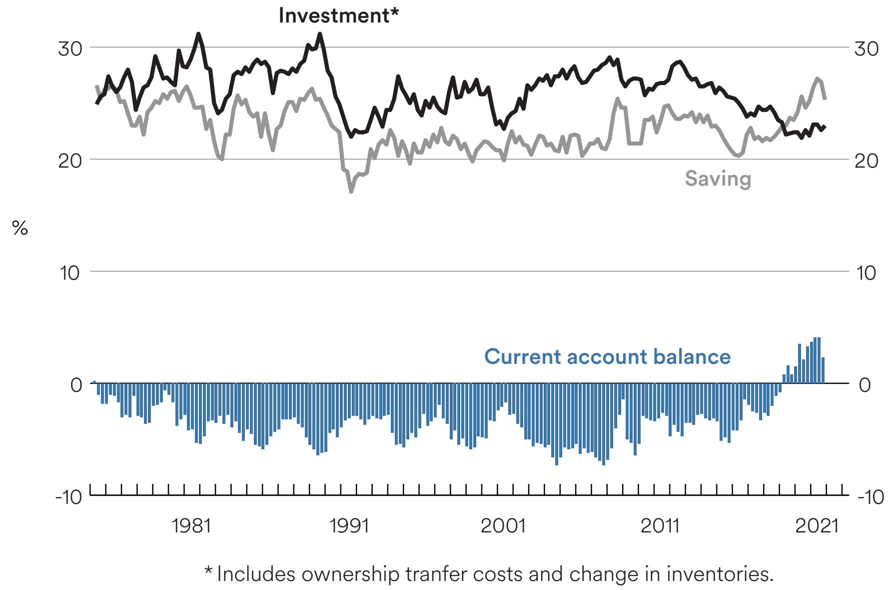
5.7. Sovereignty costs and externalities

5.7.1. The importance of sovereign AI capability

Most governments, including the Australian Government, welcome foreign investment and devote considerable resources to obtaining inward investment. However, this investment is seen as an additional or top up investment when the domestic economy is not generating sufficient internal funds.[164] Additionally, there are often a few alternative funding sources, including philanthropic donations and loans procured from international non-governmental organisations (INGOs) such as The World Bank, available to borrowers that help prevent the host country becoming too dependent on one or two sources of finance.[165]

In recent years, Australia has turned from being a net borrower of investment funds to a net lender to the rest of the world. This is a key factor in future AI investment decisions, in part removing the finance constraints.[166]

Figure 5.4: Saving and Investment: per cent of nominal GDP



(Source -ABS, RBA) [167]

However, Australia is not a lender in terms of skilled AI labour and technology, and the prospect of relying on one or two large economies for its AI needs would create a unique and difficult scenario. Generally, over reliance on overseas provision of AI technology and knowledge may prove problematic in a number of ways:

- AI systems require substantial amounts of data to generate machine learning algorithms. Nations that import AI expertise will need to surrender nation-specific data to overseas companies which may compromise both the competitive advantage of domestic firms and/or national sovereignty, reducing a nation's ability to act independently
- Importing AI technology may create security problems in crucial areas such as defence or telecommunications and facilitate industrial espionage. The concern felt in some nations over Huawei and other Chinese technology companies over their potential to engage in espionage and theft of intellectual property is an example of potential issues that may arise[168]

164. Australian Government, Department of Foreign Affairs and Trade. The benefits of foreign investment. Available at https://www.dfat.gov.au/trade/investment/the-benefits-of-foreign-investment

165. Wibbels, E (2006) Dependency Revisited: International Markets, Business Cycles, and Social Spending in the Developing World. Cambridge University Press. Available at https://www.cambridge.org/core/journals/international-organization/article/abs/dependency-revisited-international-markets-business-cycles-and-social-spending-in-the-developing-world/B849F340F9BE25D68CAFDAD279186BFB

166. Adams, N. and Atkins, T. (2022) The Significant Shift in Australia's Balance of Payments. Reserve Bank of Australia. Available at https://www.rba.gov.au/publications/bulletin/2022/mar/the-significant-shift-in-australias-balance-of-payments.html

167. Adams, N., and Atkin, T. (2022). The Significant Shift in Australia's Balance of Payments.

168. Berman, N., Maizland, L. and Chatsky, A. (2023) Is China's Huawei a threat to National Security? Council of Foreign Relations. Available at https://www.cfr.org/backgrounder/chinas-huawei-threat-us-national-security

- AI dominance in the hands of a small group of countries or corporations raises the likelihood that they will achieve economic dominance over other countries which is likely to grow over time, given the exponential growth in AI technology
- AI systems are designed and based on algorithms that reflect the value systems of their creators. This may be a mismatch for the importing country if they do not align with their value systems.

These types of issues often arise where one or a small group of countries or corporations acquire knowledge or expertise that the rest of the world does not have access to. AI has the potential to rapidly divide the world into AI-utilising and AI-deprived nations. In the future, key infrastructure (i.e., transport, defence, health, and education networks) will increasingly run off AI systems, and innovative nations will become leaders and net exporters of AI technology. The decision to share this technology and knowledge with other countries will be at their determination.[169]

The implications of AI dependency for the impacted nations are hard to both define and quantify. It is likely that AI is, and will become, increasingly non-substitutable. Dependence on its importation will constitute an ongoing economic and political burden to the impacted country, but it is difficult to provide past examples. One recent exception is that of oil and the monopsony position achieved by the Organization of the Petroleum Exporting Countries (OPEC) in the later part of the 20th century.

In their article, *The Costs of U.S. Oil Dependence,* Parry and Darmstadter investigate the economic and strategic short and long-term costs of US dependency on OPEC control of oil supplies. [170] The same issue is investigated by Duffield in his book *Over a Barrel*.[171] Their research concentrated on two issues central to dependence – monopsony and disruption costs.

Monopsony occurs when there is one or a few sellers of a product or service for which demand is highly inelastic. This situation provides the seller with the attributes of monopoly power; the ability to charge prices above (fair) market price (referred to as a price premium or in extreme cases ‘rent seeking’) and to restrict supply. Parry and Darmstadter estimate the price premium paid to the OPEC oil sellers as US$5 on a barrel where price fluctuated between $12 and $25 per barrel, indicating a percentage mark-up of between 20% and 40%, with the higher premium occurring in the high use seasons in the US. Jones and Leiby (1996) found that a 1% increase in oil prices in the US reduces gross national product (GNP) by around 0.02% to 0.08%, with most estimates clustered around 0.05%.[172]

These price mark-ups, while economically damaging to the US economy, are part of the normal cycle of monopoly pricing, eventually eroded by market forces and the encouragement of shale oil development in the US due to the high price and supply restrictions imposed by the OPEC monopsony. AI dependence, because of its ubiquitous nature, is likely to exert a much higher level of significance, particularly with the low probability of substitute products being found.

Both Parry *et al* and Duffield find that the disruption of a sudden reduction in oil supply is potentially much more serious than the measurable economic costs of high prices. This point is expanded by Fjader (2018) who said that ‘the risks include disruptions in global supply chains and illicit trade flows, as well as how the asymmetric aspects of contemporary economic interdependence enable novel disruptive practices with far-reaching consequences for national security strategies.’[173] Again, these warnings concerning disruption in supply to one or several products or services would be multiplied by the economy-wide nature of AI demand.[174]

In summary, there are significant costs to dependence on AI from international suppliers. These relate to purchase and maintenance costs and the stability of supply but take on increased significance when issues of national security and independence are also considered. AI is still in an initial stage, but while the advantages of early adoption are already present, the costs of dependency have yet to be fully felt. However, using oil dependency as an example, they will be highly significant for unprepared nations and companies in the coming years.

169. See Allen, G. and Chan, T. (2017). Artificial Intelligence and National Security. Belfer Center for Science and International Affairs, Harvard Kennedy School. Available at https://www.belfercenter.org/publication/artificial-intelligence-and-national-security

170. Parry, W. and Darmstadter, J. (2003) The Costs of U.S. Oil Dependency. Available at https://ageconsearch.umn.edu/record/10644/files/dp030059.pdf

171. Duffield, J. (2007) *Over a Barrel*. Stanford University Press. Available at https://www.sup.org/books/title/?id=10579

172. Parry, W. and Darmstadter, J. (2003) The Costs of U.S. Oil Dependency.

173. Fjader, C. (2018). Interdependence as Dependence; Economic Security in the Age of Global interconnectedness *Geo-economics and Power in the 21st century*. Available at https://www.taylorfrancis.com/chapters/edit/10.4324/9781351172288-3/interdependence-dependence-christian-fj%C3%A4der

174. Lee, K. (2018). *AI Superpowers, China, Silicon Valley, and the New World Order*. Houghton, Miffin and Harcourt, New York.

6. Conclusions and Policy Recommendations

Artificial intelligence is already altering the world and raising important questions for society, the economy, and governance. (Brookings Institute, 2018). [175]

6.1. Findings from this report

This analysis has drawn several important conclusions about the current stage of AI development worldwide, which will have significant implications for Australia.

The report found that while there are various predictions about the impact of AI (ranging from conservative views that consider it as just another technical development, albeit more pervasive in its impact, to extreme views that anticipate singularity), a mainstream and generally accepted view is emerging. To summarise this view:

- AI is a transformative technology that will impact on all aspects of the economy
- AI differs from previous technological change by its ability to imitate human behaviour and by the speed of its growth
- early adopters of AI have – and will increasingly gain – competitive advantage over slow or inadequate adopters of AI technology
- increased AI diffusion is seen as the solution to the slowdown in labour productivity that has been a feature of developed economies in recent decades
- a consensus view across most of the world's major consulting companies is that AI over the period 2023-2030 will accelerate economic growth by approximately 25%

175. West, D., and Allen, R. (2018). How artificial intelligence is transforming the world. Brookings Institute. Available at https://www.brookings.edu/articles/how-artificial-intelligence-is-transforming-the-world/

- the economic modelling in this report supports these views and argues that over a similar period, greater utilisation of AI in key Australian industries will lead to a short-term boost in GDP of over $200 billion per annum (compared to a business-as-usual case) and the creation of an additional 150,000 jobs over the period
- if (as is believed) the impact of AI on the economy is long term and non-linear, these economic benefits over a longer period will grow more than proportionally
- the opportunity costs of not expanding AI's impact on the Australian economy will amount to a sacrifice of at least 1.4% (or AU$35.7 billion) in GDP growth per year in the short run. These costs may be greater because they do not factor in the loss of competitiveness within Australian industry that may occur if other nations gain an AI advantage
- the current data indicates that Australia is underperforming in the adoption of AI despite possessing significant human capital resources that could be used in AI development and despite the apparent high interest in adopting AI shown by Australian industry. The implications of this are that Australia risks, in a relatively brief time, losing its wealthy country status with resultant economic and social consequences
- Australia increasingly runs the risk of becoming AI dependant in key infrastructure such as telecommunications, transport, and service provisions with significant consequences for national sovereignty.

6.2. Required skills needed to further Australia's AI landscape

In its relatively short life, the AI era has brought about widespread changes in social and economic life. AI has already impacted the labour market by changing job types, functions, and income distribution with those with intermediate skills being subject to most change.[176] This rapid technological change brings challenges for the education systems of host countries.

By nature, education systems operate reactively rather than proactively in response to significant technical change. In the case of AI, skills and training issues are further complicated by its ubiquitous nature in contrast to earlier periods of technical change that tended to be confined (initially) to specific industries and particular sections of the economy.

As a consequence, the educational and training needs for AI are diverse and require a mix of skills, including:

- technical skills for those developing AI systems and high-end users
- interpretation, business, and diagnostic skills for those managing front-end usage of AI systems
- re-orientation and adaptive skills, particularly for those whose occupations will disappear or be transformed
- management for those charged with managing social dislocation and re-alignment.

This skills mix will provide the structural and organisational changes required to make education and training more agile and responsive to rapidly changing AI needs.

6.2.1. Technical skills for those developing AI systems and high-end users

Of all the predicted training needs associated with AI development, technical skills are the most discussed. Merging recent studies by the UK Parliament (2024), Accenture (2016), and UNESCO (2021) provide an outline of the technical skills that will be crucial to the future development of AI.[177] These skills are:

- machine learning techniques: understanding algorithms like linear regression, decision trees, and deep learning is crucial
- programming languages: proficiency in languages like Python, R, and Java is essential for data analysis and model development
- data science
- statistical models: knowledge of statistical concepts and methods is necessary for data analysis and interpretation
- data sets: familiarity with working with different types of data sets and data wrangling techniques is valuable
- mathematical skills particularly linear algebra, a branch of mathematics used in many AI algorithms and machine learning models
- developer skills.

176. See, UNESCO (2021). Understanding the impact of artificial intelligence on skills development. UNESCO International Centre for Technical, Vocational and Educational Development. Available at https://unesdoc.unesco.org/ark:/48223/pf0000376162

177. Lewell-Buck, E. (2024). Artificial Intelligence: Skills Training. UK Parliament. Available at https://hansard.parliament.uk/commons/2024-01-10/debates/1F28838D-4B64-4C7B-8E28-6E01693CC854/ArtificialIntelligenceSkillsTraining; UNESCO (2021). Understanding the impact of artificial intelligence on skills development; and Accenture. (2016). Artificial Intelligence Poised to Double Annual Economic Growth Rate in 12 Developed Economies

Courses in these areas are all available and there have been notable increases in post-graduate enrolments in AI related technical skills, particularly in the US.

6.2.2. Interpretation, business, and diagnostic (soft) skills

The development of AI also faces challenges at the managerial level and requires the type of skills that UNESCO (2021) refers to as 'soft skills.' These include:

- problem-solving skills, including the ability to identify and solve complex problems using AI approaches
- negotiation
- communication skills to communicate effectively with both technical and non-technical audiences
- teamwork and collaboration with diverse teams, necessitating strong interpersonal skills.

6.2.3. Re-orientation and adaptive skills, particularly for those whose occupations will disappear or be transformed

The potentially disruptive aspects of AI development have been widely discussed both in this report and elsewhere. UNESCO (2021) states that:

> Workers with intermediate skills are at particular risk because of the routine nature of the tasks they often perform and the fact that the technologies that can replace them, such as AI and robotics, can create considerable cost savings for employers. [178]

However, UNESCO also states that 'TVET (technical and vocational education and training) will serve not only to allow these workers to fully adapt to the digital age but also help predict shifts in skill requirements and systemic pressure points if offered at the general and community level.' Up-skilling courses can help remove some of the anxieties towards change that are likely to occur in some demographics.

6.2.4. Management for those charged with managing social dislocation and re-alignment

Even the most optimistic of AI advocates see it causing some short-term dislocation in the labour market with the likelihood of increased disparities in income distribution. Governments need to devise adequate responses to reduce social tensions.

These responses may include fiscal policies such as a living wage but also important is the development of guidelines for the ethical management of AI systems and proper training on these guidelines for those administering them. Community education programs that stress the advantages of AI would also be advantageous.

6.3. Is there a market failure for AI in Australia?

A market failure occurs when the price signals created by the interaction of supply and demand fail to produce an efficient solution.[179] A common cause of market failure in a macro or public policy sense is whether the good or service under consideration contains externalities which are (in most cases) undervalued, often because they are not included as part of the quantifiable market system.[180]

In the context of AI, the externalities of a loss of national sovereignty are usually not included in the estimation. Forbes (2021) suggests that a major market failure already exists in the US market for AI,[181] and that the disconnect between company ambitions and the current level of investment and government support in Australia suggests a market failure here as well. Forbes's rationale for a market failure in the US that could also be used to explain potential market failures in Australia include:

178. UNESCO (2021). Understanding the impact of artificial intelligence on skills development.

179. What Is Market Failure? Definition, Types and Solutions. Indeed. Available at https://www.indeed.com/career-advice/career-development/what-is-market-failure

180. Alaluf, R. (2021). The Huge Market Failure and the sequence of Events that led us to it. Forbes. Available at https://www.forbes.com/sites/forbestechcouncil/2021/05/20/the-huge-market-failure-of-ai-and-the-sequence-of-events-that-led-us-to-it-part-1/?sh=451749733954

181. Ibid.

- benefits from AI investment may not be fully captured by individual firms or investors, leading to underinvestment
- information asymmetry whereby investors may lack complete information about the potential benefits and risks associated with AI investments
- a mismatch between the long-term nature of AI development and the short-term focus of market participants
- AI research often generates knowledge and technologies that can benefit the public, but which can't be fully allocated to the private sector investor.

In addition, there are public concerns, especially from labour unions and civil liberties groups about the disruptive potential of AI in the labour market and the implications for privacy and improper use of data. Market failure may be corrected indirectly by government intervention, such as regulation or taxation policy that alters the price of the good or service or through direct government investment as venture capital. The societal concerns are best addressed through legislation and regulation.

6.4. The importance of sovereign AI capability

Most governments welcome foreign investment and devote considerable resources to obtaining inward investment. However, this investment is seen as additional or a top-up when the domestic economy is not generating sufficient internal funds. In addition, there are often several alternative funding sources, such as donations and loans from INGOs, available to prevent the host country from becoming too dependent on one or two sources.

The prospect of Australia relying on one or two large economies for its AI needs would create a unique and dangerous scenario. An over reliance on the overseas provision of AI technology and knowledge may prove problematic in a number of ways, including:

- AI systems require substantial amounts of data to generate machine learning algorithms. Nations that import AI systems will need to surrender nation-specific data to overseas companies which may compromise both the competitive advantage of domestic firms and/or national sovereignty and reduce the nation's ability to act independently
- importing the necessary AI technology may create security problems in crucial areas such as defence and telecommunications, and facilitate industrial espionage
- AI dominance at the hands of a small group of countries or corporations will facilitate economic dominance by other countries which, given the exponential growth in AI technology, is likely to grow over time
- AI systems are designed and based on programs reflective of the attitudes and value systems of their creators. This may lead to a mismatch where the importing country does not align with the value systems of the receiving country.

These types of issues often arise where one or a small group of countries or corporations acquire knowledge or expertise that the rest of the world does not have access to.

AI has the potential to rapidly divide the world into AI *haves* and AI *have nots*. In the future, the key infrastructure of nations, transport, defence, health, and education networks will increasingly run off AI systems, with innovative nations becoming leaders in AI technology. The decision to share this technology and knowledge with other countries will be at their determination.

6.5. Policies needed to expand AI innovation and diffusion

Australia is not the only country facing policy issues over AI development, but it is currently seen as lagging in its response compared with similar countries. This inertia can be seen in the findings of the Harvard Economic Complexity Index (ECI) which has recorded Australia falling 36 places over the period 1995-2022 to 91st out of 131 countries.

Part of the reason for this inertia is the relatively narrow industrial base in Australia, particularly in exports, with above average development in agriculture and mining and an under-development in manufacturing compared to the rest of the developed world. Given the human resources available in Australia, an acceleration of investment in AI is entirely possible, but it will require unity between government and private enterprise that has seldom been seen in Australia, and an inevitable increase in government investment, including the development of AI-related government policy.

This section examines the emerging consensus put forward for AI innovation and diffusion in general, before concentrating on the specific policy requirements for Australia.

6.5.1. General policies for expanding AI innovation and diffusion

Below is a list developed by OECD (2021) of global, general AI-related policies designed to advance the practical use and spread of AI.[182]

Collaborative infrastructures (soft and physical): Dedicated support to research infrastructures; networking, and collaborative platforms; information services and access to datasets

Direct financial support: Project grants for public research; institutional funding for public research; equity financing; grants for business R&D and innovation; procurement programs for R&D and innovation; loans and credits for innovation in firms; Centres of Excellence grants; fellowships and post-graduate loans and scholarships

Governance: Formal consultation of stakeholders and experts; national strategies, agendas, and plans; horizontal STI (science, technology, and innovation) coordination bodies; regulatory oversight and ethical advice bodies; standards and certification for technology development and adoption; creation or reform of governance structure; public awareness campaigns and outreach activities; policy intelligence e.g. evaluations, benchmarking, and forecasts

Guidance regulation and incentives: Intellectual property regulation and incentives; science and innovation challenges, prizes, and awards; emerging technology regulation; labour mobility regulation and incentives; technology extension and business advisory services

Indirect financial support: Corporate tax relief for R&D innovation; debt guarantees and risk-sharing schemes; tax relief for individuals, R&D, and innovation

In all of these policies, government plays a key role in the areas of direct financial support, funding of research infrastructure, freeing up of data sources, reducing public concern, and providing regulatory frameworks through patent protection and market legislation. These policies are relatively standard government intervention policies that are applied in most areas of R&D research. Yet, it is now recognised that AI produces more complicated issues than are normally encountered within standard industrial policies. It is also increasingly recognised that:

- AI policy mixes – a combination of fiscal and monetary policies that a country adopts to manage its economy or respond to an economic crisis – are country-specific, though they may have common traits[183]
- AI policy may be divided into supply side policies (involving innovation and development) and demand-side policies (involving human capital development, increasing national AI research capacity, and fostering national competitiveness in global AI markets)
- government AI policy must also develop strategies that recognise size disparities among firms and particularly the AI needs of small and medium sized enterprises (SMEs).[184]

Country specificity of AI policy is central to developing trust and acceptance. The OECD (2020) argues that policies must be compatible and seen to be useful to the host country. The manufacturing industry is viewed as one of the sectors that could benefit the most from AI solutions, automation, and enhanced predictive capacity. If, as believed, even leading countries such as the US are suffering market failure in AI, it is important that governments take the lead in creating the consumer confidence and adequate supply of trained labour to ensure AI's diffusion, as well as recognise the differing needs of industry by size and product base.

182. OECD iLibrary. (2021). National policies for Artificial Intelligence: What about diffusion? *The Digital Transformation of SMEs*. Available at https://www.oecd-ilibrary.org/sites/cc3a9728-en/index.html?itemId=/content/component/cc3a9728-en

183. OECD iLibrary. (2021). Artificial Intelligence; Changing Landscape for SMES. *The Digital Transformation of SMEs*. Available at https://www.oecd-ilibrary.org/sites/01a4ae9d-en/index.html?itemId=/content/component/01a4ae9d-en

184. OECD (2020). National Policies for Artificial Intelligence: What about Diffusion? Below are the countries where national strategies have underlined SME innovation diffusion as a priority and that assist SMEs with AI and data-driven business development as a strategic focus:
Artificial Intelligence Mission Austria 2030 (Austria)
National Artificial Intelligence Strategy of the Czech Republic (Czech Republic)
Denmark's National Strategy for Artificial Intelligence (Denmark)
Artificial Intelligence Strategy Germany (Germany)
National Artificial Intelligence Strategy (Italy)
Malta's National AI Strategy (Malta)
National Strategy for Artificial Intelligence (Norway)
Strategic Action Plan on Artificial Intelligence (Netherlands)

6.6. Policies for large firms

Governments are of most help to large firms when they reduce uncertainty concerning regulation and policy changes. This is best achieved by creating a regulatory framework that protects innovation through strong patent legislation, allows adequate shareholder returns to be made, and provides financial incentive, normally through the tax system.[185]

In a research report produced by the Brookings Institute, the organisation identified nine key points designed to get the most out of AI while still protecting human rights and values.[186] They were:

- encouraging greater data access for researchers without compromising users' personal privacy
- investing more government funding in unclassified AI research
- promoting new models of digital education and AI workforce development so employees have the skills needed in the 21st century economy
- creating a federal advisory committee to make policy recommendations
- engaging with state and local officials to promote effective policies
- regulating specific objectives rather than specific algorithms
- taking bias complaints seriously so AI does not replicate historic injustice, unfairness, or discrimination in data or algorithms
- maintaining mechanisms for human control and oversight
- penalising unethical behaviour and promoting cybersecurity.

6.7. Government policy and size disparities among firms

Instinctively, discussion surrounding AI innovation and dispersion centres on large and multinational firms for reasons of wealth and innovation capacity. Yet, in terms of overall economic performance in an economy, SMEs take up a large share of the economy.

For example, recent estimates place the contribution to the Australian economy of SMEs at over 50% of GDP.[187] Despite this, the OECD has found that SMEs are rarely targeted by national AI strategies and policy initiatives.[188] They also found that SMEs were often reluctant to invest in AI technology due to the long gestation period before net benefits are achieved. To cope with this and other constraints, the OECD suggested the following policies to stimulate SME participation in AI adoption: [189]

- data access: governments need to be active in sharing databases and improving digital risk management
- human capital policies: reskilling SME managers and redesign in work practices
- assisting with access to/or providing venture capital [190]
- ensuring the functioning of knowledge markets that provide cloud solutions for embedding AI technologies and scaling up capacity
- supporting mutual learning, knowledge sharing, and capacity-building.

185. See O'Connell, K. et al (2023) Developments in the Regulation of Artificial Intelligence. King & Wood Mallesons. Available at https://www.kwm.com/au/en/insights/latest-thinking/developments-in-the-regulation-of-artificial-intelligence.html

186. West, D. & Allen, J. (2018) How artificial intelligence is transforming the world. Brookings Institute. Available at https://www.brookings.edu/articles/how-artificial-intelligence-is-transforming-the-world/#_edn4

187. Stephensen, G. Small business is an important part of the Australian economic landscape. Lloyds Corporate Brokers. Available at https://www.lloydsbrokers.com.au/Small-business-important-for-Australian-economy.htm

188. OECD (2020). National Policies for Artificial Intelligence: What about Diffusion?

189. OECD iLibrary (2021). Artificial intelligence: Changing landscape for SMEs. *The Digital Transformation of SMEs.* Available at https://www.oecd-ilibrary.org/sites/01a4ae9d-en/index.html?itemId=/content/component/01a4ae9d-en

190. See, Corea, F. (2018) AI and Venture Capital. Medium. Available at https://francesco-ai.medium.com/artificial-intelligence-and-venture-capital-af5ada4003b1

6.8. Australia-specific policies

In examining policy options for accelerated AI development in Australia, it is useful to establish the current position, the reasons for this position, determine what realistic future goals might look like, and plan for the optimum way to achieve them.

6.8.1. Current position

Currently, Australia is lagging in AI development, both in an absolute sense and relative to Australia's position in the world economy. There are a number of domestic firms that are either unprepared or under prepared for AI expansion. This report has shown that, while successive Australian governments have formulated plans and roadmaps for AI expansion and government investment in AI-related programs, the response to date has been inadequate when held up against comparable nations such as Canada, where it is reported government investment in AI programs (focused on both innovation and diffusion) is approximately 5 times as great as Australia.[191]

6.8.2. Reasons for this position

This under performance in AI development in Australia should not be a surprise. Australia has a history of under spending on domestic R&D and relying on the importation of technology either through parent company transfers or direct purchase internationally.

The 'technology importation solution' has been favoured in Australia by government and the private sector for a number of reasons, the chief of which is that the relatively small size of the Australian economy means that, domestically at least, it cannot fully capture economies of scale and size (although it should be noted that Taiwan, with a similar sized economy and population as Australia, dominates the world in advanced microchip production, so Australia's policy may be misdirected). Consequently, Australia has a relatively simple economic structure with 65-70% allocated to services, 15% to mining, 5% manufacturing and 3% agriculture, with mining and agriculture along with education services playing a significant role in exports. It is worth remembering that between 50% and 60% of GDP is produced by SMEs.[192]

Yet, Australia's economy was seen as one of the more resilient economies during the Global Financial Crisis and the Covid-19 shutdowns, and it has the ninth highest GDP per capita in the world.[193] This lengthy period of stability may have bred complacency and made the country reluctant to embark upon the widespread technological change associated with the rapid take up of AI. The current structure of the economy and the technology importation strategy means that significant amounts of profits are transferred overseas, even though in 2022 foreign companies invested A$4.5 trillion in Australia.[194]

This report suggests that there is currently market failure in the Australian AI arena. Based on past trends and in the absence of concerted government action, the current AI gap will lead to increased technology importation and overseas ownership.

6.8.3. Establishing immediate and longer-term goals

The current under-preparedness of Australia in terms of AI innovation and use suggests that common sense goals should be:

- immediate concentration of AI development in current areas of strength in the Australian economy particularly in mining, agriculture, and services such as education, health, and banking, which is needed to maintain competitive advantage in these industries. Australian companies have used this approach successfully in the field of robotics, particularly in mining and agriculture[195]
- encouraging the concentration of AI investment through regulation (including patent protection), direct and indirect financial support, and the creation of a data sharing infrastructure
- formation of regional partnerships for AI testing and development
- public awareness campaigns to reduce community concerns

191. Canadian International Development Research Centre. (2019). Government Artificial Intelligence Readiness Index 2019

192. Stephensen, G. Small business is an important part of the Australian economic landscape

193. Australian Government. Australia is a top 20 Country for Economy

194. Australian Government, Department of Foreign Affairs and Trade. Statistics on who invests in Australia. Available at https://www.dfat.gov.au/trade/trade-and-investment-data-information-and-publications/foreign-investment-statistics/statistics-on-who-invests-in-australia

195. Synergies Economic Consulting (2018). The Robotics and Automation advantage for Queensland. https://www.qut.edu.au/research/partner-with-us/case-study-robotics-and-automation-advantage

- increased support for AI related higher education programs
- greater focus on SMEs including financial support for R&D, training in AI uses, and integration of AI procedures into the production function
- identification of vulnerable industries for preserving national sovereignty in key infrastructure of defence, finance, communications, and health.

6.8.4. Longer term goals

To ensure that Australia's endeavours in the AI space remain sustainable for years to come, the government, in cooperation with private enterprise, should:

- identify new industries created and/or most affected by AI
- secure Australian ownership and technical control of key infrastructure
- use AI to rekindle growth in labour productivity
- utilise AI in implementing longer term social goals such as the shorter working week and reducing hazardous working environments
- use AI to improve transport systems with resultant reduction in travel time, traffic congestion, and accidents
- increase cyber security.

6.8.5. Solving the labour force skills constraint

Throughout this report, limited human capital – in terms of both the quantity and the skills base of the labour force – have been identified as major constraints to the greater absorption of AI technology. A Gartner survey in the US revealed that in 2021, 64% of executives saw talent shortages as the major constraint to AI development, compared with 4% in the 2020 survey. They conclude that a 'lack of talent availability was cited far more often than other barriers this year, such as implementation cost (29%) or security risk (7%)'.[196]

In Australia, Dawson highlighted the same problem of critical skilled labour.[197] Increasingly, AI adoption and development is seen as fundamentally dependent on the ability of universities and targeted immigration policies to service the labour supply needs of the AI industry. Zwetsloot, Horton and Arnold, in their influential report *Strengthening the U.S. AI Workforce,* argued that 'a sustained talent shortage could undermine U.S. strength in artificial intelligence; current immigration policies would make it worse.'[198] The US has responded to these issues in part through the willingness of universities to offer more AI related courses.

However, Zwetsloot, Horton and Arnold argue that the increase in PhDs is not enough, a point supported by Sayed who sees the lack of skilled labour, especially on STEM skills, growing increasingly critical across the world.[199]

Part of the difficulty in designing and implementing skills training for AI is the diverse labour requirements needed for widespread absorption. There is no one educational qualification or skill that fulfills all the needs of the AI industry. This diversity of skill needs is well described by Su, Guillaume and Cote, who note that 'AI is a total departure from the traditional pattern of technological innovations; its target is the work tool that is inseparable from the human being – its intelligence.'[200]

The authors also recognise both the destructive and creative forces of AI in the skilled labour market and the educational challenges that this produces. For example, AI requires skilled labour in the fields of: [201]

- programming and languages such as Python, Tensor Flow, PyTorch and scikit-learn
- machine learning and deep learning
- mathematics and statistics as related to AI algorithms

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196. Gartner. (2021). Gartner Survey Reveals Talent Shortages as Biggest Barrier to Emerging Technologies Adoption. Available at https://www.gartner.com/en/newsroom/press-releases/2021-09-13-gartner-survey-reveals-talent-shortages-as-biggest-barrier-to-emerging-technologies-adoption

197. See Dawson, N. (2021). Changing Labour Market Dynamics in Australia: Skill Shortages, Job Transitions and Artificial Intelligence. Opus. Available at https://opus.lib.uts.edu.au/handle/10453/150972

198. See Zwetsloot, R., Heston, R. and Arnold, Z. (2019). Strengthening the U.S. AI Workforce. Georgetown Center for Security and Emerging Technology. Available at https://cset.georgetown.edu/publication/strengthening-the-u-s-ai-workforce/

199. Sayed, Z. (2023). The STEM Skills Gap; A Growing Challenge for all Countries. HR Forecast. Available at https://hrforecast.com/the-stem-skills-gap-a-growing-challenge-for-countries-to-overcome/

200. Su, Z., Togay, G., and Cote, A. (2020). Artificial intelligence: a destructive and yet creative force in the skilled labour market. *Human Resource Development International.* Available at https://doi.org/10.1080/13678868.2020.1818513

201. Lassebie, J. (2023). Skill needs and policies in the age of artificial intelligence. *OECD Employment Outlook 2023: Artificial Intelligence and the Labour Market*. Available at https://www.oecd-ilibrary.org/sites/638df49a-en/index.html?itemId=/content/component/638df49a-en#

- data handling and pre-processing
- natural language processing
- computer vision
- software development
- cloud computing
- big data technology.

The management and interpretation of AI also requires those skilled in:

- neural network architectures
- model evaluation and tuning
- identifying business challenges and devising appropriate AI solutions
- critical thinking and problem solving
- communication skills for collaborating with team members, stakeholders, and non-technical personnel
- data ethics and privacy
- ethical considerations concerning the development of AI, and in responsible and fair AI implementations.

Added to this variety of AI related skills is the creation of new occupations that will evolve from the increased absorption of AI. Tech enthusiasts speak of the emergence of a knowledge engineer who will:

> ...Build advanced logic into computer systems with the goal of simulating human decision making. ...The main aim behind knowledge engineering is to cut down [on] the effort and time required to solve complex and large-scale problems that would take far too long to resolve manually. It is the process of creating systems to act and [m]ake decisions regarding data in the same way a human expert in that specific field would.[202]

These training and occupational structure issues are important, in varying degrees, for all nations serious about the increased and autonomous use of AI. The US is formulating comprehensive labour force policies for AI and, in this sense, is at the forefront of AI development.

But Australia is not. There are pockets of excellence at universities as well as at the CSIRO, but a comprehensive, long term AI labour force development program has yet to be designed in Australia.

Given these considerations, Australia needs to urgently address these issues with:

- a significant increase in funding by federal and state governments to universities to undertake research into AI development and implementation, coupled with the development of integrated AI undergraduate and postgraduate courses. This funding should be on a scale at least comparable to leading countries of Canada, South Korea, and the US
- the development of integrated technical, analytical, and commercial (hard and soft skill) programs at universities that address all areas of AI development and include the creation of funded chairs in science, engineering, computing, and business faculties
- the fostering of industry/university partnerships, particularly for R&D and for workplace placements for students.

202. Campana, N. (2022). What does a Knowledge Engineer do? Available at https://www.freelancermap.com/blog/what-does-knowledge-engineer-do/

6.8.6. More defined industry policy

Experience from the US and Europe has shown that much of the impetus for AI adoption is coming from the private sector, some with the benefit of active industry policy from government. While it is a long-established principle in the economics of public finance that governments should simply provide a level playing field in the economy, there is growing recognition that some targeted government assistance can be beneficial, especially where there is a full or quasi market failure in a market of national importance.

Mazzucato, in her influential book *The Innovative State*, argues that governments need to help create new markets and industries in the absence of private sector confidence or market failure. Similarly, in a reversal of previous views, *The Economist* (2022) writes that 'previously discredited approaches have found new believers' and reports that many countries are now re-engaging in industry policy.[203]

Part of the reason for this is a new world order where major corporations are concentrating economic power as never before and the opportunities for smaller and domestically based firms to realistically compete in terms of innovation, without government help, is low. This point has been expressed by Australian Industry and Science Minister Ed Husic, who argues that economic purism around supporting innovation and R&D in industry has left Australia behind in technological development.[204]

This discussion is not to advocate for speculative government investment which goes against prudent fiscal advice. However, AI is a special case. Australia, for the sake of its economic growth and national independence, simply cannot afford to be left further behind in the AI race. Specifically, Australia should:

- significantly lift support for R&D within the university and private sectors
- work with partners in key industries such as agriculture and mining to identify AI systems for the domestic market and suitable for export
- engage with the manufacturing sector in a targeted manner to modernise existing industry, and identify and support new initiatives
- provide specialist assistance to SMEs including venture capital, increased R&D taxation concessions, AI usage training, and production function re-organisation
- give priority to retaining the integrity of core infrastructure
- support AI related start-ups
- establish an AI innovation and diffusion board to target AI related projects. This could be supported by the allocation of a fixed proportion of the Australian budget earmarked for AI development
- establish benchmarks and performance indicators for government spending in the AI area
- enshrine and adopt the above policies in long-term, cross-party agreements.

Taken collectively and in line with state governments and international partners, these policies should help reverse the AI deprivation currently in Australia. The alternative, the business-as-usual approach, will see a relatively slow but consistent decline in the economic standing of the Australian economy.

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203. Piotrowski, J. (2022). The new interventionism. Many countries are seeing a revival of industrial policy. *The Economist*. Available at https://www.economist.com/special-report/2022/01/10/many-countries-are-seeing-a-revival-of-industrial-policy

204. Cranston, M. (2023) Purism around 'picking winners' has left Australia behind: Husic. *Australian Financial Review*. Available at https://www.afr.com/world/north-america/purism-around-picking-winners-has-left-australia-behind-husic-20230131-p5cgtv

7. Appendix

7.1. AIBE economic modelling including non-linear modelling

The economic modelling in this study is derived from the AIBE set of State and Regional IO tables with non-linear properties using the IO8 software developed by Guy West at the Centre of Policy Modelling at the University of Queensland. Non-linear properties are also achieved by the application of the Flagg location quotient technique and involves intermediate coefficient adjustments by reference to import propensity and regional size relative to the host table.[205]

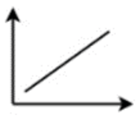
All state and regional models are derived from the 114-sector of fully disaggregated industries and sub-industries identified by ANZSIC using 2016 data, updated to 2019. The largest models have 6 final demand sectors and 6 primary inputs sectors, but both the intermediate and final demand sectors may be aggregated to match the appropriate industrial structure of the region in question. The decision on which is the more appropriate form of the model (between linear and non-linear model applications) is not clear-cut.

In terms of regional output, both techniques yield the same results but the non-linear estimates for value adding income and employment are lower in non-linear models due to greater recognition of import propensity and relative regional size than traditional IO, which in turn allows the model to depart from the fixed coefficient assumptions of earlier models. This is likely to be important where the technical progress in the industry or the region is in advance of the host table, implying increased economies of scale. Both models are essentially based on the Social Accounting Matrices (SAM) framework, which is an extension of the classical input-output framework and includes all flow of resources between economic agents through transactions at a specific period.

The table below highlights key characteristics and differences between the linear and non-linear IO models, in addition to the CGE model. Although CGE models have become the predominant economic modelling framework, they are extensive in data, time, and cost requirements and are often impractical especially for preliminary economic impact analysis. The essential differences between the major form of impact analysis, CGE, linear, and non-linear IO models are discussed further in the sections following.

205. Based upon research techniques translated by Hasham Hashimi of Synergies Economic Consulting

Table 7.1: Standard model distribution shapes

	Linear Input-Output Model 	**Non-linear Input-Output Model** 	**Computable Generalised Equilibrium (CGE) Model** 
Key elements	Assumes that factors in the production process shift proportionally Excludes economic constraints (i.e., assumes unlimited resources) Excludes price effects	Overcomes the simplifying assumption that factors shift proportionally Accounts for interregional trade more accurately Includes economic constraints Excludes price effects	Captures the whole-of-economy effects Includes economic constraints and identifies winners and losers Includes price effects
Outcome measures	Estimates direct, indirect, and induced effects on total production, components of value-added, and employment	Same as linear model	Same as linear model plus the impact on prices and wage rates by industry
Appropriateness	Suitable for impact estimation over a one to 5-year period where there have been limited changes in the state of technology and where the production functions of the main industries remain constant	Reduces the estimation errors associated with some linear models and is better suited to modelling the impacts of changes in a production function	Appropriate for shocks (small, medium, and large) that are unlikely to affect the structure of the economy

(Source: Synergies Economic Consulting, 2018) [206]

206. Synergies Economic Consulting (2018)

7.2. Traditional IO modelling

The conventional approach to IO modelling essentially assumes a constant return to scale economy. Starting from the host table (normally the ABS National Accounts), initial estimates of the state based or regional coefficients are derived using a linear IO Location Quotient (LQ) equation to regionalise the base (national) I-O table:

$$\boldsymbol{LQ_i^R}=\frac{\frac{\boldsymbol{E_i^R}}{\boldsymbol{E^R}}}{\frac{\boldsymbol{E_i^N}}{\boldsymbol{E^N}}}, \qquad (1)$$

where $\boldsymbol{E_i^R}$ and $\boldsymbol{E^R}$ are earnings in supplying industry, ***i*** and total earnings in region ***R***, respectively. $\boldsymbol{E_i^N}$ and $\boldsymbol{E^N}$ are earnings in supplying industry ***i*** and total earnings in the nation, respectively. In other words, this method measures the relative concentration (importance) of the regional industry as compared with its national counterpart in terms of earnings. By way of interpretation LQ:

$\boldsymbol{LQ_i^R}$ > 1.00 means that the specific industry in the region is producing more than the national average. This indicates that the local supplying industry can meet all requirements of regional purchasing sectors.

$\boldsymbol{LQ_i^R}$ = 1.00 means that the specific supplying industry in the region is producing the same as the national average. This indicates that the local supplying industry is sufficient to meet all requirements of regional purchasing sectors.

$\boldsymbol{LQ_i^R}$ < 1.00 means that the specific industry in the region is producing less than the national average. This indicates that the local supplying industry is unable to meet the regional demand requirements for its products or services, resulting in imports by regional purchasing sectors.

The danger here is that this approximating technique may disregard or underestimate supply imbalances and the level of interregional trade for the product as well as or non-linearities in economic production. The relative simplicity of this technique is its major strength, allowing it to be applied directly and with limited data on value added and production, which at the regional level is often the case. This advantage is often offset because it traditionally disregards or does not sufficiently account for constraints on economic activity, such as supply imbalances and a lack of interregional trade for the product or non-linearities in economic production.

7.3. Non-linear IO [207]

The Non-Linear Input-Output Model (NLIO) seeks to remove one of the major limitations of standard input-output analysis by removing the assumption of linear coefficients for the household sector and allowing adjustments of marginal income coefficients. This is because, as is widely known, the household sector is the dominant component of multiplier effects in an IO table. As a result, using marginal income coefficients for the household sector will provide a more accurate and empirically more valid estimate of the multiplier effects, which in turn, provides results closer to those of a CGE model. The transactions flows in the input-output table can be expressed in matrix equation form as:

$$\boldsymbol{T(\hat{X}^{-1})X+Y=X}$$

That is, for each industry, total industry sales equal intermediate sales to other industries for further processing plus sales to final users, where ***T*** is the matrix of intermediate transactions, ***X*** is the column vector of sector total outputs, and ***Y*** is the column vector of aggregate final demands. This can be rewritten as:

$$\boldsymbol{AX + Y = X}$$

Where ***A*** is the matrix of direct coefficients, which represents the amount of inputs required from sector ***I*** per unit of output of sector ***j***. Thus, for a given direct coefficient matrix, it is possible to solve the set of simultaneous equations to find the new sector production levels ***X*** which will be required to satisfy a potential or actual change in the levels of sector final demands ***Y***. By rearranging and converting to differences, this equation can be rewritten as:

$$\boldsymbol{\Delta X=(I-A)^{-1}\Delta Y}$$

Where $\boldsymbol{(I-A)^{-1}}$ is termed the total requirements table, Leontief inverse matrix, or general solution, and represent the direct and indirect change in the output of each sector in response to a change in the final demand of each sector. *Y* can incorporate any element of final demand expenditure, including household expenditure, government expenditure, and capital expenditure.

207. As underpinned in the IO8 software developed by Guy West at the University of Queensland, Centre for Economic Policy Modelling.

This is a linear model in which the A matrix represents a (constant) matrix of average input propensities. Normally, the A matrix endogenizes[208] the household sector so that consumption induced effects can be measured. This is referred to as the Type II model; the alternative Type I model is where households are treated as exogenous to local economic activity. The consumption-induced effects are the largest component of the total multipliers. This is because consumer driven consumption (and income) to a large extent dominates local economic activity.

Total inputs are equal to intermediate inputs plus primary inputs (labour and capital). In the conventional IO model, the inputs purchased by each sector are a function only of the level of output of that sector. The input function is assumed linear and homogeneous of degree one, which implies constant returns to scale and no substitution between inputs. A more reasonable assumption is to allow substitution between primary factors. If there is an expansion in economic activity, employers will attempt to increase output without corresponding increases in employment numbers, particularly in the short term, e.g., construction projects, where there are economies of scale in getting the existing workforce to work longer hours rather than employ additional persons. This occurs for two reasons.

First, there is evidence in Australia that labour productivity (output per employee) is increasing over time. Secondly, as companies strive to reduce costs and satisfy the micro-economic reform processes imposed on all states by the National Competition Policy, there is evidence of a shift in primary factor use from labour to capital. [209] This implies that the conventional IO model tends to overestimate income and employment impacts. Therefore, a more realistic approach to modelling impacts is to replace the average expenditure propensities for labour income by employers with marginal input propensities. In other words, the household income row in the A matrix, which are average input coefficients, should be replaced by income elasticities of demand. Note that, as in the CGE model, the linear coefficients assumption between intermediate inputs, total primary inputs, and total inputs is retained.

One problem associated with this approach is that the solution procedure is now more complex. Now the income impacts will be a function of ***X*** but the income coefficients are included in the ***A*** matrix which determines ***X***. Therefore, the equation set becomes recursive; ***X*** depends on ***A*** and ***A*** depends on ***X***. Solving the input-output equation therefore requires an iterative procedure, a common method being the Gauss-Seidel method.

The income and employment flows from the initial impact also need to be modified. In the conventional IO model, income and employment flow-ons are calculated as linear functions of the output flow-ons, but in the revised model, the parameters relating income to output are no longer constant. The impact on household income needs to be calculated as the difference between the base (i.e., before impact), income levels, and the post-impact income levels. This is equivalent to using the matrix equation:

$$\Delta Inc = \hat{X}_0^{-1}(\widehat{\Delta X})\hat{L}U_0$$

Where ***U*** is a vector of household income flows and ***L*** is a vector of sectoral household income elasticities of demand. The zero subscript denotes the base level values, and the hat denotes a diagonal matrix formed from the elements of the corresponding vector. This equation simply states that, for each sector, the change in household income payments equals the proportional change in output times the base level income payments multiplied by the income elasticity of demand. These income elasticities of demand can be shown to be equal to:

$$l_j = \eta_{WX} + \eta_{EX}$$

Where η_{WX} is the elasticity of wage rate with respect to output, and η_{EX} is the elasticity of labour demand with respect to output. Similarly, the change in sectoral employment can be calculated as the change in the sectoral wage bill times the wage rate:

$$\Delta Emp = \hat{H}_0^{-1}\hat{P}_0^{-1}\Delta Inc$$

Where ***H*** is a vector of average household income coefficients and ***P*** is a vector of coefficients representing average output per employee.

208. That is, household income varies with the level of intersectoral activity.

209. See Australian National Competition Policy. Available at http://ncp.ncc.gov.au/pages/about

There are several implications arising from the use of this model, compared to the conventional IO model. Firstly, while the output multipliers and impacts should not be significantly different between the two models, we would expect the income and employment impacts to be smaller in the marginal coefficient model. This is because many industries, especially those that are more capital intensive and can implement further productivity gains, can increase output, particularly in the short run, [210] without corresponding proportional increases in employment and income payments.

Secondly, unlike the conventional IO model in which the multiplier value is the same for all multiples of the initial shock, the multiplier values from the marginal coefficient model vary with the size of the initial impact. Thus, larger changes in final demand will tend to be associated with smaller multipliers than slight changes in final demand. Therefore, the differential impacts of the marginal coefficient model are not additive, unlike the conventional (linear) Leontief model and CGE model. Overall, within the confines of a static model, the major improvements brought by the non-linear model are increased overall accuracy of the factor income and employment impact projections. An alternative method of introducing non-linear properties is the use of the Flegg Location Quotient Technique.

210. The term 'short run' here does not refer to any specific time; rather it will vary from industry to industry. It is used here in the conventional economic sense to mean that the full adjustment from any shock has not had time to occur, i.e., the system has not yet returned to full, long run equilibrium.

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