Australasian Agribusiness Perspectives
2024, Volume 27, Paper 7
ISSN: 2209-6612

Economic Impacts of the Use of Artificial Intelligence for Australian Agricultural Production[1]

Don Gunasekera[a] and Ernesto Valenzuela[b]

[a] Centre for Regional and Rural Futures, Deakin University
[b] Business School and La Trobe Institute of Sustainable Agriculture & Food, La Trobe University

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Abstract

Recent analysis of reports regarding the applications of Artificial Intelligence (AI) has highlighted the considerable potential for productivity gains in industries such as agriculture. This latter possibility has been shown by several published examples of AI use in the Australian agriculture sector, where they are currently at an early stage of development, testing and adoption. To date, applications have been noted in the berry industry, the grain and pulse industries, the cotton industry, the mushroom industry, and in assessments of farm survey activities, and in the rural property market.

In this paper, we provide a broad review of the potential economic impacts of the use of AI in the Australian farm sector. Empirical estimates reviewed in our paper indicate that there are considerable potential farm sector benefits in Australia associated with the use of digital agriculture including AI. There are already several examples of AI use in some of these farm sectors although many of them are at an early stage of implementation. It has been pointed out that achieving these potential farm sector industry benefits in Australia require investment in all components of digital agriculture including AI.

It is noted that the policy environment associated with the introduction of AI systems is characterised by considerable liability, ethical and moral issues. In this regard, industries may need to carefully determine the level of autonomy provided to Artificial Intelligence systems. It follows that Governments will need to play a role in developing a regulatory framework to ensure the building of public trust, guaranteeing trustworthiness in the application of new systems, and establishing transparent frameworks for data access and protections associated with AI use.

Keywords: Australian agriculture; Artificial Intelligence; Economic Impacts, Productivity.

Introduction

Artificial intelligence (AI) refers to the use of machines which have been programmed to provide quasi-cognitive functions akin to those associated with human minds (McKinsey & Company, 2023a). These functions can embrace such areas as problem solving and decision-making, particularly when considerable amounts of data are involved (Tzachor, 2022). Tzachor (2022) has also pointed out that

[1] The authors gratefully acknowledge the valuable comments from Professors Vic Wright, Bill Malcolm and Garry Griffith of this Journal and Dr James Sillitoe.

in assisting difficulties facing agricultural producers, AI may be able to continuously process, synthesise and analyse complex and extensive aggregations of data, a task which may be beyond human capabilities. Further, he has highlighted that AI can help in detecting and diagnosing anomalies, such as plant diseases, and making predictions regarding crop yields. Within several agricultural areas, it has been demonstrated, according to Tzachor (2022), that AI may relieve growers from labour-intensive tasks entirely, with recorded examples describing the control of automating tilling, preparation of soil, planting of seedlings, fertilising, monitoring plant growth and harvesting. Algorithms have already been developed to regulate drip-irrigation grids, to command fleets of topsoil-monitoring robots, and to supervise weed-detecting rovers, self-driving tractors and combine harvesters (see Tzachor, 2022).

A 2021 survey by *Statista* has indicated that nearly one third of the agricultural businesses in Australia are currently serviced in some way by AI[2]. Furthermore, according to the ABS (2023), the proportion of Australian businesses which reported using AI in 2021-22 has approached 1 per cent.

There are several examples of AI use in Australian agriculture which are of particular interest, but many of them are still at an early stage of development, testing and adoption. Examples include (i) the prediction of yields in the berry industry, (ii) assessing the quality of grains and pulses, with particular regard to malting barley and lentils, (iii) contributing to the reduction of the impacts of spray drift in the Australian cotton industry, and to assisting in improved overall agricultural productivity, profitability and sustainability strategies, (iv) the reduction of waste in the Australian mushroom industry, (v) more accurately predicting which survey respondents will complete farm surveys without requiring follow-up calls, and (vi) to value rural properties (see Box 1).

Box 1. Examples of current AI technology use in Australian agriculture

Berries

In the berry-growing industry, AI technology (which involves sensing and solution suggestions) has been developed by the Food Agility Cooperative Research Centre[3] in collaboration with *The Yield Technology Solutions*[4], University of Technology Sydney[5] and a leading fresh food growing company, *The Costa Group*[6] . This work has been used to predict berry yields using a "Sensing + Yield" prediction module, involving data from harvest management systems and estimates of microclimate weather. The accuracy achieved to date has been very impressive when compared with the manual approach. The sensing and solution approach using AI is now being commercialised and is more than six months into a two-year research program[7].

Grains and Pulses

The application of AI in the Australian grain industry is still at an early stage, with cautious adoption of its output still underway. According to the review by Wells (2023a), Grain Trade Australia (GTA)

[2] https://www.statista.com/statistics/1289948/australia-industries-serviced-by-artificial-intelligence-businesses/#statisticContainer
[3] https://www.foodagility.com
[4] https://www.theyield.com
[5] https://www.uts.edu.au
[6] https://costagroup.com.au
[7] https://www.uts.edu.au/research-and-teaching/research/explore/impact/ai-provides-sweet-results-australian-berry-farms and https://www.foodprocessing.com.au/content/processing/news/using-ai-to-predict-berry-yield-1574387036

and the Commonwealth Government Department of Agriculture, Fisheries and Forestry are working together to support its development by establishing supportive industry national standards, frameworks, and a set of guidelines compatible with AI. These advances will provide criteria that will allow innovative companies to be able to further develop and refine their AI technology to assess grain quality appropriate for industry and government requirements. Wells (2023b) has pointed out that early indications are that malting barley and lentils are the two commodities lending themselves most readily to early adoption of AI in the grain Industry. In this regard, a handheld grain AI platform has been developed by Flinders University in their Tonsley Innovation District[8] in conjunction with GoMicro[9], and this platform has been used to determine lentil quality. A wheat version of this platform is on track for future release, and variants for other grains and pulses are expected to be available in coming years (Wells, 2023c). The platform has an application which can assess samples when photographed with a mobile phone and can produce results within minutes.

Wheat

According to Willinck (2023), the Australian wheat industry, through the analysis of large data sets using AI, can improve the breeding process for new wheat varieties suitable for specific conditions. In this analysis, the selection process can be accelerated using genotype and phenotype prediction (Harfouche et al., 2019). It is noted that with increased extreme and variable climatic conditions, which are expected due to climate change effects, reduced time to produce new varieties will be of significant benefit to the industry. Overall, through utilising the data-analysing capability of AI, it is likely that input decisions for wheat production can be adjusted to minimise waste and increase outputs, leading to higher yields and greater value-added production in this stage of the value chain. Willinck (2023) points out that the processing of wheat also has the potential to be enhanced using AI, with the algorithms having the ability to analyse information provided by machines used to grade wheat, thus providing quick and accurate information which can then be accurately compared with databases. AI can evaluate characteristics such as protein content, test weight and moisture levels in the wheat grains, which can then be used confidently in grading activities. This is further assisted by AI since it can compare the current results with the required standards provided for the different grades of grain (Inacio Patricio & Rieder, 2018).

Cotton

A partnership between the Faculty of Information Technology (IT) at Monash University, BARD AI, PentaQuest, and AgriSci has been formed to assist the application of AI technology solutions that support informed spraying operations in the Australian cotton industry. These applications are designed to lead to better decision-making to reduce the impacts of spray drift and improve overall agricultural productivity, profitability, and sustainability. Spray drift cost the Australian cotton industry more than $18 million in crop losses in 2018 alone, and it is noted that spray drift, together with the unwanted movement of pesticides, is currently a global environmental issue [10].

Mushrooms

[8] https://www.flinders.edu.au/campus/tonsley
[9] https://www.gomicro.co/
[10] https://www.weforum.org/agenda/2021/06/ai-revolutionizing-cotton-farming-industry-australia/ , https://www.monash.edu/it/news/2021/agtech-applications-could-revolutionise-the-cotton-farming-industry,

There is work underway at the Australian Institute for Machine Learning (AIML) at the University of Adelaide to develop AI technologies to (i) improve the efficiency and overall harvest yield of mushrooms while also reducing waste in the industry [11] and (ii) to develop water-saving plants [12].

Seafood and other industries

AI-related research at the Australian Research Council Research Hub in Griffith University is currently being used to develop new technologies, which have been introduced into both testing and production environments at Australian Bay Lobster Producers Limited[13], Sunray Strawberries[14], and Davco Agriculture[15], improving efficiency and revolutionising the way their businesses are carried out [16].

In addition, a University of Queensland researcher is using AI-related computer simulations to bring aquaculture into line with genetic advances made in land-based agriculture. This work is using software to virtually model the genetic tools available to barramundi farming and is being conducted in collaboration with the ARC Research Hub for Supercharging Tropical Aquaculture at James Cook University and the MainStream Aquaculture Group[17].

Farm and other surveys

The Australian Bureau of Statistics (ABS)[18] has recently indicated that, in a live trial, using a machine learning approach has outperformed a traditional rule-based approach by more accurately predicting which survey respondents would complete their survey without requiring follow-up calls. The latter respondents are referred to as Gold Providers (GP), and their identification enables more flexibility in the setting of the required proportion of GPs in the full sample. In this regard, a live trial of the GP strategy for the 2018-19 cycle of the Rural Environment and Agricultural Commodities Survey (REACS) was carried out, on the basis that this survey was known to be one of the ABS surveys struggling to achieve its target response rate. Two approaches were used to predict the GPs in this trial, these being a rule-based descriptive approach and a model-based response propensity approach. In this work, the model-based response propensity approach used a machine learning facility known as the *Random Forests with Regression Trees* method (ABS, 2022).

Valuing rural properties

CSIRO[19] and the rural technology start-up company *Digital Agriculture Services* have launched the Rural Intelligence Platform which uses satellite imagery to track the use of paddocks and their performance over time (Arnott, 2019). In this way, information from trusted data sources on productivity, water access, yield, land use, crop type, rainfall and drought impacts can be used to

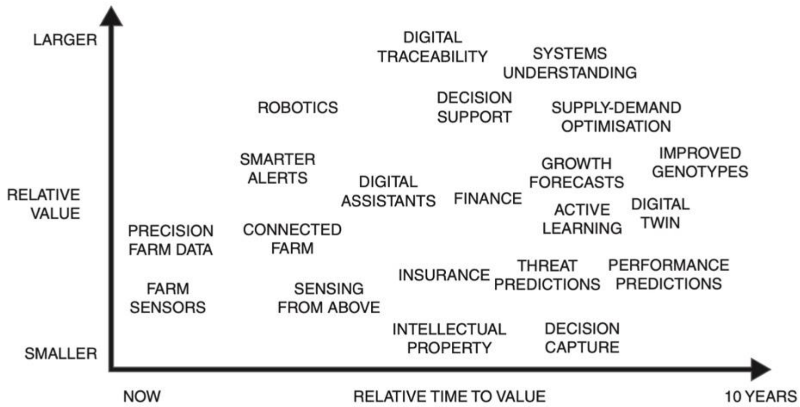
[11] https://www.adelaide.edu.au/aiml/news/list/2023/05/09/ai-mushroom-research-sprouts-400k-fellowship
[12] https://www.adelaide.edu.au/aiml/news/list/2023/04/14/ai-fast-track-for-development-of-water-saving-plants
[13] https://australianbaylobster.com.au/
[14] https://www.sunraystrawberries.com.au/
[15] https://www.davcofarming.com/
[16] https://news.griffith.edu.au/2022/03/09/strawberries-lobsters-sugarcane-industries-grow-with-ai/
[17] https://www.uq.edu.au/news/article/2023/07/ai-revolutionise-barramundi-farming
[18] https://www.abs.gov.au/statistics/research/raising-survey-response-rates-using-machine-learning-predict-gold-providers
[19] https://www.bulkhandlingreview.com.au/csiro-launches-ai-platform-to-future-proof-farms/

assess and monitor the value of rural land anywhere in Australia. The Platform also incorporates information from Australia's digital soil map, in conjunction with available climate information, to show risks of drought, frost, and heat stress for livestock. Machine learning algorithms are used to analyse the data with a clarity that was not previously possible (Arnott, 2019). It incorporates an AI-initiated Automated Valuation Model that is capable of valuing rural properties instantly with up to 90 per cent accuracy.

Against this encouraging background of the potential applications of AI in Australian agriculture, the focus of this paper is on the likely economic impacts of using this technology.

In developing this discussion, we considered several reasons which underpin the speculated need for the greater adoption of AI into the Australian agricultural Industry. First, in discussing the value to agriculture which is anticipated to be provided by AI over the next decade, Smith (2020) has illustrated a range of AI-related different innovations, indicating his assessment of the relative value and the relative time needed to implement these different advances (see Figure 1). Smith (2020), based on Banerjee et al. (2013), points out that a common framework used to think about deriving value from AI is the "descriptive, diagnostic, predictive and prescriptive" spectrum (see Box 2).

Figure 1. Artificial intelligence-enabled capabilities that will bring value to agriculture



Source: Smith (2020, p. 47, Fig.1)

Box 2. Forms of computational analytics related to AI use in agriculture

The different terms used, which relate to the role of AI-related computation in leading to an action being taken following new inputs, include:

Descriptive analytics, where computation is used only to provide data or information for human processing and, consequently, upon which to base decisions. An example in agriculture is analytics that produce a high spatial-resolution field map to indicate variations in forage quality and quantity.

Diagnostic analytics, in which computation produces relationships between datasets that may imply causality, such as relationships between nutritional components of animal feeds and milk yields or meat quality.

Predictive analytics, where computation is used to predict what would happen in space or time. An example of this action would be in the prediction of when a crop is likely to be mature enough for harvesting.

Prescriptive analytics, in which computation is used to make or take recommended actions. An example of predictive work might be in the sounding of an alarm when an unrecognised person is observed entering a rural property.

Source: Smith (2020, pp. 47-48) based on Banerjee et al. (2013)

According to Smith (2020), much of the immediate value that will be derived by farmers from the use of AI will be at the *descriptive and diagnostic* ends of the analytics spectrum. In this instance, AI will provide more and better information about a situation on the farm to enable the farmer to look at, think about and decide on management actions. This is noted as 'Precision Farm Data' in Figure 1. It is anticipated that the collection of more and better data *via* AI will enable improved *diagnostic* analyses of how different factors interact to influence key properties of agricultural systems. This phase is termed 'Systems Understanding' in Figure 1. A major area of improvement that could be developed is in the use of AI for predictive analysis to determine how different varieties of plants and animals will perform in different circumstances. This is known as 'Performance Predictions' in the terminology of Figure 1. Finally, in moving from *descriptive to prescriptive analytics*, Smith (2020) points out that once an ability to record some actionable information has been shown by using AI, it is possible to attempt an extension toward developing computational capabilities that can automate processes or perhaps perform further analytics. The most basic of these is issuing alerts immediately when something notifiable is detected, which is the 'Smarter Alerts' category mentioned in Figure 1.

Second, the Commonwealth Government Department of Agriculture, Fisheries and Forestry's publication *Digital Foundations for Agriculture Strategy* (2022), has indicated that digital technologies such as artificial intelligence, robotics and blockchain are already transforming agriculture and the food supply system. It is recognised that this advance is likely to stimulate the use of the potential of digital technologies and, in this respect, there are a range of whole-of-Government strategies and initiatives that set a pathway for widespread adoption of this technology across the entire economy. In addition, the Department of Agriculture, Fisheries and Forestry have noted that, according to the Australian Farm Institute, the full adoption of digital tools by the agriculture sector could boost productivity by around $20.3 billion each year[20] .

Third, it is realised that there is limited analysis of the economic impacts of AI use in Australian agriculture presently available. Given the paucity of this evidential background, the purpose of this paper is to review the analysis of potential economic impacts of AI use in the Australian agricultural sector. To introduce this work, we note that there are number of *AgriTech* AI start-up entities[21] operating in Australia, and examples of several of them are presented in Box 3.

Our paper is organised as follows. Section 2 provides a broad analytical framework which underpins our approach in reviewing the economic effects of AI use. In Section 3, issues relating to economic impacts of AI use are discussed. The final Section offers some concluding remarks.

[20] https://www.agriculture.gov.au/agriculture-land/farm-food-drought/innovation/national-ag-innovation-agenda#digital-agriculture
[21] https://ishango.io/agritech-ai-tools-in-australia-revolutionising-agriculture-for-a-sustainable-future/

Box 3. *AgriTech* AI start-up entities

At present, there are several relevant start-up entities operating in Australia, and these include:

- *FluroSat:* FluroSat uses remote sensing technology and AI to monitor crop health and to diagnose issues before they become unmanageable. This entity recently secured significant funding to aggregate agricultural data and provide actionable alerts to farmers [22];
- *AgriDigital:* AgriDigital leverages blockchain and AI to streamline grain supply chain operations. It offers solutions for real-time inventory management, contract management and settlement services [23];
- *The Yield:* The Yield uses AI and the IoT (Internet of Things) to provide microclimate data to farmers, helping them make faster, data-driven decisions [24];
- *Farmbot:* Farmbot offers remote monitoring solutions for agribusiness. It uses sensors and satellite technology to keep track of water tank levels and pressure [25]; and
- *DataFarming:* DataFarming utilises AI and satellite imagery to provide farm intelligence solutions. Its platform offers crop monitoring based on images and insights from spatial data and farm maps [26].

Analytical Framework

In a recent review on the economics of Artificial Intelligence, Lu and Zhou (2021) point out that economists use ‘automation,’ ‘robotics,’ ‘digitalization,’ or ‘computerization’ variously to refer to the concept of AI in a broad sense. According to Szczepański (2019), AI is a term used to describe machines performing human-like cognitive processes such as learning, understanding, reasoning and interacting. It can take many forms, including technical infrastructure such as algorithms, a part of a (production) process, or an end-user product.

AI as a General-Purpose Technology (GPT)

According to Cook (2023, pp.3-5), ‘the most consequential innovations in the past have been General Purpose Technologies (GPTs) that have broadly transformed the economy over an extended period of time’. These GPTs have three key features: (i) they are widely used across the economy, (ii) they improve steadily over a long period of time, and (iii) they raise the productivity of research and development. Cook (2023, p. 4) argues ‘that it is easy to see the potential for wide use of AI, and there is work showing that generative AI improves productivity in a variety of settings, including computer coding, customer service, language translation and robotics’. She further points out that ‘continuing advances in model architecture, data curation and computation will be essential for the continual improvement of AI models and implementation’, suggesting that ‘AI can go deeper in discovering patterns in data in previous research to generate hypotheses for testing that may not have hitherto occurred to researchers, and hence provides potential for efficiency improvements’ (Cook (2023, p. 5). Hence, Cook (2023) argues that generative AI seems promising as a general-purpose technology (GPT).

[22] https://www.regrow.ag/
[23] https://www.agridigital.io/
[24] https://agtechfinder.com/directory/yield
[25] https://farmbot.com.au/
[26] https://www.datafarming.com.au/service/agri-intelligence/

AI related to economic production

From an economic perspective, it is useful to view the role of AI from both the production side and the consumption side (Lu and Zhou, 2021). According to their review on the economics of AI, Lu and Zhou (2021) point out that, from the production side, economists tend to define AI as 'automation technology' (Aghion et al., (2019), Hémous and Olsen (2016), and Acemoglu and Restrepo (2018)) or as 'robots' (Sachs et al., 2015) in their economic models and analysis. Hence, AI is commonly assumed to be either a simple programmed machine or an advanced technology that can perform high-skill tasks, and it is one type of capital that can substitute for, or complement, labour or certain skill types of labour to different extents and on different production levels (Lu and Zhou, 2021, p. 1051).

Further, according to Lu and Zhou (2021, p. 1049), in the economic model of Aghion et al. (2019), AI can be represented as capital which can replace labour with constant elasticity of substitution. Since AI is taken as an exogenous input in the production of new ideas, Aghion et al. (2019) found that ongoing AI development can possibly generate exponential growth, when AI increasingly replaces human labour in generating ideas.

Hémous and Olsen (2016), according to Lu and Zhou (2021, pp. 1049-50), adopted an economic modelling framework where labour is distinguished as low skill or high skill and, in this regard, AI (or automation) can be a perfect substitute for low-skilled workers. In addition, a part of the composition of the high-skilled worker group is made up from those workers hired as AI technology (or automation) researchers. This direction represents a need for a significant investment for non-automated firms, which will be critical to their development of innovative actions. Therefore, it is posited that the real source of growth in these areas is in selected human capital that creates or controls the AI technology, rather than the more traditional 'capital' in Aghion et al.'s (2019) model (Lu and Zhou (2021, pp. 1049-50).

According to Lu and Zhou (2021), Acemoglu and Restrepo (2018) have provided a conceptual model to account for AI's role in economic growth, employment and task inequality. They distinguished two types of technological changes, which were (i) automation and (ii) the creation of new tasks. In their perspective, automation cannot create or introduce new tasks *per se*, but can introduce the conditions for new tasks to be created. In this latter case, new tasks which are created are those in which labour has a comparative advantage. They assume that there are certain tasks that are automated by technologies in which labour and capital are perfect substitutes, but the extent of substitution is determined by the relative prices of labour and capital. According to the model of Acemoglu and Restrepo (2018), it is apparent that, in the long run, if the relative price of capital to labour is sufficiently low, an AI world will result.

In another study reviewed by Lu and Zhou (2021), Sachs et al. (2015) introduced a model which used the term 'robots' (to define AI) to distinguish it from traditional capital. In addition, the goods were seen to be produced by two different technologies, which are (i) a traditional path that requires both human labour and capital and (ii) an emerging direction that only requires the involvement of 'robots'. This model defined the essential quality of robots (and AI in general) as to 'allow for output without labour'. Thus, in their model, AI is taken as a *substitute for labour*. However, the substitution is not embodied in one production function directly but is reflected in the total homogeneous output from two types of firms, these being (i) firms with traditional technology and (ii) firms using robots. In this regard, the term 'substitutability' refers to the mix of different production technologies. Finally, AI (or 'robotics' in their model) is based on a more aggregate level, in the sense that there is no distinction between labour and human capital, or between low- and high-skilled workers. This implies that AI or robots just replace 'labour' in general terms, and whether AI has positive or negative impacts on economic outcomes and welfare is dependent solely on the model parameters.

In summarising the review of the models above, Lu and Zhou (2021, p. 1051) point out that, in most cases, AI is used to improve either labour or capital productivity, whilst innovation is ultimately generated by human capital that controls AI technology, either in production or in research. In that sense, AI in these models is just another detailed representation of factor productivities. Consequently, the key element in such models is the relative price of labour and capital, which includes any use of AI.

According to Lu and Zhou (2021, p. 1052), all the models they have reviewed provide insights into the accommodation of AI into economic models. However, before the incorporation of AI, two important questions need to be considered. These are (i) How do different types of AI impact on the economy? and (ii) How could AI fundamentally influence the theory of economics? For the first question, most of the current models assume AI as a particular type of automation technology, where the definition of such technology is very loose. However, the development of AI will eventually reach a stage where it can replace high-skilled labour to make decisions or even generate creative ideas rather than being programmed to perform low-skill tasks. Very few economic models have captured this type of future scenario so explicitly. The second question, regarding a fundamental issue in the theory of economics, suggests that the role of human beings has usually been narrowed down to 'labour and an optimisation agent', but in endogenous growth models, 'labour' is regarded as different from 'human capital'. Thus, the development of AI further challenges the role of the human being in the economic system. Does AI bring a new production technology or is it just another (better) type of input to current production technology? Is AI a substitute for 'labour' or 'human capital', or is it possibly an independent decision-making agent? These are interesting and challenging questions to explore.

While most models focus on the production side, it is worthwhile to think about the impact of AI from the consumption side. According to Lu and Zhou (2021, p. 1051), a valid concern is regarding how AI affects the labour market.

Cook (2023, pp. 6-9) argues that 'new technologies (such as AI) may displace some types of labour, but they can also raise the productivity and incomes of jobs they either create or complement. While many workers throughout the economy benefit in such changes, a smaller set bear the brunt of the negative effects. Just as the introduction of computerized machine tools replaced skilled machinists, and personal computers made many routine clerical and administrative jobs obsolete, the widespread adoption of AI will be a difficult transition for some workers. As firms rethink their product lines and how they produce their goods and services in response to technical change, the composition of the tasks that need to be performed will also change. The ability of workers to move to where they are needed as the task composition of production changes, will also be an important determinant of how successfully the economy generally adapts to the new jobs created in response to AI'.

From a public good perspective, it is noteworthy that the public sector, where basic e-government functions are already effective, using AI could facilitate closer collaboration between different parts of government, enabling the full integration of public and private services (see Bureau of Communications and Arts Research, 2017). On the other hand, from a private good perspective, for example, Cook et al. (2021) indicate that there is evidence to suggest that digital agriculture including AI is a process led by the private sector.

The mix of private and public benefits from the wider adoption of AI fits in with the chain failure/chain goods literature[27], and has implications for who should fund, implement and manage the AI technology. Cook et al. (2021) points out that, from a public sector perspective, most governments are reluctant to invest in areas seen as the private domain (for example, digital agriculture including AI). As illustrated in Box 1, AI technology use in Australian agriculture is largely facilitated by private and non-government entities. The public sector involvement in implementing and managing the AI technology is limited except for ensuring a competitive environment for AI generation and adoption through appropriate regulatory environment and oversight as required and relevant.

Issues Relating to Economic Impacts of AI Use

An important driver of the potential economic effects of the increased use of AI technologies in the Australian agriculture sector is likely to be through productivity improvements.

Based on Leonard et al (2017, p. 29, Table 2.1), we present the potential cross sector industry benefits (see Table 1) associated with the use of digital agriculture including AI. Leonard et al (2017, p. 29) point out that achieving the potential cross sector industry benefits (see Table 1) require investment in all components of digital agriculture including AI. It is important to highlight that there are already several examples of AI use in some of the sectors covered in Table 1, as described in Box 1, although many of them are at an early stage of implementation.

Table 1. Estimated economic impact of digital agriculture (including AI) on Australian farm sectors

Sector	Baseline sector value of Gross Value of Production (GVP) 2014-15 ($M)	Estimated potential benefit to the sector GVP increase ($M)	Estimated potential benefit to the sector GVP increase (%)
Rice	260	78	30
Grains	11,522	5,930	51
Cotton	1,413	394	28
Sugar	1,257	291	23
Horticulture	1,018	403	40
Beef	10,461	1688	16
Sheep meat	2,988	516	17
Wool	2,550	452	18
Pork	1,084	55	5
Dairy	3,343	497	15
Eggs	729	180	25
Chicken meat	2,084	503	24
Wine	5,865	706	12

Source: Leonard et al. (2017, p. 29, Table 2.1)

According to the Productivity Commission (2022a), Artificial Intelligence is the ability of computers to simulate human intelligence and perform associated tasks (such as speech recognition, moving objects and strategic decision-making) in an automated fashion. In this context, machine learning is a type of AI in which a computer algorithm automatically improves its predictions through more data and experience.

[27] See Malcolm et al. (2017) for a discussion on chain goods and chain failure.

It is noteworthy that, in terms of ICT technology uptake, the share of Australian businesses using AI in 2019-20, was less than 5 per cent as reported by the Productivity Commission (2022a, p. 10, Figure 1.4) which was based on ABS 2019-20 *Characteristics of Australian Business*, (Cat. no. 8167.0). Among these businesses, Primary Industries account for around 5 per cent (according to Productivity Commission estimates using data in the ABS's Business Longitudinal Analysis Data Environment (Productivity Commission (PC), 2022a p. 12, Figure 1.5).

While Australia compares well internationally as a data producer and consumer (Chakravorti, Bhalla and Chaturvedi, 2019), it performs poorly in its use of data-driven technologies, as typified by Artificial Intelligence and data analytics (OECD 2022a, 2022b) as reported by the Productivity Commission (2022b, p. 46). The National Farmers' Federation has quoted that, according to the Australian Foundation Investment Company (AFI) forecast, full adoption of digital agriculture could yield $20.3bn by 2050 (National Farmers' Federation, 2019, p. 12) (see Box 4). Given this background, and despite the lower technology uptakes at present, in the medium-to-long term new approaches such as digital technologies and the better use of data (through artificial intelligence, for example) hold considerable promise for broadly-based productivity gains in different agriculture, fisheries and forestry industries in Australia.

Box 4. The effect of digital agriculture

Using the Centre for International Economics-Regions Food Processing Model (CIE-Regions FP model), the Australian Farm Institute (AFI) predicted the potential economic benefit of the unconstrained transition to digital agriculture.

When digital agriculture is fully implemented in Australia, it is estimated that this would boost the value of agricultural production, including forestry, fisheries and aquaculture, by 25 per cent (compared to 2014-15). This is a $20.3 billion boost to the gross value of agricultural production (GVP). The overall potential increase in national gross domestic product (GDP), including the flow-on effect to other parts of the Australian economy, is estimated to be $24.6 billion.

These estimates are based on the assumption of a 100 per cent uptake of digital agriculture and exclude any costs associated with the adoption of digital technologies.

Source: Leonard et a. (2017) and Perrett et al. (2017)

According to a global study on AI by McKinsey & Company (2023), generative AI could enable labour productivity growth of 0.1 to 0.6 per cent annually through to 2040, depending on the rate of technology adoption and redeployment of worker time into other activities. Indeed, Hajkowicz and Whittle (2023) have reported that a recent study by the US National Bureau of Economic Research found a 14 per cent increase in productivity among customer service agents who used an AI tool to help guide conversations.

According to the Australian Bureau of Agricultural and Resource Economics and Sciences (ABARES) (2023), total factor productivity (TFP) growth in the Australian cropping and broadacre agricultural industries, averaged 1.6 and 1.0 per cent per year respectively from 1977–78 to 2021–22, whilst in the dairy, beef, and sheep industries, the TFP growth averaged 1.3, 0.6 and 0.5 per cent per year respectively from 1978–79 to 2020–21. In the mixed farming industries, the annual TFP growth during the same period was 0.9 per cent. Finally, the review on the economics of AI, undertaken by Lu and Zhou (2021) and as discussed above, points out that, from the production side, AI is characterised as another detailed representation of factor productivities.

Given the above prognosis, it is plausible to argue that the Australian farm sector could benefit considerably because of widespread use of AI over the medium to long term.

Precision agricultural technologies (including the relevant AI technologies) have the capacity to raise farm productivity and contribute to sustainable farming systems. Pathak et al. (2019, pp. 1293-1294), have reported that 'Tey and Brindal (2012) have examined the factors influencing their adoption rates which include socio-economic factors, agro-ecological factors, institution factors, informational factors, farmers perception, behavioural factors, and technological factors. Operator age, years of farming experience and formal education are examples of *socio-economic factors* whereas tenure, farm specialization, farm size, farm sales, variable fertilizer rates, livestock sales, debt-to-asset ratio, production value, owned land minus rented land, yield, part-owner farmers, full-owner farmers, farm income/profitability, soil quality, percentage of main crop in total farmland, percentage of farm land as county land area, percentage of cropped land to total farmland, percentage of farmland as large farms and off-farm employment were classified into *agro-ecological factors* (Tey and Brindal, 2012). Likewise, distance from a fertilizer dealer, region, use of forward contract and development were categorized into *institution factors*, and use of consultant services and perceived usefulness of extension services in implementing precision farming practices were kept under *information factors* (Tey and Brindal, 2012). Perceived profitability of using precision agriculture is classified into farmer perception, willingness to adopt variable-rate technology was kept under *behavioural factors* and yield mapping, use of computer, farm has irrigation facility and generated own map-based input prescription were classified into *technological factors* (Tey and Brindal, 2012)'.

There are several examples of adoption rates of precision agriculture technologies in Australia. Pathak (2020, pp. 5, 11 and 51) reports that, a survey conducted by the Grains Research and Development Corporation (GRDC) found that the national average adoption of yield mapping was 13.5 per cent, 21.8 per cent, and 29 per cent of the cropped area in 2008, 2011, and 2014 respectively (see Umbers, Watson and Watson 2015). Further, an agriculture technology survey conducted by GrainGrowers Limited in 2015 showed that 16.56 per cent of the respondents had adopted variable rate fertiliser application and 14.7 per cent of the respondents had adopted satellite imagery (GrainGrowers Limited 2017). Also, an agriculture technology survey conducted by GrainGrowers Limited in 2017 showed that the adoption rate of variable rate application and NDVI (Normalized Difference Vegetation Index) crop sensors were 20.85 per cent and 5.35 per cent, respectively (GrainGrowers Limited 2017). A survey of grain growers conducted by Bramley and Ouzman (2018) identified that 84 per cent of the respondents adopted controlled traffic farming or machine guidance technologies in Australia.

These examples indicate the variability in precision agriculture technologies adoption rates and that the adoption rate is different for different technologies. Therefore, it is important to identify what factors contribute to the adoption or rejection of precision agriculture technologies. In this context Kuehne et al. (2011, p.1) have developed a tool (Adoption and Diffusion Outcome Prediction Tool (ADOPT)) designed to: predict an innovation's likely peak extent of adoption and likely time for reaching that peak; encourage users to consider the influence of a structured set of factors affecting adoption; and engage R & D managers and practitioners by making adoptability knowledge and considerations more transparent and understandable. The tool is structured around four aspects of adoption: characteristics of the innovation, characteristics of the population, actual advantage of using the innovation, and learning of the actual advantage of the innovation.

Concluding Remarks

There are currently numerous applications of AI in Australian agriculture, with many cases at an early stage of development, testing and adoption, and we have earlier noted that they already cover several relevant applications. Further, as discussed in this paper, it is likely that the widespread use of AI in

Australian agriculture will have considerable economic benefits. However, it appears that the policy environment associated with AI systems is characterised by liability, ethical and moral issues.

In this regard, industry may need to determine the level of autonomy provided to artificial intelligence systems, and Governments will need to develop appropriate regulatory frameworks to ensure safety on farms[28]. In this respect, Bremmer and Suleyman (2023) argue that AI related policies and good governance would be best served by adhering to five guiding principles on which AI policymaking can be based. They include precautionary, agile, inclusive, impermeable and targeted as described by (Bremmer and Suleyman, 2023, pp.10-12) and quoted below.

'*Precautionary*: The risk-reward profile of AI is asymmetric; although there are vast benefits to AI's potential, policymakers must guard against its potential downsides. The already widely used precautionary principle needs to be adapted to use in AI contexts and should be enshrined in any governance regime.

Agile: Policymaking structures tend to be static, prizing stability and predictability over dynamism and flexibility. However, this approach will not work with a technology as unique as AI. AI governance must be agile, adaptive and self-correcting, in parallel with AI's development to be fast-moving, hyper-evolutionary, and self-improving.

Inclusive: The best industry regulation, especially when it comes to technology, has always worked collaboratively with the commercial sector, and this is especially true for AI. Given the exclusive nature (at least for now) of AI development—and the complexity of the technology— the only way for regulators to properly oversee AI, is to collaborate with private technology companies. To reflect the borderless nature of AI, governments should make involved companies party to various international agreements. The inclusion of private companies in high diplomacy may appear to veer toward unprecedented, but the exclusion of those who have so much product knowledge and management control, would doom any governance structure that excludes them before it even starts.

Impermeable: For AI governance to work, it must be impermeable. Given AI's recognised ability to proliferate in a range of directions, just one defection from the regime could allow a dangerous model to escape. Therefore, any compliance mechanisms should be watertight, with easy entry to compel participation and costly exit to deter noncompliance.

Targeted: Given AI's general-purpose nature and the complexities involved in its governance, a single management regime is insufficient to address the various sources of AI risk. In practice therefore, determining which tools are appropriate to target various risks will require developing a live, working taxonomy of discrete potential AI impacts. AI governance must therefore be targeted, risk- based and modular rather than one- size-fits-all' (Bremmer and Suleyman, 2023, pp. 10-12).

There is already a recognition that Governments have an important role to play as enablers and as standard setters, particularly regarding the ethical considerations of AI implementation. As an example of an enabling support, the Commonwealth Government has announced a $1.2 billion Digital Economy Strategy. A key feature of this Digital Economy Strategy is an additional $124 million commitment to AI initiatives. In relation to standard setting, the Governments' AI Action Plan is designed to progresses the implementation of Australia's AI Ethics Principles**.** These principles include (i) that AI systems should respect human rights - such as privacy, diversity, and autonomy, (ii) that AI

[28] https://www.agrifutures.com.au/wp-content/uploads/publications/16-038.pdf

systems should be reliable in operating for their intended purpose (iii) that there should be transparency with its use so people can reasonably know when they are engaging with AI, and (iv) that there should be human oversight, with the people responsible for AI systems being identifiable and accountable for their outcomes (Hume, 2021).

The Productivity Commission (2024a) points out that the Government should focus on ensuring Australia has the skills and digital infrastructure to integrate AI in more specific, local use cases. This includes the implementation of the technology, particularly through digitised firms and software as a service. It is noteworthy that the role of Governments is to provide the legal backbone of the regulatory framework relevant to the particular digital technology. But for many technologies the value chains themselves govern and manage the implementation especially if there is a chain failure. Many individual industries (grains are a good example) have industry organisations to provide the relevant advice on particular goods and services to their levy paying members.

According to the Productivity Commission (2024b), the challenges presented by AI are particularly acute in the case of data collections, dissemination and use. Data is a vital input into AI technologies and, generally, increased accessibility of quality data would contribute positively to productivity. But at the same time, wider use of data (particularly with inadequate regulation) increases ethical risks to individuals and raises questions about the custodial/ownership rights of those generating, curating and using data. Many of Australia's existing technology-neutral laws and regulations already apply to the use of AI technologies. This includes regulatory frameworks in areas such as consumer protection, privacy, antidiscrimination and negligence, together with sector-specific and profession-specific requirements. However, it is anticipated that the implementation of AI will be likely to quickly highlight gaps in these regulations (Productivity Commission, 2024b).

A particular challenge is therefore to improve public confidence in data-sharing, including transparent enforcement of existing protections for individuals. Another challenge is to establish clear and consistent arrangements for text and data mining for the purposes of training AI models. It is understood that existing Australian data collections remain an underutilised resource, and it is suggested by the Productivity Commission (2024c), that it will be increasingly valuable to access and harness the potential of AI to utilise some of this data as relevant.

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