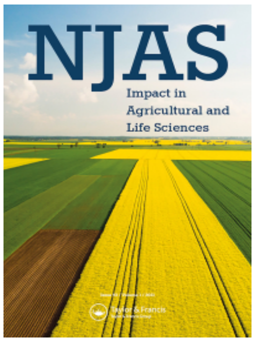

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An interdisciplinary approach to artificial intelligence in agriculture

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ABSTRACT
Innovations in digital technologies, especially in artificial intelligence (AI), promise substantial benefits to the agricultural sector. Agriculture is increasingly expected to ensure food security and food safety while at the same time considering the environmental aspects. AI in the agricultural sector offers the potential to feed a continuously growing global population and still contribute to achieving the UN's Sustainable Development Goals (SDGs). Despite its promises, the use of AI in agriculture is still limited. We argue that the slow uptake is due to the diverse ways in which AI impacts the agri-food industry, due to the diversity of foods, supply chains, climates, and land in the agricultural sector. We propose that this is also exacerbated by ethical concerns arising from AI use, the varying degrees of technological development and skills, and the economic impacts of agricultural AI. A literature review of multiple disciplines in agricultural AI (economic, environmental, social, ethical, and technological) and a focus group of experts. AI-powered systems in agriculture raise various sets of concerns in multiple disciplines that need to be aligned to provide sustainable AI solutions for the agriculture domain. Our research proposes that it is important to adopt an interdisciplinary approach when developing AI in agriculture. AI in agriculture should be developed by interdisciplinary collaboration because it has a greater chance to be robust, economically-valuable and socially desirable, which may lead to greater acceptance and trust among farmers when using it.

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KEYWORD Artificial intelligence; ethics; social-economic; technological; interdisciplinarity; digital agriculture

1. Introduction

Innovations in digital technologies hold great promise for the future of agriculture (Bacco et al., 2019; Lajoie-O'Malley et al., 2020; Marvin et al., 2022; Shepherd et al., 2020). Automation, precise prediction, process and resource optimisation will help produce a larger quantity of good quality food more efficiently and with less burden on the environment (Shepherd

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et al., 2020). Digitalisation provides precise information for the producers to use and optimise their production system. Moreover, digital technologies offer possibilities to develop new innovative production and consumption models by linking diverse agri-food system actors (Lajoie-O'Malley et al., 2020). One of the fast-progressing digital technologies in agriculture is artificial intelligence (AI). AI is becoming an obtainable technology for firms in agriculture, thanks to advanced AI research, increasing investments in AI solutions, drastically improved computing power, and relatively cost-effective access to computing and cloud technologies.

The agricultural sector is expected to see huge investments in AI in the coming years, with an estimated increase of 25.5% compound annual growth rate (CAGR) between 2020 and 2026 (MarketsandMarkets 2020). AI can change the way agri-firms organise, compete and engage in the food chain. These will be envisioned through strategic steps towards improved technology and the motivation of businesses and farmers to benefit from the rewards of AI (greater production levels, reduced pesticide use, and lower environmental impact). AI will also cope with some of the most striking societal challenges, such as addressing labour shortages, and the pressing need to produce more while decreasing harmful environmental outputs.

The development of agricultural technology solutions to our environmental and developmental challenges is nothing new, as precision agriculture technologies, such as GPS guidance, VRT and yield mapping, are already widely practiced (Franzen & Mulla, 2015). Smart farming extends precision agriculture through enhanced management tasks and decision-making based on data (Wolfert et al., 2014). Converting precise data into actionable knowledge to support farm management and decision-making brings precision agriculture to a new level, towards digital/smart agriculture (Shepherd et al., 2020). Digital/smart farming promises to build upon precision agriculture by integrating innovative digital solutions, such as AI, to advance the agricultural sector. Therefore, the use of AI in agriculture can be seen as one of the tools within the arsenals of precision agriculture and smart farming to meet the growing food needs, while still ensuring profit and development of the sector. However, the impacts of agricultural AI (e.g. benefits and risks) are often discussed theoretically, and separately in social and technical disciplines.

In this paper, we survey the technological, social, economic, ethical, and environmental impacts of using AI in the agricultural sector, and try to find cross-cutting edges of multiple disciplines. By doing so, we answer the following research questions:

> To what extent do technological, social, economic, ethical, and environmental issues play arole in AI in the agricultural sector?

To what extent do the disciplinary challenges found in the literature review require interdisciplinary solutions?

We initiate a literature review to draw a landscape of current uses of AI in agriculture and raised multidisciplinary discussion on technological, social, economic, and ethical consequences of using AI in agriculture. Although AI impacts the entire agri-food systems, we have specifically focused on crop farming. This focus was led by the research objective of the peer-reviewed literature we studied. Most of the articles (about 98%) presented empirical research of AI in crop farming. Our literature study results based on explored evidence of agricultural AI impacts are supplemented with the results of a focus group discussions with 10 academics working in various disciplines.

The paper is structured as follows: Section 2 explains the methods used, Section 3 presents a general introduction to the current state of play and uses of agricultural AI. The consequent sections provide analysis and breakdown of the literature on the economic (Section 4), social (Section 5), environmental (Section 6), the ethical (Section 7), and technological (Section 8), aspects of agricultural AI. Section 9 reflects on why we need an interdisciplinary approach to the use of AI in the agricultural sector based on the findings throughout our paper.

2. Methodology

For the purpose of this paper, we conducted a narrative desk study and short communications with several business developers, managers, scientific coordinators, computer scientists, economists, and ethicists: all involved in AI-related research and innovation activities at a leading agricultural university and research centre.[1] We conducted a literature analysis of the empirical studies on agricultural AI in relevant domains of AI in agriculture. The workflow steps of the adopted research methodology are shown in Figure 1.

The goal of the literature review was to survey the existing knowledge about agricultural AI by studying the current academic publications in the relevant disciplines (e.g. computer science and engineering, ethics, and economics).[2] We used the Scopus database and applied similar search criteria for all three disciplines, but this brought back such a disparate amount of articles (for example, 2150 for technology, while only 50 for ethical). Thus, we felt that a systematic review would not work well because it would provide

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[2]This is not to say that other aspects, such as legal, political, and governance are less important. Many of the topics discussed in the literature also have distinct legal and political dimensions (e.g. justice and privacy are ethical issues but also have strong legal implications). However, due to the relatively low level of technological and social readiness level of agricultural AI, the technological, social-economic and ethical aspects are of more importance. Once agricultural AI achieves a higher readiness level, we expect the legal, political and governance disciplines to play a more important role.

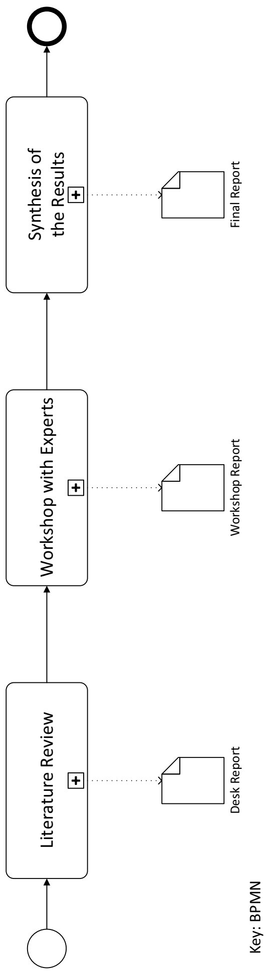

Figure 1. Workflow of the adopted research methodology.

a completely imbalanced analysis, as there was such an uneven distribution of papers among the multiple disciplines. We limited each discipline using the following exclusion criteria:

- Not focused on agriculture
- Not focused on AI technologies and impact
- Non-English
- Not final and not peer-reviewed
- No technological, social, environmental, economic, or ethical content

Following, we have screened the abstracts and methodology section of the articles using these exclusion criteria. The exclusion and the preliminary screening refined our searches down to approximately 20 articles on the topic of agricultural AI per discipline, so that the reviews would be relatively balanced. These articles were chosen based on the exclusion criteria, citation, relevance to the topic, and/or if they appeared to provide a different response/insight from the other literature analysed. Then, we have carefully read and analysed the contexts of the selected and additional articles to extract technological, environmental, social, economic and ethical challenges of agricultural AI use and development.

Following the literature review, we conducted a focus group with academics and researchers working in the area of agricultural AI, with a focus on bringing together various disciplinary experts (see Appendix for more details). The goal of this discussion was to explore and better understand the opinions, experiences, and perceptions of academics and researchers working in various AI disciplines. Thus, the focus group objective was to discuss the literature findings and to postulate on ways forward and possible solutions to some of the challenges raised. We also wanted to examine to what extent the disciplinary challenges identified in the literature required interdisciplinary consultation and solutions. We have integrated the findings to a suggested interdisciplinary approach to the use of AI in agriculture.

3. Current state-of-the-art developments in agricultural AI

AI is a form of intelligence that can perform actions that would have previously been done by human beings, such as vision, language processing, understanding, and communication. AI composes a series of approaches, methods, and techniques to simulate intelligent behaviour (Cook & O'Neill, 2020). AI is, therefore, used to solve complex tasks and actions that other forms of digital technologies are incapable of (T. Davenport et al., 2020). AI can perform such tasks as reasoning, planning, learning, perception, and the ability to move and interact with its environment, in a similar way that humans can, and even more, some AI solutions can exceed human capacities and intelligence, and be used to serve more sustainable production (Sparrow et al., 2021).

AI composes programmes and algorithms in the form of software that often can be embedded in physical devices, such as drones, cars, humanoid robots, or agricultural machinery (broadly construed as "robots"). For this paper, we include AI software and AI robots in our analysis of AI in agriculture. However, it must be made clear that there is a distinction between smart and non-smart digital technologies, as well as between AI robots and non-AI robots. Non-smart technology examples are websites, electronic commerce, social networks, whereas smart technologies are IoT, AI and Blockchain. As well, non-AI robots are, e.g., milking robots, that have been used on the farm for decades, whereas AI robots carry out tasks that require context awareness, learning, problem-solving, and logical reasoning, which are traditionally understood as human capacities. AI robots in agriculture are still relatively new but have been adopted for scouting crops, controlling pests and weeds, harvesting, spraying, pruning, and sorting.

To make sense of the potential of AI, it is important to distinguish the different types of AI. In principle, three different AI categories can be distinguished. (1) *Artificial Narrow Intelligence (ANI)* relates to machine intelligence that equals or exceeds human intelligence for a particular domain, such as chess, self-driving cars, disease detection, or automated plant classification. ANI has been proven for various domains, and it is expected that the number of domains in which ANI is applied will grow further. (2) *Artificial General Intelligence (AGI)* refers to a computer that is as smart as a human being and can perform intellectual tasks that a human being can. (3) *Artificial Super Intelligence* refers to the hypothetical intelligence that greatly exceeds the cognitive performance of humans in virtually all domains of interest (Bostrom, 2014).

For the purpose of this paper, we will solely focus on artificial narrow intelligence because it is what is currently being implemented and both general and super intelligence are still in development and have not reached practical applications yet. Furthermore, we will apply artificial narrow intelligence to specific applications of the agricultural domain. This can be divided up between livestock and crop management. While the application of AI to livestock management is important, there is much less of a focus on it in the literature, so we opted to primarily focus on the application of AI in crop applications, such as soil management, pest and weed management, disease management, crop management, and water-use management (Figure 2).

Figure 2 shows the relation of AI approaches to agriculture. From the literature, we can state that current approaches are mainly focused on narrow AI in selected agriculture domains (and mainly focused on crop applications).

Agricultural AI often clusters many different sources of data; for example, high-resolution aerial images, temperature readings, humidity measurements,

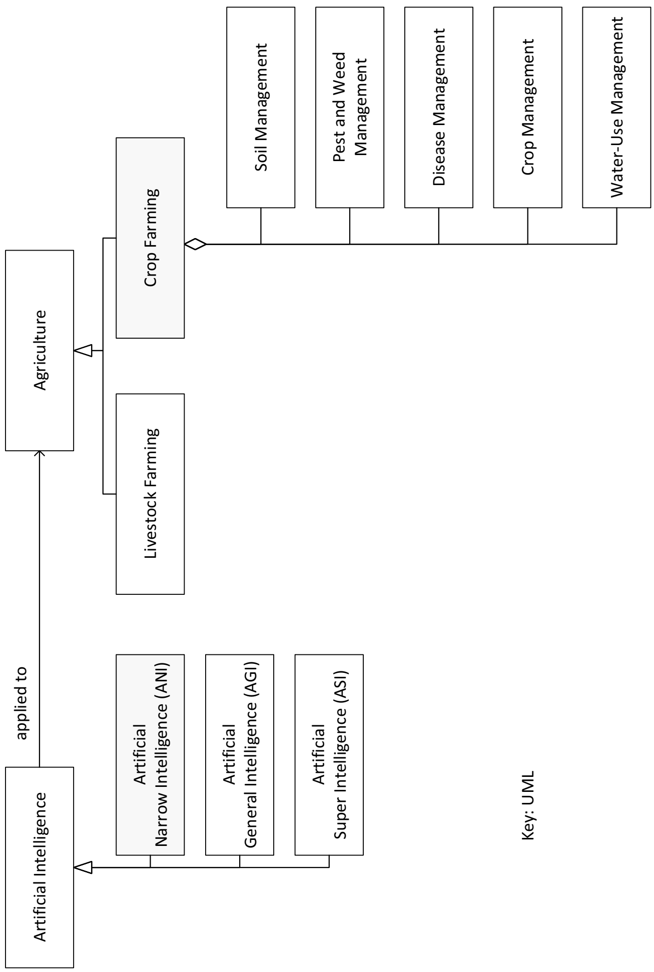

Figure 2. AI types and agriculture domains.

rainfall, soil samples, terrain type, equipment utilised, planting rates, applications, and uses various learning techniques. It applies hyperspectral analysis, computer vision, machine learning and deep learning to identify patterns and build a complete and precise situational representation of every monitored field for the entire growing season (Cook & O'Neill, 2020).

AI integrated into drones, tractors, and other farming machinery are meant to measure, determine, and recommend the best ways to farm. Precise advice about how and how much to spray, how often, and when to harvest, are all being given to the farmer. For example, drones are an effective means for spraying fields, taking aerial photos, and providing data that was not previously possible. They have also been used to map land, scout ways to improve the farm and give insights about obstacles on the farm. Self-driving tractors offer the potential to allow farmers to concentrate on other tasks and ease the burden of tractor use. Robots are also being used for many other purposes: the SWEEPER robot harvests bell peppers, LELY robots collect manure from stables, the "Weed Wacker" robot extracts weeds from arable farms, and NAIO Technologies are developing robots to hoe and harvest (Ryan et al., 2021).[3] In addition, drones are being deployed to measure crop health (see Agribotix) and to plant seedlings (Duckett et al., 2018).

Moreover, sensors and cameras are being installed around the farm as input for AI analysis. Sensors and cameras measure necessary parameters, such as soil and plant humidity, pest presence, and animal behaviour. These parameters are used by AI to develop decision-support systems and to help farmers make accurate predictions. Processed images can be used for rigorous field analysis, monitoring crops and scanning fields. When combined with computer vision technology, AI can help farmers take rapid actions whenever needed (Lezoche et al., 2020).

With the increased potential to store and process data quickly, innovation and productivity can be increased (Wolfert et al., 2017; Krisnawijaya et al., 2022; Weersink et al., 2018; Coble et al. 2018). Sensor technology, the internet of things, and cloud computing real-time data can be used to support the various agriculture domains such as soil management, pest and weed management, disease management, crop management and water-use management (Basnet & Bang, 2018. Data analytics is not only useful for describing but also predicting the weather and environmental conditions that impact the agribusiness supply chain. The health of crops can be monitored, predictive and prescriptive analytics can help farm management decision-making.

The use of AI within agriculture also allows farmers to identify the health of their plants and identify if they are sick, and what can be done about it (Ryan, 2019). AI has also been used to map the growth cycles of crops, when to

[3]See: http://www.sweeper-robot.eu; http://trimbot2020.webhosting.rug.nl; and https://www.lely.com/solutions/housing-and-caring/discovery-collector.

harvest, and provide market pricing and other insights. Table 1 presents the five main applications of agricultural AI.

While precision agriculture has been around for a few decades, AI offers new opportunities and challenges. The following sections will highlight some of the main economic, environmental, social, ethical, and technological impacts, of using AI in the agricultural sector.

Table 1. Five main applications of agricultural AI.

Application	Description of the Application Area
Soil Management	AI for soil management uses management-oriented modelling, decision support systems, fuzzy logic, and artificial neural networks. Neural networks have highly demanded predictive abilities on e.g. soil structure, temperature, texture, nutrients and moisture. However, this technique requires big data which is not always available and is sensitive to failure if the meteorological conditions are unpredictable (Eli-Chukwu, 2019).
Pest and Weed Management	AI for pest and weed management helps farmers accurately monitor and identify infected plants, handle the disease quickly and reduce further spread. Having real-time data at hand, farmers can take quick action to avoid losses. AI used for weed management include artificial neural networks using genetic algorithms (Tobal, 2014), sensor machine learning (Liakos et al., 2018), digital image analysis (Gerhards & Christensen, 2003), learning vector quantisation (Udupi, 2019) and artificial neural networks for weed detection (Yang et al., 2002).
Disease Management	AI for disease management can improve on-farm management of pests and diseases (Cook & O'Neill, 2020). Early detection of diseases is essential for disease management (Khoshnevisan et al., 2020). Captured images of crops and animals serve as input for AI to analyse e.g. plant leaf images and detect healthy and infected areas of the leaf way before it becomes visible to the human eye (Bestelmeyer et al., 2020). AI-based image recognition systems can recognise plant diseases with a high degree of accuracy (Liu, 2020). AI used for disease management include computer vision systems (Kakani et al., 2020), a genetic algorithm trained artificial neural networks (Fang et al., 2007), a web-based intelligent disease diagnosis system, fuzzy logic (Kolhe et al., 2011), and a web-based expert system (Thomson & Willoughby, 2004).
Crop Management	AI for crop management provides tailored recommendations on crop choice, seed choice, and optimal pest management, and where crops require water, fertiliser and pesticides (Dharmaraj & Vijayanand, 2018). This allows farmers to act preventively. CALEX (Plant, 1989), PROLOG (Lal et al., 1992), FARMSYS (Lal et al., 1992), ROBOTICS Demeter (Pilarski et al., 2002), and artificial neural networks (Kamilaris & Prenafeta-Boldú, 2018), are used to manage crop growth and health. In larger farms, AI is used (e.g. remote sensing with hyper spectral imaging and 3D laser scanning) to map and monitor crops over thousands of acres (Dharmaraj & Vijayanand, 2018). They can predict crop yield, detect nutritional disorders with up to 90% accuracy (Eli-Chukwu, 2019).
Water-use Optimisation	Sensors that measure soil and plant humidity transmit real-time data to the AI management systems, where optimal water use is calculated. Water use optimisation (which is very often linked to water use reduction) can lead to a yield increase. Kakani et al. (2020) show examples of how a yield increase can be achieved when the irrigation system is managed by smart systems and combined with the soil characteristics and meteorological data (Kakani et al., 2020).

4. AI for economic performance in agriculture

Technology has always been central in social and economic research due to its impact on firms, industries, and economies, on the labour market and human capital (Gentili et al., 2020). Digitalisation has received increasing attention in economic research in the agricultural domain. The number of firms adopting AI technologies has remarkably increased the last decade (T. Davenport et al., 2020).

In general, agriculture is constrained by various requirements, such as food quality and human health, production optimisation without increasing fertilisers, antibiotics, and anti-pest treatment use. Another major challenge for agriculture is seasonality. Each season (and year), the production circumstances vary, climates change, and prices for farming materials (such as seed prices) fluctuate. Additionally, soil loses quality, weeds grow in unpredictable ways, pests are not always foreseen, and viruses create unexpected epidemics and pandemics among animals (Eli-Chukwu, 2019). Primary production, therefore, entails complicated and risk-taking decisions during uncertainties (Sparrow et al., 2021). Agricultural AI is promoted to address these challenges (Mhlanga, 2021; Sparrow et al., 2021), and accordingly, AI has an impact on the agricultural economy. In agriculture, AI-powered technologies are expected to impact the industry, including the way that food is produced, processed, and consumed (Dolfsma et al., 2021).

The literature emphasises economic factors and business opportunities as main drivers behind agricultural AI. As a result, these discussions largely focus on the benefits and advantages of adopting AI (T. H. Davenport, 2018). Some of the economic drivers of AI in agriculture are innovation, productivity, savings (e.g. reduced equipment costs, reduced human error), enhance analytics and accuracy (inspection and disease assessment), monitoring and improvement of food quality, and even efficient market strategies (Cubric, 2020; Sood et al., 2022).

Agricultural AI is used for more efficient production with less resource use (such as water, land, pesticides, fertiliser) while increasing the farmer's return on investment (Cook & O'Neill, 2020). On the one hand, the use of AI has the potential to reduce variable costs through efficient use of labour and resources and precise actions. Seo and Umeda (2021) have found cost reduction in the use of AI via smart aerial vehicles (e.g. drones) in Japanese rice fields. This technology appeared to provide up to 15% more cost-efficient compared to traditional sprayers (Seo & Umeda, 2021). Through precision control and systematic monitoring of inputs (e.g. water, soil, fertiliser and pesticides), the production costs can be decreased (Haque et al., 2021). Eli-Chukwu (2019) found at least 60% accuracy in weed detection when using AI. AI for pest and weed management technologies are cost-effective and enhance performance through time-saving (Eli-Chukwu, 2019). AI technologies are cost-effective mainly due to their predictive features, and ability to reduce errors (Eli-Chukwu, 2019). Schimmelpfennig and Ebel (2016) show a significant reduction of production variable costs in farms that use AI-related technologies compared with the traditional farms (Schimmelpfennig & Ebel, 2016).

However, there are also economic challenges to AI-use, such as high investments (e.g. highly qualified and expensive labour forces, expensive equipments, installations, training and maintenance costs), insufficient support infrastructures (e.g. Wi-Fi, cloud storage), and the sustainability questionability of AI. Agricultural AI is reliant on sensors, cameras, smart weeders and tractors, to retrieve data. These technologies are relatively new to the market, are expensive and often sensitive to maintenance. Additionally, the integration of systems is needed to link available data and create systemic AI, and that comes with higher costs for storing and handling data (Gallinucci et al., 2020). Moreover, AI requires physical, human and capital investments, continuous updating and upgrading (Lassoued et al., 2021). While the cost of digital products is expected to decrease with technological improvement, the initial costs and maintenance remain an obstacle to the introduction and adoption of AI-powered technologies (Lassoued et al., 2021; Seo & Umeda, 2021). Also, software updates are regularly required, and unfortunately, are not always free of charge (Awasthi, 2020). Hence, farmers need to anticipate the frequency of updates and maintenance in cost-efficiency calculations (Awasthi, 2020). Currently, farmers are often reluctant to invest in expensive devices that are served by AI-powered systems requiring regular updates.

Therefore, AI solutions that rely on data provided by expensive digital devices are often not affordable for small farms, especially in emerging economies (Dharmaraj & Vijayanand, 2018). Smallholder farmers do not have the necessary start-up capital to invest in AI (Cook & O'Neill, 2020) or can afford the costs of maintenance (Seo & Umeda, 2021). Consequently, economies of scale due to cost-efficiency make the impacts dependent on farm size. Agricultural AI often provides a greater benefit to larger farms (Rotz et al., 2019). Larger farms apply the start-up costs easier and book more reduced variable costs than smaller farmers (Schimmelpfennig & Ebel, 2016). The efficiency of using AI, for example through unmanned aerial vehicles, was measured higher, than traditional sprayers, in farms bigger than 10 ha (Seo & Umeda, 2021). Although the price of technologies is expected to go down over time, the benefits are often more visible for larger farms, making it more difficult for smaller farms to see the advantage of investment (Seo & Umeda, 2021). The question here is, therefore, to what extent the use of different AI technologies can polarise farming providing benefits to large-scale industrial farms and agricultural productions and leaving small-scale farmers behind.

Regarding the impact of AI on risk management, the literature is scarce in providing empirical evidence. In general, food production takes place in highly unpredictable environment due to fluctuations in weather, food quality demand, market, and therefore, the risks are higher (Isakhanyan & Dolfsma, 2020). The ability of agricultural AI to analyse and predict for crop cultivation, harvest times and conditions, potential pest attacks, water level use, and forecast soil conditions (Dharmaraj & Vijayanand, 2018; Liu, 2020) can determine the likelihood of successful production. Agricultural AI can reduce uncertainties (Kakani et al., 2020), as well as human errors. For example, a forecast of harvest can reach up to 96% accuracy (Awasthi, 2020). This offers huge potential for risk management in terms of harvest loss on the farm.

Early detection of diseases is essential in the farming (Khoshnevisan et al., 2020). Traditional crop health monitoring is labour-intensive and time-consuming (Liu, 2020). AI for disease management can reduce risks of on-farm pests and diseases break out (Cook & O'Neill, 2020). Captured crop images serve as input for AI to analyse, e.g. plant leaf images and detect healthy and infected areas of the leaf way before it becomes visible for the human eye (Bestelmeyer et al., 2020). AI-based image recognition systems can detect plant diseases with a high degree of accuracy (Liu, 2020). AI used for disease management include computer vision systems (Kakani et al., 2020), a genetic algorithm trained artificial neural networks (Fang et al., 2007), a web-based intelligent disease diagnosis system, fuzzy logic (Kolhe et al., 2011), and a web-based expert system (Thomson & Willoughby, 2004). These technologies are more accurate (up to 95% accuracy) and cost-effective (Eli-Chukwu, 2019) compared to traditional crop health monitoring methods.

Although the rapid development of AI in agriculture is promising, attention should be given to avoid unintended consequences, such as high investments with long-term payback period (Shepherd et al., 2020), or expensive AI solutions that can polarise the sector (Sood et al., 2022). Additionally, AI brings new risks to the farm as well: overreliance on AI computational alerts. AI technologies are not (yet) perfect and a wrong signal sensing is probable, while food safety is imperative. If the whole process is not fully automated from field to plate, enough security checks need to be incorporated to control if anything goes wrong at the field or storage level. Therefore, human monitoring on-farm is necessary and most probably will always remain essential (Smith, 2020).

5. Agricultural AI in emerging Economies

AI-powered technologies are dominant in higher-income economies, but these technologies are also beginning to take off in emerging economies (Cook & O'Neill, 2020). Farmers in emerging economies often experience a lack of information, knowledge and data on optimal production conditions, such as timely and reliable weather forecasts, pests, and market information to predict demand. AI-powered technologies give farmers access to much valuable information. These technological solutions give recommendations on how to manage risks, improve efficiency, reduce costs, and plant cultivation and harvesting times, according to market dynamics (Cook & O'Neill, 2020), a much-demanded value for farmers, especially in emerging economies.

There is the hope that AI will help farmers overcome market asymmetries in regional and global value chains. This is particularly relevant for emerging economies, where farmers have less access to market information. Agricultural AI that focuses on external factors, uses data on market trends, crop prices, consumer needs, requirements and aesthetics, may allow farmers to make more market-savvy decisions (Dharmaraj & Vijayanand, 2018).

Nevertheless, emerging economies are starting to benefit from the use of AI-based apps (e.g. StellaApp https://www.stellapps.com/) and platforms via mobile phone. Although AI-powered devices are often expensive, AI in mobile applications is relatively cheap so farmers with low income can profit (Mhlanga, 2021). Mobile app embedded AI helps farmers to obtain supply contracts and to reduce the likelihood that they will face market failure, e.g. data collected on livestock, food safety and conservation, reservation equipment used to generate recommendations for the farmer on actions to take. When AI is applied, it can be used to trace the volume and quality measures throughout the supply chain. This information is especially relevant for investors and loan providers (Cook & O'Neill, 2020). Improved traceability of origin and quality reduces market failures, allow farmers to access premium markets whenever they have the right scores of product quality (Cook & O'Neill, 2020). Machine learning technologies generate credit scores and prices that reduce the information asymmetry among value chain partners, as well as give access to microloans and insurance (Cook & O'Neill, 2020). Machine learning platforms also help credit providers to assess the farmer's financial health and the sustainability of their business models. Thus, AI that reduces information and market asymmetries, use local data to provide tailor-made production optimisation, will eventually improve the agricultural sector in emerging economies, while (hopefully) without creating any burden to the environment.

Consequently, AI will reduce the poverty by helping farmers produce more with less input, improve product quality, and by doing so, facilitate the speed to market entry (Mhlanga, 2021). Awasthi (2020) have found that the right moment of sowing crops can increase the yield by 30–40% (Awasthi, 2020). In India, the application of AI at 175 farms has brought about a 30% increase in crop yield per hectare (Dharmaraj & Vijayanand, 2018). Additionally, mobile phone-based AI applications can help through translations, text-to-speech, and speech-to-text functions. Furthermore, capturing crop images and uploading them is often an easy task for farmers, which can allow AI to run crop and field analysis and provide advice on best sowing, irrigation and harvest times (Cook & O'Neill, 2020). AI solutions that can process images and provide advice through mobile apps work well in developing countries (e.g. AgroCares https://www.agrocares.com/products/lab-in-the-box/) and can help solve many agricultural challenges due to their high performance and cost-efficiency (Eli-Chukwu, 2019).

However, AI technologies can, in many cases, only be applied when proper infrastructure is in place, e.g. telecommunication and internet coverage, transport and irrigation systems, and data protection protocols (Cook & O'Neill, 2020). Most AI systems rely on the internet, which is particularly restrictive in poor and remote areas (Eli-Chukwu, 2019). These are challenges that must be overcome for poorer countries to fully benefit from agricultural AI.

6. Social aspects of AI in agriculture

According to researchers (e.g. Rotz et al., 2019), by 2030, 97% of manual labour and pesticide applicators will be automated. However, AI goes beyond automation, and in the future, it aims to replace human intelligence, such as that of farmers, advisors, experts, and agri-food managers. Automation will undoubtedly have an essential impact on labour in the short and long term. However, with more use of AI, new roles emerge that require human skills, such as human judgement in complex and, for AIs, yet unsolvable situation. Currently, AI systems replace automated actions that are labour-intensive and require little or no professional judgement (Clifton et al., 2020). In agriculture, human judgement is still often needed to ensure standards are met and new insights are detected (Smith, 2020) to avoid food safety issues.

Researchers also expect that farmworkers and advisors will be difficult to fully replace with AI. However, farm workers will need to learn and develop new skills, such as working with AI systems, data analytics and interpreting the AI outcome (Smith, 2020). In this context, automation and agricultural AI improvement are expected to take over physical and intellectual tasks, unburden the farming jobs, and meet the (seasonal) shortage of farmworkers, rather than being a threat to employment, at least for the coming years (Lakshmi & Bahli, 2020; Legun & Burch, 2021).

Consequently, agricultural AI demands high-skilled labour in the sector. High technological and engineering skills are required from farmers. The need for new roles, such as digital farm advisors, rises (Smith, 2020), such as advisor humans or chatbots or a combination of both. Effective AI application requires skilled analytical skills and specific agronomic expertise (Lassoued et al., 2021). Therefore, employees with high technological skills in combination with agri-food expertise are needed to successfully deploy AI (Lassoued et al., 2021; Rotz et al., 2019). This creates a shift from low-skilled labour towards expensive AI technologies and conjoined expensive skilled staff (Ciruela-Lorenzo et al., 2020; Rotz et al., 2019). Thus, AI creates new jobs for higher-skilled employees in the industry (Ciruela-Lorenzo et al., 2020; Seo & Umeda, 2021) and by doing so, will probably in a long-term attract the population to live in rural areas (Ciruela-Lorenzo et al., 2020).

Due to the dynamic nature of agricultural practices, and changing environment, the collection of more and improved data allows a better prediction, but it also demands new skills in data interpretation into actionable insights (Smith, 2020). Thus, the labour demand will not change, but the roles and functions will do.

Agricultural sector faces a huge labour shortage and ageing farmers, especially in advanced economies. Robotics-based AI is an opportunity to solve labour shortage issues in especially high-income countries with ageing farmers (Smith, 2020). Language-based AI, in contrast, can translate the tasks helping foreign employees get going even if they do not speak the local language (Smith, 2020). This might lead to an easier and freer labour movement across borders. Nevertheless, less-trained workers that run routine tasks are prone to be replaced by AI robots (Clifton et al., 2020). Here, we identified a gap in the literature that when discussing the benefits of AI the impact on low-skilled labour are often neglected.

Finally, AI systems are safety-critical systems, the failure or malfunction of which may result in serious harm to people or the environment, cause loss or severe damage to equipment and property (Knight, 2002). AI robots lack a deeper understanding of their surroundings and once an object is out-of-vision, it ceases to exist. While self-driving tractors are trained on recognising visible objects (Vernaza & Rhinehart, 2019), other objects that exist outside of their range of vision are ignored. Thus, current AI robots lack the understanding of object permanence (Kakani et al., 2020). Developing an ability to detect objects beyond the vision is a technical challenge, while a failure of such AI-powered technologies can create ethical impacts such as harm to the farmer or their livestock.

7. Environmental aspects of AI in agriculture

Much of the literature focuses on the environmental impacts of AI (Albiero, 2019; Bogomolov et al., 2021; Krishnan & Swarna, 2020; Ruiz-Real et al., 2020; Vasconez et al., 2019). The literature claims that agricultural AI can improve the sustainability of food production and consumption. The main discussions in the literature focus on resource use optimisation, negative impact reduction in terms of leaching and biodiversity, as well as food availability and food safety (Ciruela-Lorenzo et al., 2020; Dharmaraj & Vijayanand, 2018; Liu, 2020; Smith, 2020). AI-powered technologies hold promises for reducing negative impacts of farming practices by allowing less fertiliser and pesticide use, enhanced accuracy of pest and disease detection, reduced water use without reducing the production level (Ciruela-Lorenzo et al., 2020; Cook & O'Neill, 2020). Thus, agricultural AI can reduce the negative impact on the natural environment and resource use (Hatfield et al., 2020). As AI-powered technologies are expected to become cheaper and increase production efficiency, AI in agriculture is perceived as one of the solutions to feed a growing population, preserve natural resources and the environment at the same time (Eli-Chukwu, 2019). Although the scholars are explicit in their expectations, hardly any empirical evidence has been published.

However, good evidence is found in predicting food quality. Penning et al. (2020) measured between 81.5% and 99% accuracy in predicting quality traits when applying AI (Liu, 2020; Penning et al., 2020). Real-time estimations of crops, lands and areas indicate where crops require water, fertiliser and pesticides (Dharmaraj & Vijayanand, 2018). Advanced AI predictive analytics, thus, help farmers protect natural resources, i.e. land, air, and water, and reduce the number of inputs needed for successful harvests (Hatfield et al., 2020; Liu, 2020).

Nevertheless, while agricultural AI offers many solutions and ways to adopt more environmentally sustainable practices, it also needs to consider potential harms on the natural world. For instance, AI robots should be designed to avoid leakage of toxic material or pollutants, and not stress, harm, or kill animals on, or around, the farm (Ryan, 2019). Carolan (2020) states that the way the AI is deployed needs careful attention, so that it does not become a way for humans to control and dominate nature. For example, using AI should not alter biological life (such as plants) to better accommodate AI robots on the farm (so it is easier for the robots to pick fruit, for example) (Sparrow & Howard, 2020).

8. Ethical aspects of agricultural AI

While AI provides economic and social benefits and opportunities for the agricultural sector, the development, implementation, and use of AI should be in an ethical way. In recent years, the sub-field of AI ethics[4] has emerged because of the monumental impact that AI can have on human lives in the coming decades. AI ethics is important for all domains of application, but

[4]This section does not go into the diversity of ethical frameworks (e.g. utilitarianism, Kantianism, and virtue ethics) that could be applied in such analysis, but will take a more pragmatic approach, providing concerns, impacts, and debates, around ethical topics and themes within the agricultural AI literature. While these frameworks may be useful for providing prescriptions and recommendations, the level of analysis aims at collecting the diversity of viewpoints on ethical issues, rather than limiting to one framework, which may exclude many relevant ethical topics discussed within the debates.

often has a different emphasis or different issues take a greater significance, depending on the context, application, and stakeholders involved.

One of the main concerns of agricultural AI is the health and safety of farmers (Vasconez et al., 2019). Some claim that AI allows farmers to maintain their farms more safely, reducing exposure to chemicals that impact their health (Rodzalan et al., 2020). AI may also help reduce accidents on the farm (Ryan, 2019a; Vasconez et al., 2019). Others state that AI may be more harmful (to others, e.g. through greater pesticide use) because it allows farmers to take greater risks, as they are not directly harmed (robots are, instead) (Gardezi & Stock, 2021). In addition, farmers may also be placed at greater risk of sabotage, hacking, and malpractice from others, if their farm is more digitalised (Carolan 2020). There is the threat that farm machinery will be hacked and used for malicious purposes, costing farmers money, creating stress, and damaging their business (Ryan 2019).

While AI offers many advantages, it should be implemented in an ethically sound way to ensure that it is used inclusively and fairly (Aggarwal & Singh, 2021). This is to ensure that farmers are also able to benefit from the incorporation of AI on their farms, instead of it simply being beneficial for agribusinesses (Ryan 2020). Farmers should be allowed to question these impacts and direct the development and use of AI in a responsible way (Rose & Chilvers, 2018). It should be clear how farmers benefit from the deployment and use of AI on their farms.

The introduction of AI also often brings confusing legalistic and technological contracts that the farmer must sign to avail of these services (Ryan, 2019b). This has caused problems, with many agribusinesses now prohibiting farmers from repairing their machinery or limiting what they can do on their farm, which disrespects the freedom and autonomy of the farmer. Furthermore, farmers may be told that AI decision-making is better than theirs, which impacts the choices they take (Gardezi & Stock, 2021). They "give over" control to the AI system, despite apprehensions about those decisions. They must believe in AI decision-making because it is more "scientifically authoritative" or because they invested so much money into it, that they feel that they have to (Ryan, 2020; Ryan, 2022).

Some papers criticised "Big Tech" and agribusinesses for not including farmers in how AI is designed and implemented (Camaréna, 2020; Ryan, 2019b). Farmers need to be included in this process to ensure that they can co-develop AI that benefits them (Camaréna, 2020). Farmers should also not feel pressured or forced to adopt AI (Gardezi & Stock, 2021). Sometimes, farmers feel that they are left with the choice of either adopting AI and being seen as innovative and forward-thinking; and if they do not, they are seen as regressive and lazy (Gardezi & Stock, 2021).

AI use may also cause digital divides within the agricultural sector, between those who can afford it or are willing to accept the terms and conditions of agribusinesses, and those who cannot, or will not (Ryan, 2019a, 2019b). A digital divide is when there is an inequality in access to digital technologies. This digital divide could materialise between smaller and larger farms, richer and poorer farmers, or between the Global North and South. Others have pointed out the historical gender imbalances within agriculture and STEM, which may exacerbate with greater digitalisation and AI use (Carolan, 2020). While there has been development and innovation of agricultural AI in recent years, they are still far from fulfiling most tasks on the farm (Ryan, 2019a).

There was some concern in the literature that AI robots will replace seasonal and immigrant workers (Carolan, 2020). Others claim that AI robots may bring improved welfare to those working on the farm, making it a safer and more enjoyable profession (Carolan, 2020; Rose et al., 2021; Klerkx, Jakku, & Labarthe, 2019; Rodzalan et al., 2020; Stock & Gardezi, 2021). There is a need to incorporate AI because of the increasing labour prices, the demographics of farmers are ageing, and there will be future staffing problems (Carolan, 2020; Rose et al., 2021; Klerkx et al., 2019; Rodzalan et al., 2020; Stock & Gardezi, 2021).

Data retrieved and used by AI also raises concerns about the privacy of the farmer and those working on the farm (Wang et al., 2021). Farmers are sometimes forced to decide between the benefits of using AI and trade-offs to their privacy or forego the use of AI and risk being left behind (Stock & Gardezi, 2021). In one study, 78% of the farmers said that they were worried about corporations selling their data (Stock & Gardezi, 2021). As a result of this threat, it adds to the strong degree of mistrust within the sector (Christos et al., 2021). This is partly exacerbated by the uncertainty over control of data, which could be used against them (R. Ryan, 2019, M. Ryan, 2022). Farmers are worried that AI will be implemented on farms to surveil them, but also, to use data retrieved about them for malicious purposes. It could be used to sell more products, sold to other businesses, or given to the government to be used against them (Ryan 2020). In other circumstances, agribusinesses have pressured farmers to become customers of their seeds or machinery to avail of their AI solutions (Ryan 2020).

While ethical challenges and issues can certainly be analysed in isolation, their solutions may not always be so easily addressed from within the silo of ethics. Many of the challenges listed in this section may even require technical or economic solutions entirely. For example, much of the potential physical harm done by AI may be dramatically reduced if the technology is robust and functions correctly. The digital divide and inequality caused lack of access to agricultural AI may be alleviated by sufficient economic policy and governance. Therefore, it is important to link these ethical challenges with other disciplines in an overall interdisciplinary approach.

9. Technological aspects of AI in agriculture

One of the defining characteristics of AI is the types of computer science approaches typically used. In soil management, for instance, artificial neural network (ANN) models predict soil texture (sand, clay and silt contents) based on attributes provided by soil maps combined with hydrographic parameters (Zhao et al., 2009). The neural networks can then characterise and estimate soil moisture dynamics (Eli-Chukwu, 2019). Artificial neural networks cope with unstructured data and need a tremendous amount of data for training. While natural language processing (NLP) focuses on non-numeric data, specifically, understanding human language, the contents and contextual nuances, which can effectively understand the requests of farmers.

These applications of AI open new avenues in farming (Kakani et al., 2020). They support agricultural industries to become more efficient, intensive and advanced, through decision support, marketplaces, digital management and optimisation, financial services, livestock solutions, irrigation solutions, and plant treatment optimisation (Cook & O'Neill, 2020). Along with the increased benefits of these methods, some technological challenges need to be addressed for farmers and the industry to effectively benefit from AI.

With the increased need for digitalisation, computing power and proper resource management has become also critical for the agricultural domain (Perakis et al., 2020), (Silva et al., 2014), (Singh et al., 2020). For the use of AI in agriculture, high-performance computing is necessary to provide efficient solutions (Triantafyllou et al., 2019), (Ferrandez-Pastor et al., 2016), (Chen et al., 2015). For example, climate data, environmental data is used to apply smart data analytics to support water and drought management in vulnerable areas (Bryan, 2013; Viktor et al., 2021). The storage and the processing of the huge data and the analytics for the decision-making processes in these domains are not possible without a high degree of computational power. The access to this computation power and the knowledge and skills to map existing agricultural problems to parallel algorithms on HPC is a challenge for applying AI in the agricultural sector.

The quantity and quality of data are very important for the robustness and accuracy of AI. A challenge in developing effective AI is having large repositories of training data. Within the agricultural sector, data is often limited due to a lower technological literacy than other fields and (sometimes) a lower willingness among farmers to share data with "outsiders" (Ryan et al., 2021). This harms the effectiveness of AI. The absence of proper training datasets impedes AI's ability to function correctly (Cubric, 2020).

Agricultural data are also dependent on the seasonal cycle. In crop production, for instance, harvest data can be obtained once or twice a year. The database for AI training, thus, takes time to mature and it takes several years to construct a robust AI model (Dharmaraj & Vijayanand, 2018). Because agricultural systems are unpredictable and changeable (Bestelmeyer et al., 2020), also due to climate change, much of the available data is not sufficient to reach the desired accuracy of predictions. For example, crop production is variable, depending on changing weather conditions, seasons, and so forth. Cultivation plans that schedule seeding and harvesting should be flexible to include these parameters (Dharmaraj & Vijayanand, 2018). Due to the seasonality of the agricultural sector, AI technologies need a long time to be developed, which creates a huge time-lag for replication validity (Cook & O'Neill, 2020).

If there is available and suitable data, pre-processing techniques are still needed for training, testing and validation of the ML models. Multiple ML algorithms might need to be selected and tuned for selecting the most feasible algorithm. For the best results, often large data sets are required, and the training and testing are time-consuming. Once the ML models have been prepared these need to be deployed in the target context. This is also an important challenge due to the absence of deployment skills, third-party library dependencies, the size of ML models, the complexity of real-world scenarios, and limitations of the deployment platform (Meshram et al., 2021).

In recent years, both shallow machine learning (ML) and deep learning (DL) have gained attention in different domains and stages of agriculture (Joshi et al., 2011,Ghaffarian et al., 2021, Athey, 2018; Meshram et al., 2021). ML has been applied in different stages of farming including pre-harvesting, harvesting and post-harvesting. ML has also been used for different risk assessment types (Almeria et al., 2009; Chavez et al., 2015; Esgario et al., 2020; Picon et al., 2019; Taneja et al., 2020; Zhong & Zhou, 2020), including

(i) production risk, e.g. for crop leaf disease detection (Zeng and Li, 2020);
(ii) (ii) Financial risk, e.g. evaluation of insurance risk in case of climate change using different regression models (Lyubchich et al., 2019);
(iii) (iii) Institutional risk, e.g. assessment of the seeding policies in the face of climate change (Westengen et al., 2019);
(iv) (iv) Market risk, e.g. a heuristic ML approach for agriculture supply chain risk assessment (Yan et al., 2019);
(v) (v) Personal risk, e.g. artificial neural network (ANN), K-nearest neighbours (K-NN), and support vector machines (SVM) methods to evaluate the effects of the pesticides and/or cigarette smoke to farmers' health (Tomiazzi et al., 2019).

While ensuring the technological capacity and functioning of agricultural AI is fundamentally important, implementing technical solutions without interdisciplinary consultation runs the risk of overlooking important issues and requirements. For example, while relying on comprehensive datasets is a requirement for effective agricultural AI use, if these datasets go unquestioned, there is the possibility that agricultural AI will use discriminatory and harmful biases found within such datasets. In addition, the importance and use of high-speed computing for developing agricultural AI should be contrasted with the high power consumption and processing required. The potential sustainability of developing and deploying agricultural AI should not be evaluated apart from the huge environmental impact that it will have on the planet.

10. Interdisciplinary alignment of AI in agriculture

In single-disciplinary research, a problem is tackled from one scientific discipline. In interdisciplinary research, experts from different scientific disciplines collaborate on a common theme or issue. On the other hand, interdisciplinary research requires the insight and synthesis of ideas from multiple disciplines to provide a solution that meets diverse concerns.

As we have shown in the previous sections, there are many interwoven and complex challenges from various disciplines that need to be addressed when developing and using AI in the agricultural sector. We mapped some of the most significant challenges within five disciplines in the context of agricultural AI, demonstrating an abundance of issues that often do not have straightforward answers. Agricultural systems using AI usually have to cope with more than one of five disciplines (economic, ethical, social, technological, environmental). Many of the problems intersect and overlap within these different disciplines or have residual or knock-on effects with one another. Hence, all the relevant disciplines need to be considered to provide a proper solution and avoid incomplete or conflicting solution alternatives. For example, if AI is not affordable for most farmers (economic), this will create a digital divide between those who can afford it, and thus benefit from it (ethical). This could have an impact on further research funding for topics related to AI technology in agriculture, impeding advancements in the area (technological), while also impacting the potential sustainability benefits from deploying AI (environmental) and relieving strains on a reduced labour force in the sector (social).

In addition, there is a need for interdisciplinarity in the field because if these disciplines work in their silos, they may not benefit from, and even lose out, on the knowledge and insights from one another. There is a need for greater communication between disciplines so that they can implement the insights from other fields, can develop AI in a more beneficial way, and can implement AI in a more sustainable and practical way. For example, if and when agricultural AI is developed with solely economic benefits in mind, this could lead to privacy infringements, destruction of crops, harm to the farmer or farm worker, or disenfranchisement of the farmer and their control of the farm. Similarly, if agricultural AI development solely focuses on technological aspects, then there is the potential that the technology will be designed without a sound business model, and the AI research could end up being discontinued. Likewise, if agricultural AI development only focuses on the ethical issues and challenges involved with the technology, it may overlook the technological developments and economic benefits that it can bring, impeding it from being developed altogether.

Overall, AI in the future may replace some human labour, augment human capabilities, and transform data usage for macro and micro-economic growth (Bessen, 2016). Although the rapid development of AI in agriculture is promising, attention should be given to avoid unintended consequences and risks from AI (Shepherd et al., 2020). The early introduction of AI may be profitable due to the market's pioneering position, but it may also entail technological faults or raise ethical issues. The building of technologically robust AI may, on the other hand, be economically unsound if it does not meet a specific market demand. In addition, if ethical aspects are not considered when designing agricultural AI, this may cause harm to individuals and the environment, and infringe upon the autonomy and privacy of users. Therefore, the future of AI should not be left in the hands of one discipline entirely, and active interdisciplinary engagement is fundamentally needed (Clifton et al., 2020). An interdisciplinary approach may help ensure stakeholders' interests are considered and new and effective solutions are found for building agricultural AI ecosystems (Shepherd et al., 2020; Wolfert et al., 2014).

As part of the interdisciplinary alignment that we propose in this paper, we held a workshop with 10 academics and professionals working in the area of AI in agriculture to discuss the findings from our literature analysis and our proposal for greater interdisciplinarity in the field. We aimed to find out their critical thoughts about the challenges and impacts covered in the literature, to debate the representativeness of the literature results, and to postulate on possible interdisciplinary research areas and ways forward in the face of such issues. Overall, the main research question for the workshop was: To what extent do the disciplinary challenges found in the literature review require interdisciplinary solutions?

One of the findings from the workshops was the need to improve accessibility of AI in the agricultural sector. The participants stated that while technological solutions aim to improve economic performance, more near-term solutions are needed, such as agricultural AI-as-a-service or leasing AI solutions to farmers, rather than requiring high initial investment costs (workshop participants, 2021). Instead of paying a lump sum for hardware devices, there should be options to rent or lease, or pay-by-harvest solutions that stimulate investments in agricultural AI (Awasthi, 2020).

The participants stated that in many countries farmers cannot afford basic production resources, such as seeds, let alone highly expensive tractors, farming machinery, and AI-powered systems (workshop participants, 2021). However, mobile phones are relatively inexpensive in many countries, and the added benefit of using AI applications through mobile phone could bring great improvements and benefits to the farming practices. Relatively affordable AI solutions reduce the lack of access to resources impacting farmers' welfare; ethical issues caused by digital technologies identified earlier (workshop participants, 2021). The digital divide could be reduced by ensuring the distribution of mobile phones, development of affordable AI applications or schemes to increase their adoption. Perhaps, governments could play an important role here as well, particularly in developing countries where their extension services are still run by a public institution. Currently, there are other institutes (e.g. CGIAR) that are playing a role in this (see https://bigdata.cgiar.org/) (workshop participants, 2021).

As discussed in previous sections, one of the fundamental requirements for adopting AI is that it provides accurate, tailored recommendations and can work as intended (Lokers et al., 2016). Accurate recommendations and technological solutions are often part of an ecosystem (e.g. farming system) that requires integration of metadata, field data and expert opinion (Eli-Chukwu, 2019). However, these data can source from different timelines and be non-standardised causing AI to deviate from the original purpose. Undoubtably, AI should be developed to meet a specific and needed purpose. To maintain the fit-for-purpose, a critical, interdisciplinary discussions and regular measures during all stages of AI development, deployment, and use are needed (workshop participants, 2021). The benefits and added value should be outlined from the start in a way that ethical concerns provide the impetus for the acceptable and trusted design of agricultural AI (workshop participants, 2021).

One way to build this trust is through better access to training and education of farmers using AI solutions. The literature analysed for this paper stated that the information asymmetry between farmers and AI developers on how to use agricultural AI is large (Mhlanga, 2021). Working with and maintaining data, and understanding software and its updates, demands special skills that farmers often do not possess (Awasthi, 2020). Farmers need to be educated and trained to use AI-powered devices (Cook & O'Neill, 2020). Strengthening farmers' skills to become familiar with and capable to operate AI is critical for user acceptance and its deployment (Seo & Umeda, 2021). However, many respondents in the workshop discussion stated that farmers should not be burdened with having to become "data scientists" (workshop participants, 2021). AI should be easy to use and minimally cumbersome as possible. AI should be user-centric, improving the lives of farmers (workshop participants, 2021). They also suggested this could be achieved by greater user involvement in the design process and developing robust technological solutions to overcome user concerns (workshop participants, 2021).

The discussions during the workshop often directed towards the needs for greater interdisciplinarity and dialogue for solutions to the challenges raised in the literature. Involving social scientists, economists and ethicists, to provide input about potential challenges for AI development and use is perceived as one of the crucial steps towards robust, trusted, and accepted AI (Sparrow et al., 2021). Interdisciplinary dialogue should bring ideas, insights, and impacts onboard to address challenges at an early stage, rather than later, which may have greater economic costs for the company or create greater ethical problems because of the lack of foresight (workshop participants, 2021). The implementation of critical judgement on AI may provide added insights into the demand of AI application (Sparrow & Howard, 2020), spotting issues with using certain data sources, limitations, and identifying required alternatives.

11. Conclusion

Many of the themes discussed are quite common to other domains and fields, and many are not necessarily unique to agriculture. For example, the competitive advantage of pioneering firms, in equal access to innovation due to high investment costs, and data use privacy. Therefore, agriculture can look to other industries to glean insights, as AI in agriculture is still relatively new compared with domains, such as communication, infrastructure, manufacturing and health.

However, what was demonstrated in this paper is the clear need for an interdisciplinary approach in developing agricultural AI. The agricultural domain requires a careful approach to AI developments as agriculture provides food for human beings to survive. Our dependence on successful methods for producing more food for a growing population is a fundamental requirement, and not simply a luxury product, as the application of AI is in many other domains. It is (arguably) the most fundamental industry for human survival, so the success or failure of AI may have significant ramifications for our place and future on the planet. It is expected that through interdisciplinary collaboration the agricultural AI will become robust, trusted and accepted by the farmers.

We have conducted a literature study and focus group discussions. The main limitation of this paper is the focus on crop farming because the literature published about AI applications in agriculture are on crop production. Additionally, not many empirical research has been published. We recommend empirical studies in various agricultural areas using an interdisciplinary approach. Thus, when studying the business implications also consider the ethical, environmental, and social impacts of agricultural AI.

Finally, this research focuses on the direct impact of agricultural AI use on the farmers and farm workers. However, we expect agricultural AI have impact on the entire value chain: from farm to fork. The research needs to discover the impact of extensive use of agricultural AI on other actors of the chain, such as retail, processing companies, and on cooperatives.

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Appendix

Overall, we established a protocol to ensure the structure of the discussion, the questions, and the themes that we asked, serve the research objective. This included an agenda and a set of sample questions for each of the social-economic, ethical, and technological sections. The main aim of the workshop discussion was to provide participants with our findings to uncover alignment between the three disciplines towards the goal of sustainable agricultural AI.

We carefully selected the participants and invited them to attend the live meeting. Among 21 invited individuals, 10 agreed to join. This comprised of eight men and two women, including AI professors (5; two of which were the women in the group), AI developer (1), business developers for AI (1), managers for research organisations developing and using AI (1), a scientist working on AI (1), an economist working on AI (1).

The workshop discussion lasted two hours with the focus on the three main sections of this paper: 1. economic impacts; 2. ethical impacts; and 3. technological impacts. Within these three sections, we asked participants their opinion on the literature results and if any aspects were missing; and secondly, how can some of the challenges identified in the literature be overcome or addressed in the future. However, it became apparent during the review process, and feedback form the workshop, that two additional sections needed to be added, which did not appear in our original analysis (technical, economic or ethical sections); namely, social and environmental impacts.

The workshop took the form of a roundtable discussion to maximise the input from the participants and to tease out some of the ideas among the group. We took notes and transcribed, and later, analysed and incorporated the findings into Section 9 of this paper. The sample questions that we aimed to ask in the workshop can be seen in the Table below.

Sample Questions
-Costs: how can we make AI affordable for all farmers?
-Crop production appears to be more advanced; do you agree? Why is this?
-Impact on the labour market: how do you view the labour market changing with the widespread introduction of AI on the farm?
-Who is going to pay for the training of the farmers? Are farmers able to train themselves? Do they need to be?
-Do you think AI will bring about the sustainability benefits that it promises? (speculation or reality)
-The impact of AI in emerging markets is higher, but it is also more difficult to apply because of high costs. What are some solutions to this?
-Do you think AI will cause harm to harm on the farm? How can we ensure that these are reduced in practice?
-How do we ensure that everyone can benefit from AI? That nobody is left behind?
-Responsibility: who should be responsible when things go wrong? How do we implement this?
-Data and privacy: can technological methods overcome this? Data in agriculture is non-GDPR proof, usually, how do we protect privacy?
-Employment: what is fair? How can we ensure that individuals do not lose their livelihood livelihood jobs/livelihoods?
-Data availability and data quality (BIG issue!): data is unstructured and unpredictable in agriculture; how can AI be trained on such data? How can AI overcome these challenges?
-Object permanence: Is this a major problem for agriculture? Is it an issue for all AI?
-Technological interference: how can we reduce this?
-Not fit for purpose: which types of AI are better for which processes process applications/processes? Crop production, dairy, etc.?
-Infrastructure: how can we implement this better?