Harvesting Innovation: AI's impact on barriers of organic arable farming adoption.

MSc Thesis

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Abstract

The role of AI technologies in conventional arable farming practices is a topic that has been researched extensively. However, the potential of AI technologies has not been investigated for alternative farming practices like organic farming. Especially, as the switch from conventional farming to organic farming brings about several challenges, the question arises: How can AI technologies mitigate the challenges that arable farmers experience when switching to organic farming practices. Therefore, this research aimed to investigate the potential role of AI in the most important challenges of organic farming and the status of current performance. The relevant data was obtained by interviewing 16 experts on organic farming and AI by performing a linear best-worst method (BWM) and an importance-performance analysis. From the outcome of the BWM, it became clear that economic and environmental challenges are most important for farmers when switching to organic. It was found that the current performance of AI technologies in solving these important challenges is rather low. Nevertheless from the interviews and literature, it became clear that the potential of AI in solving these challenges is high. The results show that there are still many opportunities to increase the use of AI technologies in Dutch organic farming. Furthermore, these findings provide insights into areas that policymakers should prioritize when supporting organic farming. Additionally, they offer guidance to technology companies on selecting specific AI applications to concentrate on.

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List of abbreviations

EU= European Union

SKAL= “Stichting Keur Alternatief voortgebrachte Landbouwproducten” en= Foundation for Quality of Alternative Produced Agricultural Products

MCDM= Multi-criteria decision-making

AI= Artificial Intelligence

BWM= Best-Worst-Method

IPA= Importane-Performance-Analysis

OF= Organic Farming

OA= Organic Agriculture

SDG= Sustainable development goal

TBL = Triple Bottom Line

1.Introduction

The intensification and enlargement of agricultural production in The European Union (EU) over the past century made agricultural production rise to levels that have never been reached (Peer et al.,2020). Despite, the risen food security in the EU, the intensification of agriculture has led to severe changes in important facilities of the ecosystem like carbon sequestration, nutrient cycling, soil structure and functioning, water purification, and pollination (Moonen & Barberi, 2008; Peer et al.,2020). These changes eventually caused the loss of biodiversity and ecosystem services and the changing climate that the EU faces (Peer et al., 2020).
To combat the degradation of the European landscape, the European Commission introduced the EU Farm to Fork Strategy in 2020, a comprehensive and ambitious plan aimed at transforming the European food system to make it more sustainable, healthy, and environmentally friendly (EU Farm to Fork strategy, 2020). For this purpose, 25% of the arable land in the European Union is aimed to be cultivated organically by 2030. Moreover, the remaining 75% of the arable land should also be committed to reducing the use of chemical pesticides and synthetic fertilizers (EU Farm to Fork strategy, 2020).

Organic arable farming is a form of agricultural production that proves to enhance the sustainability of farming practices (Lone, 2023). The major pillars on which organic farming is based are dismissing synthetic fertilizers and pesticides, prioritizing practices such as crop rotation, soil fertility enhancement, and closed-loop nutrient cycles which eventually will lead to greater biodiversity and ecosystem support (Muller et al., 2017).

Although the benefits of organic arable farming are clear there are some major challenges for farmers to switch to organic production. For instance, the crop yields are on average 20% lower in comparison to the conventional growers, labour costs are higher due to increased weed management and limited pest and disease control measures (Łuczka-Bakuła, & Kalinowski, 2020;Migchels et al., 2023). These challenges of organic farming are evident, however technological advancements like artificial intelligence may be able to make the challenges for organic farming lower by eventually leading to fewer bottlenecks (Singh & Jain, 2022; Bellon-Maurel & Huyghe, 2017). This is confirmed by the fact that AI technologies have shown to reduce the dependency on manual labour in several industries including agriculture (Ryan et al.,2023). Also, the ability of AI to perform predictive analyses can have positive influence in detection of pests and diseases (Laniza et al., 2021).

1.1Theoretical perspective

The existing literature on organic arable farming often addresses the possible major benefits that it can have and it reviews the challenges that farmers experience when switching to organic arable farming. However, most studies do not address the relative importance of these challenges, hence it is not clear where policymakers should specifically focus on when tackling these challenges (Muller, 2017; Migchels, 2023).

In addition to the lack of literature on the importance of the challenges that organic farmers experience, there is a lack of literature on the current performance of AI technologies in alternative farming systems including organic farming (Klerkx et al., 2019). While the application of AI in agriculture has gained substantial amounts of papers in literature, much of the existing research has mostly focused on its implementation in conventional farming practices (Bellon-Maurel & Huyghe, 2017). The potential of AI to optimize crop management, better yield predictions, and optimize resource allocation has been extensively investigated in the context of conventional agriculture (Singh & Jain, 2022;)

1.2 Problem statement

Existing literature confirms that AI can have a significant impact on sustainable agriculture practices (Sing & Jain, 2022; Zambon et al, 2019). However, there seems to be a lack of research on how AI technologies can have a transformative role for farmers (Klerx et al., 2019). To be more specific, the role of AI technologies in enabling the transition towards organic farming has not been performed before.

Nevertheless, the little literature that is performed on how digital technologies can enable transition pathways in farming are hopeful. (Bellon-Maurel & Huyghe, 2017). This gap becomes especially relevant in light of the growing importance of organic farming in making European farming practices more sustainable (Koopmans et al., 2021). As the EU requires an increase in organic agricultural area to 25% by 2030, but the current area in the Netherlands is only 3.9% (EU Farm to Fork, 2020). It therefore, seems evident that the role of AI technologies in the further transition from conventional farming to organic farming must be investigated as it is not clear what role AI technologies have in reducing the challenges of organic farming.

Moreover, the barriers and challenges that farmers experience when switching to organic farming practices have been identified in some studies (Scheeberger et al., 2002; Łuczka-Bakuła & Kalinowski 2021). However, most of these studies have been performed a long time ago, which means that there could be new challenges or that there are challenges that already have been solved. Moreover, the importance of the challenges have not been assessed by performing any kind of MCDM method. Nevertheless, these studies form a starting point for identifying the challenges that are relevant to this specific study.

1.3 Objective

The main objectives of this research study are to identify the relative importance of the challenges that Dutch organic farmers face and to identify what challenges can and cannot be solved by AI technologies. AI technologies are thoroughly investigated to assess what implications they can have for organic farming and to what extent they can contribute to the increase of EU organic arable lands to 25%. The research is limited to Dutch arable farmers because of the relatively low share of organic farmers in this country and for practical reasons. By narrowing the scope to Dutch arable farmers only, it is possible to gain in-depth insights into the challenges specific to this subset of the organic farming community. This approach allows to obtain meaningful insights and make practical recommendations for AI technologies specific to the Dutch organic farming community and other relevant stakeholders like governmental organizations, technology companies, and advisory companies in the agricultural industry. In the meantime, it can contribute to valuable knowledge and recommendations that can potentially benefit the broader organic farming community in Europe. To summarize, this study wants to give an overview of the actual challenges that arable farmers switching to organic and organic farmers experience and give an identification of which challenges can be solved with the use of AI technologies in organic farming.

1.4 Central research question

How can the current potential of AI technologies mitigate the challenges of Dutch arable farmers that are switching to organic practices?

1.5 Sub questions:

1. What are the challenges that Dutch arable farmers encounter when transitioning from conventional farming practices to organic farming practices?
2. Which applications of AI are applicable to agricultural practices?
3. How do the challenges that farmers experience relate to one another in the form of relative importance?
4. To what extent are AI technologies already able to solve these challenges for organic farming?

1.6 Key Concepts & Definitions

Table 1 presents some important key concepts of this research together with a definition.

Table 1: An overview of important definitions in this research

Key concept	**Definition**	**Source**
Artificial intelligence	a machine's capacity to perform tasks that used to require human intelligence	Soori et al., 2023
Organic farming	Organic farming is a holistic production management system that promotes agro-ecosystem health, including biodiversity, biological cycles, and soil health. It relies on natural substances and processes, avoiding the use of synthetic fertilizers and pesticides.	IFOAM, 2021
Sustainability	“meeting the needs of the present without compromising the ability of future generations to meet their own needs”	Brundtland United Nations, 1987
Challenges/ criteria	Challenges & criteria are considered to have the same definition in this research. When these terms are mentioned in the text, it is referred to the 10 criteria/challenges used in the linear BWM	X
Social challenges	Challenges on organic farming that arise due to the direct social environment farmers are in.	Barbosa et al., 2022
Environmental challenges	Challenges on the ecological nature of organic farming that hinder the adoption.	Barbosa et al., 2022
Economic challenges	Challenges on financial viability and continuity that hinder organic farming adoption.	Barbosa et al., 2022
Academics	In this research academics are defined as university members that perform research or provides education	X
Industry experts	In this research industry experts are defined as professionals that work in the field of AI and organic farming	X

2 Literature review

In this section, an overview will be given of the challenges that organic farmers experience in the transition to organic practices. Furthermore, an overview of the applications of AI in agriculture will be given to explore its potential to eventually retrieve applications that are useful for organic farming.

As the challenges that organic farmers experience are a form of MCDM, the literature review will also evaluate different MCDM techniques and choose the most suitable for this thesis.

2.1 Sustainability of organic farming

The United Nations defines sustainability as "meeting the needs of the present without compromising the ability of future generations to meet their own needs"(Brundtland, 1987). It emphasizes the importance of addressing economic, social, and environmental challenges in a balanced and integrated manner to ensure that current actions do not reduce the well-being and resources available to future generations (Brundtland, 1987). The concept of sustainability consists out of considerations of long-term viability, equity, and the connection of economic, social, and environmental systems (Brundtland, 1987). A wide range of articles have also defined sustainable farming practices. The FAO defines sustainable farming as farming practices with minimal impact on ecosystems, safeguarding land and water quality. These practices also have the capacity to meet global food needs, making them truly sustainable. (FAO, 2014). Latruffe et al. (2016) state that sustainable farming consists out of three main functions: economic (the industrial production and services), ecological (the balanced usage of natural resources), and social (support of agricultural areas). While there are different ways of defining sustainable farming from the literature, most papers agree on the fact that a comprehensive evaluation of sustainability must consist out of economic, natural, and social dimensions (Chand et al., 2015).

Although there is a significant overlap in definition and function between organic farming and sustainable farming, a key distinction lies in their regulatory frameworks. Organic farming strictly adheres to specific rules and regulations, holding an internationally recognized certification. In contrast, sustainable farming does not follow a standardized set of regulation (Jouzi et al., 2017). Organic farming characterizes itself as a more sustainable form of farming by sticking to four major principles formulated by the Federation of Organic Agriculture Movements (IFOAM). These four major principles are ecology, health, care, and honesty.

Care stands for protecting and nurturing natural resources, keeping the planet liveable and healthy, and soil management so that future generations can also produce products sustainable. Ecology stands for promoting biodiversity, cooperation with nature, cycling of water, soil, and plants. Health goes beyond human health, it is also about healthy soils, plants, and animals. And finally, Honesty or fairness, which stands for mutual respect and fair prices for farmers, justice in the supply chain in which every player receives the appreciation it deserves (IFOAM, 2024). To sustain these principles organic products meet strict internationally recognized legislation, making them unique in the agricultural sector. It is the only globally recognized quality mark for sustainability in arable farming (SKAL,2023). The increased sustainability of organic farming characterizes itself with sparing the environment and increased resilience to climate conditions. Organic farming has shown its potential for improving soil structure, preventing leaching of chemicals, and less emission of greenhouse gases.(Binta & Bruno, 2015). However, the share of organic farmers remains low, despite the major advantages that organic farming has in contrast to conventional farming (Koopmans et al., 2021).

2.2 Triple bottom line

To identify the bottlenecks in organic farming it is useful to consider all the pillars of sustainability as most studies on the transition to organic farming and sustainable farming practices only considered the environmental challenges (Barbosa et al.,2022). However, it is important to also include social and economic criteria in the adoption of organic farming (Qureshi et al., 2018). Especially as the adoption of organic farming affects all of these three pillars (Qureshi et al., 2018). The Triple bottom line is a sustainability accounting framework that uses these three different pillars of performance: social, environmental, and economic, known as people, planet, and profit. The TBL dimensions are also commonly called the three Ps: people, planet, and profits (Slaper & Hall, 2011) The economic line in the TBL refers to the financial impact that a company has on its direct surroundings of the economy and how this can provide an economically viable ecosystem for the next generations. The social pillar of TBL refers to conducting business in a way that is ethical and beneficial for direct stakeholders like the employees and the surrounding community (Elkington, 1997). Lastly, the environmental pillar in TBL refers to the use of the services of nature's ecosystem without comprising the same potential to future generations (Elkington, 1997). Next to the TBL model, additional conceptual frameworks have been developed that measure the performance of sustainability. First of all, there are the 17 goals for sustainable development (SDG) by the United Nations. The goals are developed to elaborate on a wide range of global challenges and make an effort to a world with more sustainability and prosperity. The SDGs consist out of a wide range of dimensions of development, mainly based on social, economic, and environmental criteria (United Nations, 2015). Secondly, there is the ESG framework, which measures the companies' performance based on environmental, social, and governance factors. However, this study will make use of the TBL model as the TBL model is seen as a more comprehensive model to account for the sustainability of a business and the three pillars of TBL correspond best with the above defined definition of organic farming (Martins & Pato, 2019). Moreover, researchers widely used it in studies on sustainability in organic and conventional arable farming practices and to find challenges in sustainable development (He, et al.,2021; Lone & Rashid, 2023). Even though former studies used to measure the performance of organic farming on sustainability, this study will use the TBL model in identifying and categorizing the major bottlenecks in organic farming. Identifying bottlenecks in sustainability implementation has been performed in earlier studies (van den Berg et al., 2023). Moreover, the TBL model can be used to identify and group the challenges that farmers experience when switching to a more sustainable form of farming(Barbosa et al., 2022). In addition to the use of TBL in identifying barriers to sustainable agriculture, the TBL model is also used in identifying barriers to implementing sustainable supply chains and sustainable plant disease management (He et al., 2021).

2.3 Challenges Organic Farming

The transition to organic farming and organic farming, in general, brings about a lot of different challenges in the daily practices of a farmer. This section entails a literature review of current literature about challenges in organic farming grouped according to the pillars of the TBL.

2.3.1 Environmental challenges

This section identifies environmental challenges as challenges that arise because organic production focuses on sustaining the ecosystem by prohibiting the use of products that negatively impact the conservation of natural systems.

Organic farming characterizes itself with stricter regulations on the use of external inputs like synthetic fertilizers and pesticides compared to conventional farming (Jouzi et al., 2017). These regulations are designed to sustain the principles of organic farming, which emphasizes more environmentally friendly and sustainable practices. However, the stricter environmental regulations on the use of external inputs initiate challenges for farmers in organic agriculture (Schneeberger et al., 2002).

The first major problem that appears with the inability to use external inputs is weed control. Weed control on arable farms is generally considered to be the greatest bottleneck for conversion to organic farming (Migchels et al., 2023). Especially, the need for manual weed control is costly, as on average 80 to 100 hours of hand weeding per ha is needed for crops like carrots and onion, which is an additional cost of 1800 to 2000 euros per ha (KWIN,2022). Organic farming places a greater emphasis on preventive measures compared to conventional farming in weed control (Ramankutty et al., 2017). These measures include practices like maintaining farm hygiene and implementing crop rotation. During the growing season, mechanical methods, including hoeing, harrowing, and brushing, are performed as much as possible for weed control. Weeds that manage to withstand these mechanical interventions must be manually removed (Scheepens et al., 2001).

Secondly, while conventional farmers can use chemical fertilizers to maintain a fertile soil, organic farmers have to use organic nutrient resources to keep the soil fertile (Schneeberger et al., 2002). Youzi et al found that organic nutrient resources face limitations in several agricultural regions worldwide, making them an unsuitable replacement for synthetic fertilizers (Youzi et al., 2017). The production of organic nutrient supplies necessitates additional resources, including land, people, essential elements, and water, which are often lacking in several areas. the nitrogen release of organic manure mostly does not correspond with the crop demands, the efficiency of organic nitrogen is relatively lower than synthetic fertilizer. Therefore in comparison to conventional nutrient supply, organic nutrient supply can be late which can account for major yield losses (Youzi et al., 2017).

Thirdly, Yield losses due to pests and disease do influence the yield gap between organic and conventional farming (Schneeberger et al., 2002). The amount of crop protection products approved for organic farming is relatively low (Röös et al., 2018). Regarding fungal or bacterial diseases, there is currently no consistently effective treatment available, except for the use of copper. As these copper-based crop protections have shown to be reliable, their environmental implications, both during the copper production process and in soil, particularly concerning aquatic environments, are interpreted as unacceptable according to general environmental standards (Alloway, 1995; SKAL,2023). This is especially relevant when aligning with organic principles. Consequently, copper-based crop protection has already been prohibited in various European countries, including the Netherlands, the country being researched (Finkch et al., 2006; SKAL, 2023).

Lastly, a different crop rotation in organic farming is used to address two issues. Its goal is to have soil fertility and lower the incidence of pest and diseases. In organic farming practices, it is needed to have a broader crop rotation in comparison to conventional farming, because of a higher chance of pests and diseases. This entails that, for organic farming a broader diversity of crops is needed. This broader diversity of crops can be challenging as it means that more knowledge is needed of the new crops and a new crop also means that there is a different sales channel needed (Koopmans et al., 2021; Schneeberger et al.,2002).

2.3.2 Social challenges

In this section, social challenges are referred to as challenges that arise due to the negative impact of the direct social environment of farmers.

The role of the direct environment of farmers plays a key role in the adoption of organic farming practices. The further growth and acceptance of organic farming is hindered by social norms that are against the principles of organic farming (Läpple & Kelley, 2013). Inadequate social and network support for farmers who want to organic has also reduced its adoption (Schneeberger et al., 2002). Moreover, an American study shows that there is a significant preference for conventional farming within society, including government institutions, universities, corporate entities, and rural communities, and forms a significant barrier to the further growth of organic farming (Constance & Choi, 2010). This preference is supported even more due to the absence of research support, minimal public funding for farm advisors, and a scarcity of government-funded researchers have presented substantial obstacles to the adoption of organic farming(Constance & Choi, 2010; Cranfield et al., 2009). This major concern of conventional farmers when switching to organic practices is confirmed by the lack of information about organic farming practices, and the amount of external support, especially from government and marketing agencies (Schneeberger et al., 2002).

The market for organic products is mostly separated from the market of conventional agricultural products (Hamm et al., 2002). This means that sales channels for farmers who want to make the switch to organic drastically change. In arable farming, growers often have long-term relations with large agricultural trading companies and processors, often in the form of contract cultivation. In most cases, switching also means switching to another sales channel (Silva et al., 2014). Organic supply chains moreover characterize themselves with shorter supply chains by supplying directly to retailers, catering, or consumers (Silva et al., 2014). These supply chains are often smaller and could be harder to find as organic supply chains only provide 3% of consumer expenses on food in the Netherlands (Logatcheva & Herceglic, 2022).

2.3.3 Economic challenges

In this section economic challenges are referred to as challenges that negatively influence the financial viability and continuity of an organic arable farm in comparison to the conventional counterpart.

Organic farming is often perceived as risky by farmers as it is associated with low yields and low production volumes (Bouronikos, 2021). According to a Polish study, over 80% and nearly 60% of surveyed farmers indicated that they considered the production risk to be very high or high in the context of organic farming. This indicates a significant concern for farmers regarding the potential challenges and uncertainties associated with organic farming (Łuczka-Bakuła, & Kalinowski. 2020). High prices for organic products influence the competitiveness of organic products in comparison to conventional ones (Bouronikos, 2021). This higher price for organic products mainly sources from the fact that organic farmers have higher production costs, mainly due to the stricter regulations on external inputs mentioned in the environmental section (Bournikos, 2021). The current solution to overcome the challenges and the slow growth of organic farming is partly based on subsidies from the European Union in which cost coverage is offered for farmers to partly compensate for their higher costs, lower production, and innovative behaviour. Furthermore, the EU also provides subsidies for farmers who want to make the transition to organic farming. Between 2023 and 2027, €38 billion to €58 billion will be reserved for farming systems that facilitate the restoration of eco systems, including organic farming. (Crowder& Reganold, 2015).

On organic farms, labour costs are significantly (7-13 percent) higher compared to conventional businesses. (Crowder et al., 2015) organic farms employ 2 to 12 percent more workers per hectare. Especially hand weeding is a job that requires a major share of manual labour up to over 100h per ha which is considerably higher than the 0-15 per ha for conventional farmers (KWIN, 2022). According to Koopmans et al 2021, there is a major shortage on the availability of manual labour making it a vulnerability for farmers to get the work done right and on time. Especially, when the amount of organic farms remains growing it is expected that the availability of manual labour will become a major bottleneck in organic production (Migchels et al., 2023).

Another specific economic barrier is the export of Dutch organic products is hindered by the increase in the domestic supply of organic products abroad, leading to the fact that Dutch exports of organic products are under pressure (Migchels et al., 2023). The organic areas in the EU have been growing gradually in the EU between 2012 and 2021 there was an increase of 6.5 million hectares, which aligns with a growth of 68% (Eurostat, 2021). In Germany and Switzerland, import only is done if its own organic product is no longer available (Migchels et al., 2023). The major reason for sourcing organic products in the same country as the consumption is that consumers' perception of organic products is that they should be produced locally as a condition to be organic (Bakker & Bunte, 2009). Long transport distances of organic products reduce the positive perception of organic products by European consumers (Bakker & Bunte, 2009). However, the consumption of organic products remains low in the Netherlands in turn that means that the export dependency remains high. Therefore the growth of Dutch consumption is needed for further growth and development of organic arable farming in the Netherlands(Migchels et al., 2023).

2.3.4 Research diagram challenges in organic farming

(Figure 1) gives an overview of the identified main criteria based on the TBL model. Moreover, the challenges that were defined at the beginning of this chapter were grouped as sub criteria.

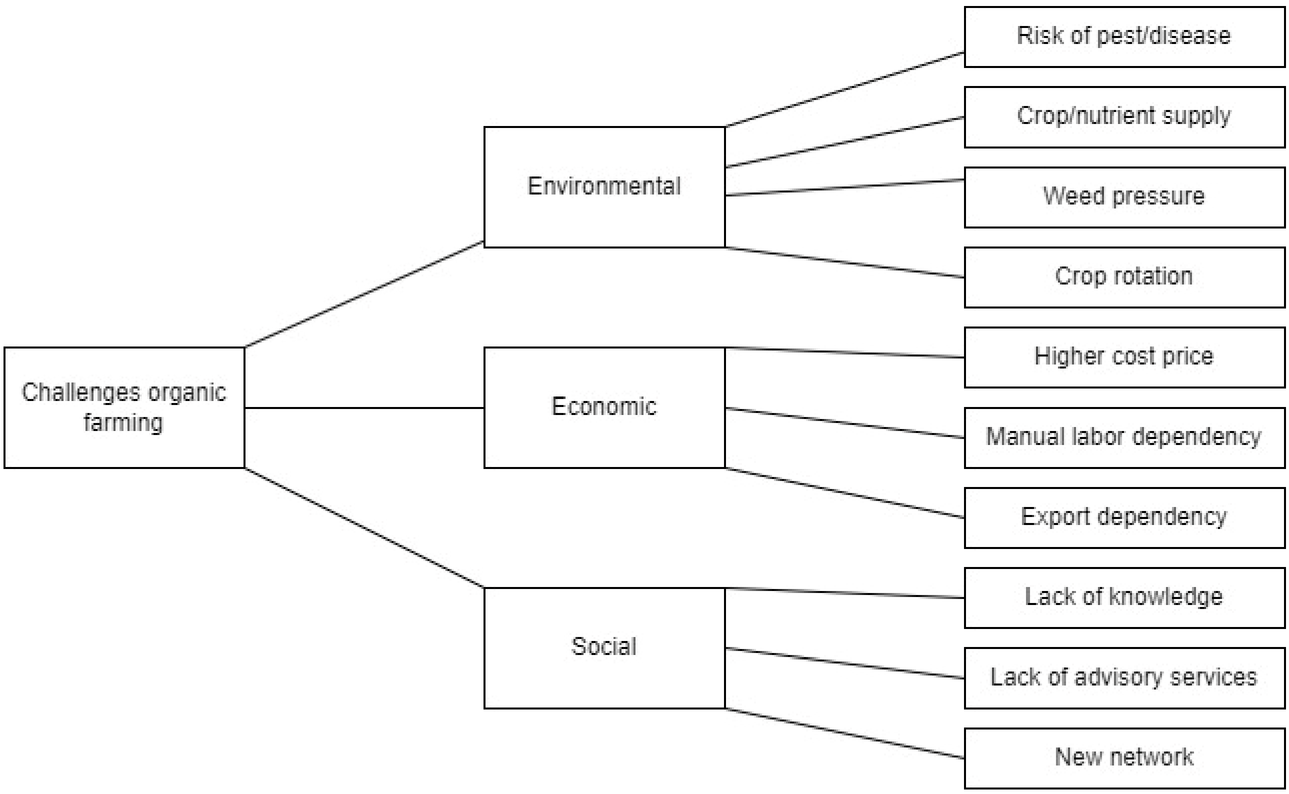

Figure 1: Framework of the challenges organic farming

2.4 Potential of AI on sustainable agriculture

2.4.1 Research on AI in sustainable agriculture

As stated in chapter 1.1, AI technology development in farming practices has mainly focused on its implementation on large-scale conventional systems (Bellon-Maurel & Huyghe, 2022). However, these technologies have been barely researched for the sake of organic farming (Klerkx et al., 2019). On the other hand, it is found that AI technologies are potentially able to help farming practices to be more ecologically friendly by generating new knowledge, reducing workload, and analyse complex systems (Bellon-Maurel & Huyghe, 2017), but follow-up research still is limited which means that the relation of digital technologies in making farming practices more ecologically friendly is low (Klerkx et al., 2019). Moreover, the role of AI technologies in adoption of organic farming remains unknown. Current research on AI technologies mainly focuses on improving irrigation and water use efficiency (Abioye et al., 2020), weed management (Knoll et al., 2018), disease detection (Ahmed et al., 2019), and yield detection (Sundaramoorthy & Dong, 2019) of conventional farming practices. In section 2.4.2 a more elaborate explanation of AI applications will be given.

2.4.2 AI in industry 4.0

Artificial technologies are among other technologies like big data and analytics, blockchain, cloud, internet of things, and simulation part of industry 4.0 (Bai et al, 2020). Big data analytics is a tool that can analyse a lot of data in a short time span to make decisions based on data and it can optimize production and see patterns (Zambon et al., 2019). Blockchain is a decentralized platform that can increase transparency and security in supply chains that is accessible to any stakeholder in the supply chain (Frank et al., 2019). Cloud computing is an application in Industry 4.0 that can facilitate the sharing of data and services via the web (Zambon et al., 2019). IoT is a network wherein different physical devices that contain sensors are in connection with each other to exchange data, real-time monitoring and communication between systems (Zambon et al., 2019; Frank et al., 2019)

The landscape of manufacturing business models is undergoing a fundamental transformation with the growth of Industry 4.0. These technologies facilitate production flexibility, efficiency, and productivity by implementation of a wide range of emerging communication, information, and intelligence technologies (Bai et al.,2020). However, AI distinguishes itself from other technologies in industry 4.0 while it focuses on creating data processing systems that are able to replace jobs that used to be done by humans. These tasks include activities like reasoning, learning, and self-improvement (Ryan, 2022). Generally, The term AI describes a machine's capacity to perform tasks that used to require human intelligence (Soori et al., 2023). AI can be defined as learning systems originating from computer science, able to autonomously process data, acquiring the ability to identify patterns within the data, and independently performing specific tasks (Soori et al., 2023). This is the main reason why AI has become the most disruptive technology able to revolutionise the management and business models of companies by using extensive technologies based on AI and computer vision (Megeto et al., 2020) The features of AI technologies are considered to be important factors for the use of more sustainable practices in agriculture like organic farming (Megeto et al., 2020). These features consist of an intelligent management system that deeply zooms in on the distinct attributes of plants, soil varieties, and animals (Mohr & Kühl, 2021). This research will therefore solely focus on the use of artificial intelligence because this application seems to hold the greatest potential for reducing the barriers to the adoption of organic farming and it allows for a more in depth understanding of AI technologies.

2.4.3Domains within AI

Computer vision is considered as a major domain within AI applications, that should control algorithms that not only assist and simulate but also surpass human decision-making processes using unstructured data interpreted as images (Ryan et al., 2023). Various devices and sensors, including cameras, smartphones, and electromagnetic spectrum sensors like infrared, can obtain this data (Bini, 2018). Machine learning is a sub form of AI technologies as it creates algorithms that can analyse datasets and with that have the ability to improve the performance and efficiency of a computer system. The basis of machine learning is statistical programmes that are able to let computers learn from data, identify patterns, and make decisions or predictions (Bini, 2018).

Deep learning is another example of an application of AI technologies. Deep learning makes use of neural networks, that consist out of multiple layers of interconnected nodes. These networks are designed to act and function like the human brain (Megeto et al., 2020). The multiple layers of the technology make it able to retrieve and analyse forms of data with an increasing degree of data abstraction, as every layer dives into a more abstract form of data (Nisk, 2015). This technology has the potential to automate and optimize various agricultural processes like, reducing the dependency on labour-intensive working conditions, specialized professionals, and large employee numbers or equipment. This is particularly beneficial for tasks that are laborious, stressful, or has high-risk for human labour (Megeto et al.,2020).

2.4.4 AI applications

The application of AI technologies in agriculture is divided into two subtypes AI software and AI robots. Wherein AI robots are dependent of AI software, but AI software is not dependent on AI robots for its functioning (Ryan, 2022).

The usage of conventional robots in agriculture has a longstanding history, especially with robot milking in practice for over 20 years (Singh & Jain, 2022). In contrast, the usage of AI-driven robots in agriculture is a relatively recent development. These agricultural robots have diverse functions such as crop sorting, pest and weed management and harvesting, (Ryan, 2022). Most AI robots are still in the premature stage of development, as most of the inventions are still in the research stage. Only a few robots have made it to the market yet, as the capacity mostly cannot cope with the speed of human activities (Bhagat, 2022).

AI technology is finding applications in various robotic platforms, including drones and autonomous tractors. Drones are currently employed for tasks such as watering crops and applying pesticides and herbicides, as well as capturing aerial photographs of the farm and its surroundings (Ryan, 2022). These drones offer valuable insights and facilitate farm mapping that was previously unattainable. On the other hand, self-driving tractors hold promise in allowing farmers to engage in other tasks. However, the implementation of self-driving tractor technology is still in its premature stage of development and has not yet been implemented in a commercial context (Ryan, 2022).

Furthermore, AI is implemented into applications, recommendation systems, and software. For instance, image recognition technology enables farmers to assess the well-being or health of specific plants or crops, and it offers guidance on appropriate actions to take (Ryan 2019). Additionally, AI is used to monitor the developmental stages and growth of plants, predict changes over their life cycles, and provide farmers with detailed information on plant growth. (Ryan, 2022).

In addition, Artificial intelligence has the potential to take over various responsibilities traditionally assigned to agronomists, with the help of above mentioned application farmers can simplify their record-keeping and administrative responsibilities (Sing & Jain, 2022).

2.4.5 Economic benefits AI

The economic benefits that drive the integration of AI in agriculture are for example innovation, increased productivity, reduced human error, improved analytics and accuracy for tasks like pest detection and control(Sood et al., 2022). Especially because farming, in general, is seen as a high risk form of production, AI is considered to especially address these higher risks for farmers and can have an impact (Mhlanga, 2021). As AI makes it possible to predict the cultivation season, By predicting the harvest time, pest pressure, water usage, and actual soil conditions the probability of a good production can be measured. Some studies state that the harvest forecast by AI can already get accuracy levels up to 96% (Awasthi, 2020). This in turn, has outstanding consequences for the risk management for farmers as predictability gets a lot more accurate (Awasthi, 2020).

Another major aspect of AI usage in agriculture is the potential to significantly reduce the non-structural production costs in farming. These non-structural costs can be reduced because fertilizer, pesticides and water can be given in a more efficient way.

Moreover, the reliance on manual labour in farming can be reduced by AI. (Ryan et al., 2023). As AI has the potential to take over tasks that were normally assigned to humans, like weed control, sorting, grading and harvest (Lassoued et al, 2021). This is especially relevant as Dutch organic farmers already have severe problems finding enough skilled manual labour, which follows the current trend of urbanization wherein less farm hands are available in the country side (Koopmans et al., 2023; Jafaid et al., 2023).

2.4.6 Environmental benefits of AI

Modern intensive farming practices have negative environmental consequences by inefficiently using resources for production (Peer et al., 2020). AI driven technologies have the potential to reduce the use of fertilizers and pesticides, enhance accuracy in detecting pests and diseases, and decrease water consumption without cutting back on production (Cook & O'Neill, 2020; Ruiz-Real et al., 2020). Consequently, AI has the capacity to reduce the footprint of farming practices on the environment and make use of its resources in the most efficient way.(Megeto et al., 2020). By optimizing the usage of chemical pesticides through AI technologies, a significant impact can be made on efficiency and accuracy (Jafaid et al., 2023). This approach addresses the environmental impacts associated with the current combat of pests and diseases, making farming more sustainable (Jafaid et al., 2023). This resource efficiency by AI technologies is also mentioned to have a positive impact in other manufacturing industries l (Peer et al., 2020; Braccini and Margherita, 2018). By trusting on the trend that AI technologies becoming more affordable over time and enhancing production efficiency, AI in agriculture is seen as a solution to address the challenges of feeding a growing population while in the meantime preserving natural resources and the environment (Ryan et al., 2023).

2.4.7 Social benefits of AI

The growing usage of AI technologies enables farmers to move from a subjective approach to a data-driven approach to retrieve and analyse the information about the crops on the fields (Javaid et al., 2023). This switch to a data-driven decision making in farming makes the problem of a knowledge gap less relevant as human intelligence is less important (Linaza et al., 2021). This switch to reliance on artificial intelligence could also have far-going consequences for agronomists, managers and advisors as it could make these jobs less relevant (Ryan et al., 2023). However, new functions arise that need skills that only humans can perform, like human judgement in situations that require ethical considerations. Nowadays, AI technologies are able to replace repetitive actions that have a high labour intensity, but do not require ethical judgement (Clifton et al., 2020). For the farming sector, human judgement will for the future still be needed to set standards and detect new insights (Ryan et al., 2023).

2.5 MCDM

To get a hold of the importance of the different challenges of organic farming that are affecting the decision to switch to organic farming Multi Criteria Decision Making (MCDM) method was applied. MCDM techniques allow for the modelling of factors, which can help to identify the most important criteria from a wider range of criteria. MCDM methods are based on the opinion of experts, therefore it is essential to find experts that both are knowledgeable on AI and organic farming (Salimi, 2021). In this study an expert is identified by "a person whose knowledge in a specific domain is obtained gradually through a period of learning and experience" (Cornelissen et al., 2003)

The triple bottom line model which is used in this study consists out of three main criteria (social, environmental and economic) and are further defined by the challenges in the sub-criteria. This research makes use of MCDM as it is possible to find out what the most important criteria of sustainability are in considering the challenges of arable farmers in transition to organic farming. MCDM methodologies have been applied in identifying challenges across various areas, including engineering, science, and technology (Malek& Desai, 2019).

In MCDM, there is a wide range of methods of weight evaluation like(" Weighted Sum Method (WSM), Simple Multi-Attribute Rating Technique (SMART), Weighted Aggregated

Sum-Product Assessment (WASPS), Multi-Objective Optimisation Ratio Analysis (MOORA), Fuzzy-Analytic Hierarchy Process (Fuzzy-AHP), Simple Additive Weighting (SAW), Weighted Product Method (WPM)")(Malek & Desai,2019). However, this study will make use of the Best Worst Method (BWM) because it requires fewer pairwise comparisons an provides more consistent and reliable results than other MCDM methods (Rezaei, 2015).

By initially identifying the best and worst criteria before conducting pairwise comparisons, the expert gets a better understanding of the range from the best criteria to the worst which increases the total reliability of the comparisons. Eventually, this leads to more consistent pairwise comparisons (Rezaei, 2015). By implementing two pairwise comparison vectors, based on the opposing references (best and worst), this model helps to reduce the risk of potential bias by the decision maker that may be formed during the pairwise comparison process (Rezaei, 2015). The "consider-the-opposite" strategy, has already shown to be reliable in reducing the potential bias in other research (Rezaei, 2015).

2.6 MCDM/ BWM in other research

The identification of barriers or challenges for the implementation of organic or sustainable farming practices has been performed with the help of MCDM methods (Dixit et al., 2022; Fernandez-Portillo et al., 2023). These barriers were identified by an MCDM method called Grey Decision-Making Trial and Evaluation Laboratory (DEMATEL)(Dixit et al., 2022) and even BWM has been used to identify strategies that best serve organic farming adoption (Fernandez-Portillo et al., 2023). Moreover, several papers used MCDM to assess sustainability of agricultural systems (Mangan, 2022), crop choice (Sari and Koyuncu, 2021) and issues for agricultural research (Lim et al., 2021).

The identification of important barriers or challenges based on the three pillars of TBL has been performed with MCDM methods (Barbosa et al., 2022). For this research, a DEMATEL method has been used to find the most important barriers of sustainable agriculture adoption based on the opinion of 30 experts (Barbosa et al., 2022).

3 Methods

3.1 Research design

For this research about the role of AI in the transformation to organic farming, a descriptive study seems suitable as the role of AI technologies in the further transformation to organic farming has not been performed yet. However, there is enough literature on AI technologies in agriculture and there is limited literature on the challenges in organic farming. Descriptive studies are especially formalized studies with research questions that have a clear purpose, to obtain concrete answers.(Blumberg et al., 2014).

The data collection methods that are used include the use of secondary sources, such as search engines like Google Scholar, Scopus, and WUR library, and primary data from the retrieved information of interview questions with experts. A cross-sectional study seems suitable to use in this research design as it allows for investigating multiple variables at the same time as we want to research multiple variables that affect the implementation of organic farming practices. These variables consist of the challenges that organic arable farmers experience and the solvability of these problems by AI technology. The research methodology is predominantly quantitative.

3.2 Literature study

To answer the first two sub research questions a thorough literature review is done

- *What are the challenges that farmers encounter when transitioning from conventional farming methods to organic farming practices?*

-*Which applications of AI are applicable to agricultural practices?*

3.2.1 Identification of (sub) criteria

This first research question is aimed at identifying what the current challenges (criteria) are for Dutch arable farmers when switching to organic farming. The criteria were identified by reviewing research papers that discuss the challenges that organic farmers experience. Different research papers that identified the challenges of switching to organic farming were found (Schneeberger et al.,2002; Scheepens et al., 2001; Youzi et al., 2017) Moreover, there were two governmental documents that also provided relevant information for the identification of challenges (Migchels et al.,2021; Koopmans et al., 2021). Ultimately, an overview was made that divides the most important criteria into the three different categories. These categories were found by the identification of overarching criteria based on the TBL model (environment, social and economic) as discussed in the literature review. After finding and categorizing the criteria in to the diagram of (Figure 1) it was important to validate these challenges. Validation was needed because the literature that was found was not always specifically written for the Dutch organic arable farming. Therefore, to enhance the accuracy two interviews were conducted with experts on organic farming to remove irrelevant criteria and add significant criteria where needed. It turned out that all of the challenges that were found from the literature study were valid except from the addition of the criterium of 'new network' and removing the sub criterium 'dissuading neighbours' and the removement of the main criterium regulation. After finding the sub-criteria for the BWM method a correct definition and description was added to (Table 2) which gives an overview of the criteria + sub criteria.

Table 2: description of the different challenges in organic farming

AREA	CHALLENGE	DESCRIPTION	SOURCE
Economic	Labour dependency	increased manual labour in organic farming	Koopmans et al., 2021 Migchels et al., 2023
	Export dependency	higher dependence on exports	Migchels et al., 2023 Bakker & Bunte, 2009
	Higher production cost	Increased cost of organic production	Łuczka-Bakuła & Kalinowski, 2020, Bouronikos, 2021, KWIN, 2022
Social	Lack of knowledge	Lack of knowledge on organic farming	Schneeberger et al., 2002
	New network	New sales channels that need to be found	Validation interviews
	Lack of advisory services	Reduced amount of knowledge institutes to reach out to	Schneeberger et al., 2002 Cranfield et al., 2009
Environmental	Risk of pest/disease	Less measures to combat and prevent pests/diseases	Röös et al., 2018 Schneeberger et al., 2002, Ramankutty et al., 2017
	Weed infestation	Reduced ability to combat weeds chemically	Migchels et al., 2023 KWIN, 2022
	Crop nutrient supply	Reduced measures to supply nutrients for the crop	Youzi et al., 2017
	Crop rotation	Higher diversity of crops is needed	Scheeberger et al., 2002 Koopmans et al., 2021

3.2.2 Current applications of AI

To answer the second research question, an overview was made of the different AI technologies that are available for the agricultural industry. Firstly, the definition of AI technologies in the agricultural sector was made by a thorough literature review. Secondly, an overview was made of the different AI applications that are available for farmers.

3.3 Empirical research

To answer research question 3; *How do the challenges that farmers experience relate to one another in the form of relative importance?* Experts on AI and organic farming are interviewed about the current challenges that organic farmers experience. With interview questions that are based on the linear BWM, it is possible to calculate the priority of every individual criterion. The challenges that are used to answer RQ3 are based on the list of criteria that were identified by RQ1.

To answer research question 4; *To what extent are AI technologies already able to solve these challenges for organic farming?* Experts on AI technologies & organic farming will be interviewed to retrieve information about the current performance of AI in solving the challenges that organic farmers experience.

3.3.1 Data collection

In most research, researchers typically want to examine a subset of a larger group, known as a sample, to retrieve findings about the entire population. This sampling practice is motivated by the need for empirical data collection and precise results, as lack of time and extensive data collection may lead to bias (Blumberg et al., 2014). Given the context of this study, a sample consisting of experts from the Dutch organic arable farming sector and AI experts in agriculture was approved to be an appropriate expert profile. Due to the context of the research which dives into the relationship between AI and organic farming, it was essential to find these specific experts. Preferably, the experts are working on an academic level, therefore, the first focus was on academic experts on both organic farming and AI technology.

As these experts both have the theoretical knowledge and could bring about critical perspectives from research on organic farming and AI. When there is no satisfaction or insufficient respondents (n= <15) also experts from the industry are included as expert for the BWM interviews. Their firsthand experiences, challenges faced, and expectations from AI technologies in organic farming will give a hands-on perspective. The first academic experts were specifically selected through scanning wur.nl/ LinkedIn/ proeftuinprecisielandbouw.nl on the expertise profile of the potential interviewee. After conducting the first interviews, the respondents were asked if they knew any other experts in their field. Moreover, interviewees were raffled by visiting the Biobeurs in Den Bosch, which is a fair for all involved companies in the organic farming industry. An overview of the selected experts is shown in (Table 3).

To increase the validity of the research, the experts selected for the interviews were provided with the interview guide at least one week before their scheduled interview.

Moreover, this makes the interview more efficient as the experts already know about the criteria that are discussed during the interview. The interview guide included a description of the structure of the interview with a description of the topic, a description of the (sub) criteria and a description of the BWM method & ranking of AI performance in organic farming. The interview guide is included in the Appendix.

The interviews were conducted either in person or online via Microsoft Teams. The interview started by asking the expert to give a general introduction and their experience with AI and organic farming and ask if it is allowed to record the interview. After the introduction, the interviewee was asked to perform the pairwise comparisons between the main criteria, whereafter the pairwise comparisons between the sub criteria were done. While doing the pairwise comparisons, the spreadsheet for linear BWM was filled in to ensure that the comparisons were consistent. After finding an inconsistent pairwise comparison, the best to other and others to worst vectors were changed by the interviewee to obtain consistent results. Lastly, the interviewee was asked to rate the current performance of AI in solving the challenges of every individual sub criterium.

Table 3: Overview of selected experts for the BWM interviews.

Expert nr:	Gender:	Background:	Experience in the field (year)
1	M	Academic	8
2	M	Industry	7
3	M	Academic	22
4	M	Academic	34
5	F	Industry	15
6	M	Industry	22
7	M	Academic	6
8	M	Academic	3
9	M	Industry	11
10	M	Industry	4
11	M	Academic	6
12	M	Academic	14
13	M	Industry	5
14	M	Industry	15
15	M	Academic	8
16	M	Academic	9

3.3.2 Interview guide

Blumberg et al. (2014) found two ways of conducting interviews where the researcher either observes certain interactions and behaviour (observation approach) or directly ask questions to retrieve answers (communication approach). This research makes use of a quantitative approach to retrieve the answers for the research, therefore the setup of the interviews is highly structured to get the desired outcomes of the interview and therefore the communication approach seem highly suitable to perform. The interview guide is included in the appendix.

3.3.3 Linear BWM

To answer research question 3: *How do the challenges that farmers experience relate to one another in the form of relative importance?* Interviews were conducted in accordance with the protocol of the linear BWM. By using the linear form of BWM also the assumption is made that there is no interaction between the criteria and that linearity is assumed (Rezaei, 2016)

The 5 steps below, show how a linear BWM is solved (Rezaei, 2015).

Step 1 - Determine the set of decision criteria [c_1, c_2, … c_n].

The main criteria were determined to be the three dimensions of triple bottom line namely environment, economic and social. To further operationalize the main criteria environment, economic and social; sub-criteria are formed.

Step 2 – Selection of best (c_B) and the worst criteria (c_W) from C

Experts were asked which of the (sub-)criteria they found the most important (c_B) in the challenges of organic farming and which (sub-)criteria they found the least important (c_W)

Step 3 - Best-to-Others vector (a_{B1}, a_{B2} … , a_{Bn})

Pairwise evaluations were conducted between criterion B (**c_B**) and other criteria with the aim of determining the Best-to-Others vector (a_{B1}, a_{B2} … , a_{Bn}). In this vector, aij signifies the preference of criterion 1 over criterion j. The pairwise comparisons utilized a 9-point scale, where 1 stated equal importance, 3 signified moderate preference, 5 indicated a strong preference, 7 represented a very strong preference, and 9 represents an extremely strong preference. Additionally, the even-numbered values on the scale represent intermediary positions.

Step 4 – Perform Others-to-Worst vector (a_{1W}, a_{2W} … , a_{nW})^T

After performing the best to others vector, pairwise comparisons were done by rating the importance of other (subcriteria over c_W using the same scale as in step 3. The pairwise comparison between c_W and c_B was not needed to do again as it would yield the same result. Therefore, the amount of comparisons is *2n-3.*

Step 5 Identify the optimal solution [w_1*, w_2*, …w_n*].

The optimal weight for the criteria is found if each pair of $\frac{w_B}{w_J}$ and $\frac{w_j}{w_w}$, we have $\frac{wb}{wj} = a_{Bj}$ and $\frac{w_j}{w_w} = a_{jW}$. Therefore, $\left\{\left|\frac{w_B}{w_J} - a_{Bj}\right|, \left|\frac{w_J}{w_W} - a_{jW}\right|\right\}$ should be minimized. When transformed to a linear model, the following model should be solved, where w_i* represents the weight of the criteria and ξ^L is the value of the objective function:

min ξ^L

subject to the constraints:

Equation 1

$$|w_B - a_{Bj}w_J| \leq \xi^L, \qquad for\ all\ j$$

Equation 2

$$|w_j - a_{jw}w_W| \leq \xi^L, \qquad for\ all\ j$$

Equation 3

$$\sum w_j^* = 1$$

Equation 4

$$w_J \geq 0\ for\ all\ j$$

The averages of the weights of different experts were found by using the geometric mean, as it has shown to be more resistant to outliers than using the arithmetic mean (Das & Imon, 2014) and thus will give results that are more reliable.

3.3.4 Importance-Performance-Analysis

A way to give a representation of the current performance of AI in Dutch organic arable farming to policymakers, government, tech companies, and farmers is by conducting an Importance Performance analysis. Identifying the importance level of the challenges in organic farming is not enough as it only indicates the urgency of the challenges. To be more precise, only the challenges that present a high importance but have a low AI performance are relevant for the stakeholders. Therefore this method identifies the challenges that have most space for improvement. By using a scale from 1 (very low) to 5 (very high), the performance of AI on the challenges of Dutch organic arable farmers was rated by the experts. The model of Martinelli seems more suitable for this research as it makes it able to discover underdeveloped (low-performance) areas with a high importance (Salimi, 2021). Ultimately, it can become clear for developers of AI applications where to focus on when developing new applications for organic farming. (Figure 2) gives an example of a representation of an ordinary importance/performance grid with a description.

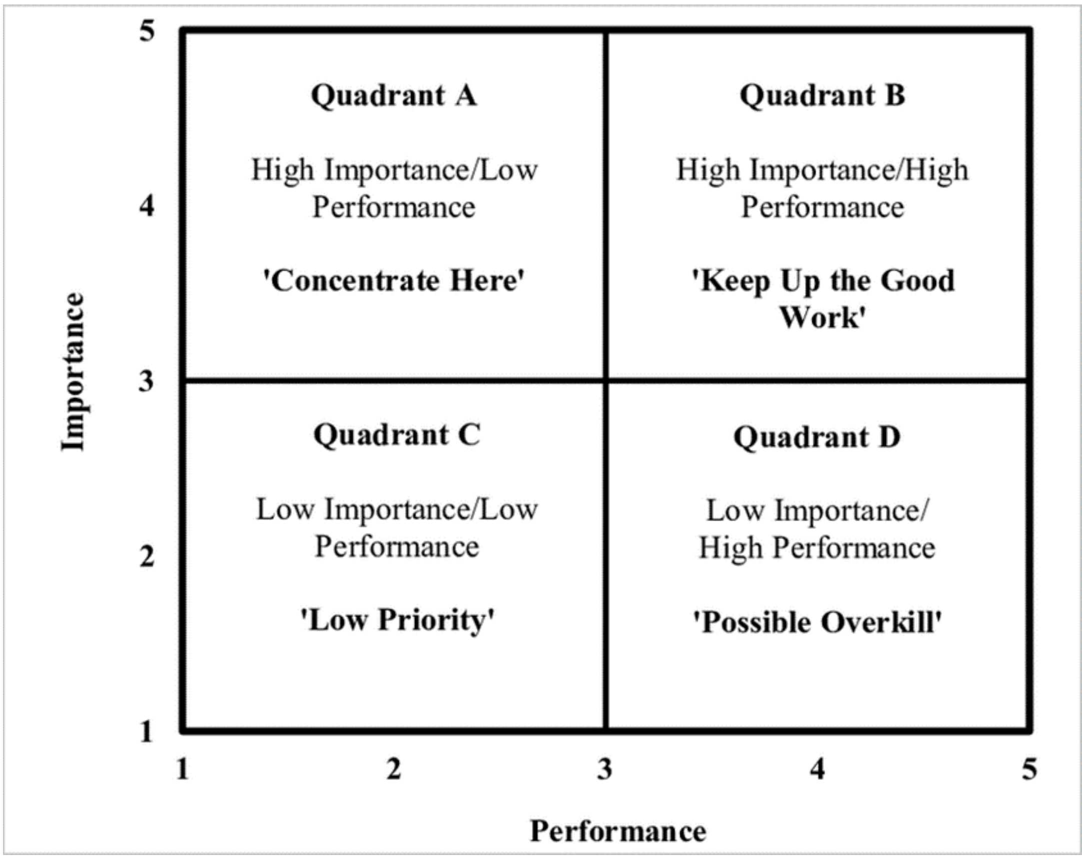

Figure 2: Importance/performance grid by (Martinelli & James, 1977)

(1) Quadrant A: This area involves the most important challenges which have a low performance of AI. This area should obtain the most attention in comparison to the other quadrants. Therefore, this area is in need of implementation of any AI technologies that can help the evolution of the industry.

(2) Quadrant B: The challenges are seen as important in this quadrant, however, the performance level of AI is also very high. These criteria may be not in need of any further

improvements of AI technologies, and any additional effort could result in in non-beneficial outcomes.

(3) Quadrant C: The challenges are characterized by having a low importance and performance, therefore it is not necessary to focus on these challenges. Investing in these challenges could mean to have no significant effect.

(4) Quadrant D: This area consists out of all the challenges that have less importance for Dutch organic farmers, however AI has a high performance. Therefore it is not needed to focus on these challenges (Martinelli & James, 1977)

3.3.5 Mann-Whitney U test

To analyse the influence of the background of the experts the non-parametric Mann-Whitney U test was used. This test was used as it gives the possibility to compare two independent samples (Mann & Whitney, 1947). A second benefit of the Mann-Whitney U test is that it is able to analyse small samples as well (Mann & Whitney, 1947), which is the case in this research. The test was conducted via the statistical program of SPSS version 29 (IBM group, 2022).

3.3.6 Overview data collection

Table 4: Overview data collection

Sub question	Data	Source	Method
1. What are the challenges that Dutch arable farmers encounter when transitioning from conventional farming methods to organic farming practices?	Overview of the challenges that arable farmers experience when switching to organic	Literature review/ Validation by experts on organic farming	-Literature research by Scopus, WUR library and Google scholar - Validation interviews
2. Which applications of AI are applicable to farming practices?	Overview of applications of AI in arable farming	Literature review	Literature research by Scopus, WUR library and Google scholar
3. How do the challenges that farmers experience relate to one another in the form of relative importance?	Importance of different challenges in organic arable farming	Experts on organic arable farming	Expert interviews
4. To what extent are AI technologies already able to solve these challenges for organic farming?	Performance of AI on the challenges	Experts on AI in arable farming	Expert interviews

3.3.7 Validity & reliability & generalizability

To obtain high-quality results in research, the data that is obtained has to fulfil the requirements of validity and reliability.

Validity is a measure that describes to what extent the measure that is described is targeted by the description that is measured, So in other words it is a measure of how accurate the research results are described in a paper (Blumberg et al., 2014) This research ensures validity as much as possible because before conducting the actual BWM interviews, two experts on organic farming are interviewed to check if the identified challenges are correct and representative.

Reliability is a measure that concerns about the consistency of the results. It represents to what extent the results are similar if the research was conducted under the same conditions over time (Blumberg et al., 2014). The outcomes of a study are poor when either validity or reliability of the results is missing (Heale& Twycross, 2015). For this research, the results are reliable if the importance of the challenges of organic farmers does not change too much over the years as this can cause unreliable results and furthermore the advancements of AI need to be taken into account as predicting the future as much as possible.

To obtain the high-quality results in this research several measures were taken. First of all, the participating experts in this research received an extensive e-mail with all the details and the structure of the research with the amount of time it will take. By having a strict interview protocol across all interviews the amount of error was reduced as much as possible.

This research has its limitations so the results can and should not be generalized for the full agricultural sector. First of all, as the topic concerns arable farming only it is not representative to interpretate these results for other types of farming like horticulture, livestock farming and fruit farming. Second of all, this research specifically focuses on the context of Dutch farmers so it may not be possible to use these results in countries with conditions that differ much of the situation in the Netherlands. The results could be different because of a different soil type, regulations or climate for example.

3.4 Research framework

In (Figure 3), the research framework is illustrated which highlights the main research activities that took place during this thesis. The first step is the literature review wherein the challenges of organic farming practices are reviewed and the potential of AI technologies is discussed, which eventually led to the construction of the overview of the challenges. At the start of the data collection, experts on organic farming were interviewed to rate the main criteria and to determine the importance of the sub criteria. In the second stage of the interview experts on AI and agriculture were asked to rate the current performance of AI in the challenges of organic farming. After retrieving the data from the interviews, the challenges were prioritized with the help of the BWM method. After that, the importance-performance analysis was constructed to identify the criteria that need the most improvement and the challenges that may have low priority or where AI already has sufficient performance. In conclusion, this led to a recommendation report for policy makers, organic farmers, developers of AI applications, and other stakeholders that see benefits from a better functioning organic farming sector and applications of AI in agriculture.

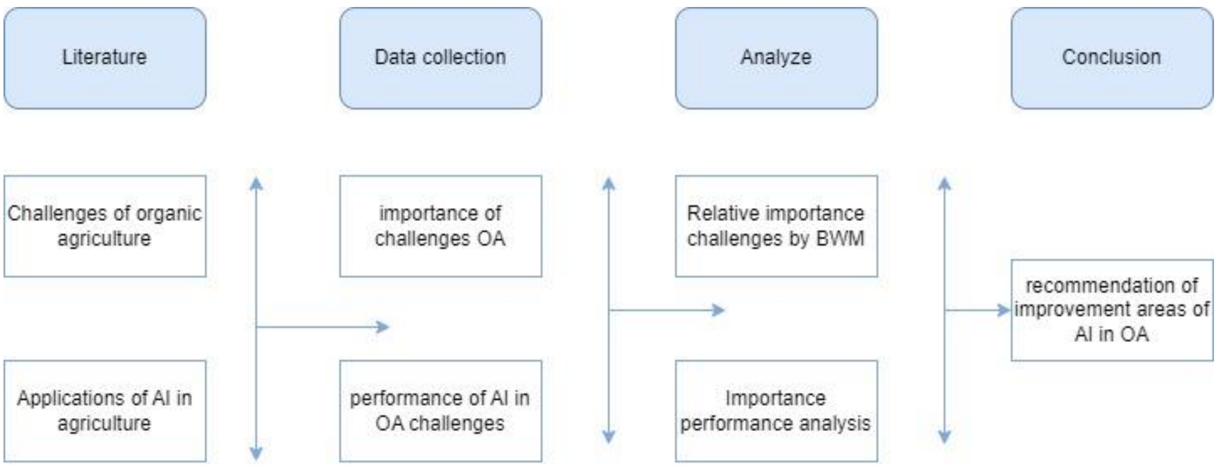

Figure 3: research framework

4 Results & Discussion

This thesis report was developed to investigate how the current performance of AI technologies is able to mitigate the challenges that Dutch arable farmers experience when switching to organic farming practices. To obtain these results first, the challenges in organic farming (criteria) were identified, categorized and ranked according to their respective importance. After finding the weights of these challenges, the current performance of AI was investigated by rating the performance of AI on the different criteria. Eventually, 16 experts on organic farming and AI technologies participated in the interviews.

This discussion session will dive into how the defined criteria and sub-criteria affect the adoption organic farming practices by organic farmers The results of the linear best-worst method are compared to the literature review, validation interviews and individual opinions of the experts. Additionally, the role that AI technologies can play in mitigating these challenges was analysed by an importance-performance-analysis. This study gives recommendations on first what are the most important challenges in organic farming that AI technology should focus on and second identifies the current performance of AI technologies in solving these challenges.

4.1 Results linear BWM

This section dives into the results of the linear BWM (Table 5). The results are discussed based on the three different main criteria.

4.1.1The influence of economic criteria on the adoption of organic farming

The most important criterium that resulted from the interviews was the economic criterium *(weight = 0.52)*. Experts 2,4,5,7,12 mentioned that higher production cost in combination with the risk of lower production is an important reason why conventional farmers don't make the switch to organic farming and is also confirmed by the weights of the sub-criterium 'higher production cost' with a weight of *(0,17)*. This is in line with the findings of (Łuczka-Bakuła, & Kalinowski. 2020) wherein the risk of low production was the most important barrier for farmers that want to make the switch to organic. Economic factors are more often found to be the most important barrier when implementing more sustainable practices (Malek & Desai, 2019). As the implementation of sustainability is seen as a cost-effective strategy, organizations still need enough incomes to implement organic farming. Especially, because the implementation of sustainability inside an organization has higher costs in several stages of the implementation (Malek & Desai, 2019). An explanation why economic factors like higher production cost are rated as most important may be caused due to the fact that a growing group of starting organic farmers are identified as "pragmatic" organic farmer (Łuczka-Bakuła & Kalinowski,2020). A pragmatic organic farmer is referred to as an organic farmer who ranks securing income above other non-economic principles of organic farming (Schneeberger et al., 2002). Consequently, this could mean that especially these economic barriers are most important when considering to switch to organic farming practices.

The 'dependency on manual labour' was ranked as the most important economic criterium, for farmers switching to organic farming. Expert 4, mentioned that currently in the Netherlands the availability of labour is scarce and that available labour is expensive. Especially when the amount of organic farmers will rise this challenge could be a growing issue. Expert 6 mentioned that labour scarcity is mainly caused by the fact that the labour requirement on an organic farm is very variable. the demand for external labour during the weeding season is high, while at other times of the year there is hardly any need for the use of external labour (Migchels et al., 2023). Therefore it is hard for organic farmers to contract employees for a longer time and the struggle to find the right skilled labour is a repeating element. Earlier studies, from Austria and Poland did not find that manual labour dependency was in the most important criteria. However, studies from the Netherlands mention manual labour dependency to be an important and growing challenge (Migchels et al., 2023; Koopmans et al., 2021). A possible reason for this international difference could be the labour market in the Netherlands. The Dutch labour market faces an oversupply of vacancies compared to the number of unemployed, with on average 410.000 vacancies and 360.000 unemployed persons in 2023 (CBS,2023). From these numbers it can be concluded that the dependency of manual labour is seen as severe problem in the Netherlands, especially as labour is not always available.

The ‘export dependency’ was mentioned to be the least important criterium of the economic challenges. Expert 6 mentioned that organic farmers don’t perceive the ‘dependency on expert’ as a major challenge, while Dutch organic arable farmers are generally able to produce organic crops of the highest quality in comparison to organic farmers in other European countries. This means that Dutch export products in general find their way to supermarkets abroad due to their superior quality and its storability. However, according to expert 4, the dependency on export could be a growing challenge when the organic production abroad is rising. As stated in chapter (1.3) The organic areas in the EU have been growing gradually, with a an increase of 6.5 million hectares between 2012 and 2021 (Eurostat, 2021). This is a possible obstacle for the sales of Dutch organic farmers, as more supply means more competition and eventually could lead to lower revenues (Migchels et al., 2023)

4.1.2 The influence of social criteria on the adoption of organic farming

Social criteria were evaluated with the lowest weights of the main criteria by the interviewees with an overall weight of (*0.09*). These results are in line with the results of (Schneeberger et al, 2002), who described that social influences had the lowest impact as a barrier on the adoption of organic farming practices. The similar sub-criteria, 'lack of knowledge' and 'lack of advisory services' both were ranked to be of minor importance (Schneeberger et al, 2002). Expert 7, confirms that the 'lack of knowledge' and the 'lack of advisory services' are no major challenges as most knowledge on organic cultivation is available and farmers are willing to share this among other organic farmers.

An interesting finding of this study shows that the 'new network' in this research was perceived to be the most important social challenge. This criterium was added as a challenge during the validation interviews as this criterium has not been identified in earlier research on adoption barriers in organic farming. Expert 1 and 5 mention that 'finding new buyers and setting up new relationships is one of the most underestimated challenges for starting organic farmers'. In addition to this Expert 4 mentions that 'Geographic dispersion of organic farmers plays a key role in the importance of finding this new network'. It is shown that organic arable farming in the Netherlands is mainly concentrated in the province of Flevoland with a 18,4 % share in comparison to the 3,4 % average of the Netherlands. Consequently, knowledge centers, buyers and processors of organic farming are located in this area (Dekking et al., 2020). Expert 4 also mentions that in some regions outside of Flevoland that have a low concentration of organic farmers, social pressure plays a role in the further growth of organic farming. In the literature it is also found that especially unsupportive family members and to a smaller extent pressure from neighbours plays a role in the adoption organic farming practices (Schneeberger et al, 2002).

4.1.3 The influence of environmental criteria on the adoption of organic farming

Environmental criteria were found to play a major role in the adoption of organic farming, and have an area weight of *(0,276)*. In contrast to earlier studies, environmental criteria were not rated as most important challenge (Schneeberger et al., 2002; Röös et al., 2018).

'Risk of pest and diseases' was rated as most important criterium in the environmental challenges with a global weight of *(0.108)*. Several experts (1,3,6,14, 16) mention that pests and disease play the biggest role in the yield reduction of organic farming in comparison to conventional farming. The risk of pest and diseases is mainly reduced by preventive measures like crop rotation. Some experts see the growing amount of organic farming in the Netherlands as a major risk in food security as less measures can be taken to combat these yield reductions.

*'*Weed pressure*'* was also rated as an important criterium in the environmental criterium with a global weight of *(0.08)*. Weed pressure is seen as an important criterium as of the amount of manual labour that is needed. However, most experts mention it to be less important than risk of pest and diseases, because when enough labour is available weed pressure does not account for too much yield reduction. In addition expert 6 mentions that weed pressure and dependency on manual labour are co-related to each other as weed pressure accounts for most of the extra manual labour hours in organic farming in comparison to conventional farming.

'Crop rotation' is identified to be a minor barrier in organic farming . These results correlate with the findings of (Schneeberger et al., 2002), wherein crop rotation is not seen as a major barrier when switching to organic farming. Expert 6 mentions that colleagues, advisory services and the internet can provide enough information on finding the right crops in the right sequence. Moreover, Expert 11 mentions that finding the right crop rotation is also something of personal opinion and is subject to trial-and-error to find the right balance.

'Crop/nutrient supply' is identified to be of minor importance as a barrier to go for organic farming, as confirmed by the low global weight of (*0.033)*. The supply of nutrients in organic farming is currently doable. One expert mentioned that, currently the Netherlands deals with an oversupply of nutrients in the form of manure in the Netherlands. However, this oversupply is already shrinking and the availability of nutrients can become a major problem if the amount of organic arable farmers continues to rise. Moreover, as the Dutch government wants to cut the amount of livestock farming in the Netherlands, the current oversupply could rapidly decrease into a shortage.

Table 5: Area weights, local weight and global weights of linear BWM

Criteria	**Criteria weight**	**Sub criteria**	**Local weight**	**Global weight**
		Lack of knowledge	0.275	0.026
Social	0.092	*Lack of advisory service*	0.128	0.012
		New network	0.422	0.039
		Higher cost price	0.335	0.167
Economic	0.570	*Dependency manual labour*	0.388	0.194
		Export dependency	0.123	0.061
		Risk of pest/ disease	0.355	0.108
Environmental	0.276	*Weed pressure*	0.315	0.096
		Crop rotation	0.093	0.028
		Crop/nutrient supply	0.108	0.033

4.2 The effect of working background on the weights of the criteria and sub criteria

This study made use of two different groups of experts, namely experts who work as a researcher at Wageningen University & Research (academics) and experts who originate from the organic farming sector and AI sector (industry experts). It may be possible that these two different groups of experts had a different view on the importance of the criteria in organic farming. Therefore, the results of the different expert groups were compared by performing a Mann-Whitney U test. From (Table 6) it can be seen that there is no significant difference in the importance of the main criteria between the two groups. The same test was performed for the sub criteria. It was found that there were no significant differences found between the two groups, except for the sub-criterium 'weed pressure' ($p<0.05$) (Table 7). As for industry experts the importance of weed pressure (Geomean: *0.466*) is higher than for the academics (Geomean: *0.278*). An explanation for this difference could actually be the increasing implementation of AI systems in detecting and removing weeds from the fields. While this disruptive innovation is a recent development, there could be disagreement between the experts about the extent to which AI is solving this problem already and thus a difference in opinion about how important this issue still is currently. This was also mentioned in an earlier literature review, which mentioned that the application of these new weeding machines is low. However, current benchmark technologies are able to detect and remove up to 80% of weeds from the experimental fields (Li et al., 2022). As earlier mentioned in section (3.3.1), industry experts are more closely related to the practices of organic farming in the field, and they might observe that weed pressure is still one of the most important barriers. In contrast to the academic experts who may not be too alert on the current application of weeding robots in practice.

Table 6: Test statistics of the Mann-Whitney U test on the main criteria

	Environmental	*Social*	*Economic*
Mann-Whitney U	15.500	23.000	47.500
Wilcoxon W	43.500	51.000	75.500
Test Statistic	-1.700	-0.910	1.700
Asymptotic Sig. (2-tailed)	0.089	0.363	0.089

Table 7: Test statistics of the Mann-Whitney U test on the sub-criteria

	Lack of knowledge	*Lack of advisory service*	*New network*	*Weed pressure*	*Crop rotation*	*Crop/nutrient supply*	*Risk of pest/disease*	*Manual labour dependency*	*Higher cost price*	*Export dependency*
Mann-whitney U	26.500	35.500	32.000	51.000	46.000	16.000	13.000	27.000	34.500	33.000
Wilcoxon W	54.500	63.500	60.000	79.000	74.000	44.000	41.000	55.000	62.500	61.000
St. Test Statistic	-0.530	0.424	0.053	2.066	1.538	-1.643	-1.961	-0.478	0.319	0.159
Asymptotic Sig.(2-tailed)	0.596	0.671	0.958	**0.042**	0.124	0.100	0.050	0.633	0.750	0.918

4.3 Importance-Performance Analysis

Performance AI in the sub-criteria

During the literature review, it was found, that the potential for AI technologies on economic related challenges is high. From the interviews it was found, that the two most important criteria ‘higher production cost’ & ‘dependency on manual labour’ currently have a low AI performance. The opinion of the experts corresponds with what has been found in the literature review that AI has enormous potential to contribute in solving these specific challenges. Especially, the dependency on manual labour is seen as a challenge that has a major potential to be solved by AI technologies. Concrete solution are already introduced to the market, however these are still at a very early stage of development. Weeding robots are currently achieving higher accuracy rates in detecting and removing weeds (Li et al., 2022).

Expert 9 confirmed to this that there are many variables in the field that reduce the accuracy of detection by weeding robots like weather conditions, weed densities and weed species. e These weeding robots show that they are able to reduce labour dependency and weed pressure at the same time. This is also confirmed by earlier studies which show that a lot of challenges are interrelated and AI applications can solve different challenges at the same time (Ryan et al., 2023). Moreover, dependency on manual labour is currently starting to be reduced by AI technologies in a lot of farm jobs that require manual labour like sorting and packing of crops, but these innovations are mutually beneficial for organic and conventional farmers.

Higher cost price:

The current assessment of AI's effectiveness in reducing cost prices in organic farming yields a low performance rating, with an average of (*2.13)*. Expert 16 mentions that currently, the software of AI technologies is very expensive and that the amount of experts on AI that do the maintenance of AI applications in agriculture which makes it expensive are scarce. Therefore, manual labour practices and non-AI technologies are currently seen as cheaper alternatives in the most application in which AI can play a role. This perspective aligns with the findings of Ryan et al., (2023) who states that as current AI applications in farming practices are in need of sensors and cameras, to retrieve data. These products are relatively new to the market of agricultural products which makes them expensive to purchase and in need of maintenance. Nevertheless, it is expected that these products will become cheaper over time and will be able to reduce current cost prices (Lassoued et al., 2021). This reduction in cost price by AI technology is confirmed by the fact that AI has proven to increase productivity and efficiency in farming practices (Sood et al., 2022).

Export dependency:

Most experts state that currently there are few applications of AI that help in reducing the dependency on export, concluding that the current performance is relatively low. However, it must be stated that a major share of the experts don't see a major role of AI technologies in reducing the dependency on export or playing a role in the trade of farming commodities. This is in line with the literature which does not state that AI technologies are able to reduce the dependency on export directly. Instead, the potential for AI lies in creating a more efficient supply chain by predicting consumer demand, reducing trade costs and analyse macro-economic trends (Zhang, 2023).

Risk of pest and diseases

The current performance of AI technologies in reducing the risk of pest and diseases was ranked as low by the experts. Combined with the fact that this criterium is one of the most important challenges for organic farmers and as the potential is high it is an important area in which AI technologies can make a difference. Expert 9 mentions that ‘AI technology is able to detect pest and diseases in an early stage of development, however currently there are no machines on the market that actually have a practical solution for it’. Especially as organic farming practices are not able to use control measures like pesticides, it heavily relies on preventive measure like early detection. From literature, it is clear that AI can use captured images of crops as input for analysis, such as the examination of plant leaf images. This enables AI systems to detect healthy and infected areas of plants well in advance of the human-eye (Ryan et al., 2023; Balaska et al., 2023). To make a difference in organic farming practices, AI applications in pest & disease management should therefore be focused on accurate and early detection of pest & diseases that play a crucial role in yield reduction.

Crop/nutrient supply

The current performance of AI technologies in efficiently applying fertilizer are relatively high. Expert 8 mentions that with the help of task maps, farmers are already able to map which parts of a plot need more or less fertilizer. This also was found in earlier research wherein sensors, drones, and advanced data analysis based on AI are often used to monitor the condition of the crop and the soil. Based on the data analysis of AI, the right fertilizer, the right amount and the right time of application can be found (Singh & Jain, 2022).

Crop rotation/lack of knowledge/lack of advisory services

Currently, the performance of AI in assisting farmers in crop rotation choices is low. As mentioned before expert 6 mentioned that the role of AI in assisting in crop rotation might be low as too many variables play a role for AI to give accurate outcomes. Nevertheless, the development of an AI tool that bundles the information available to provide knowledge and insights from research can be a very helpful tool for farmers. This also accounts for the criteria ‘lack of knowledge’ and ‘lack of advisory services’. Expert 16 mentions that the development of generative AI-systems like ChatGPT will be able to solve these three challenges at the same if these generative AI-systems become more reliable and accurate. This is in line with the literature which states that one potential of AI systems lies in better support systems for farmers in different fields like crop rotation, water management, planting moment, and harvest time (Javaid et al., 2023). This support system must fuse the use of big data and the analytics of AI to give real-information on crop growth (Megeto et al., 2020).

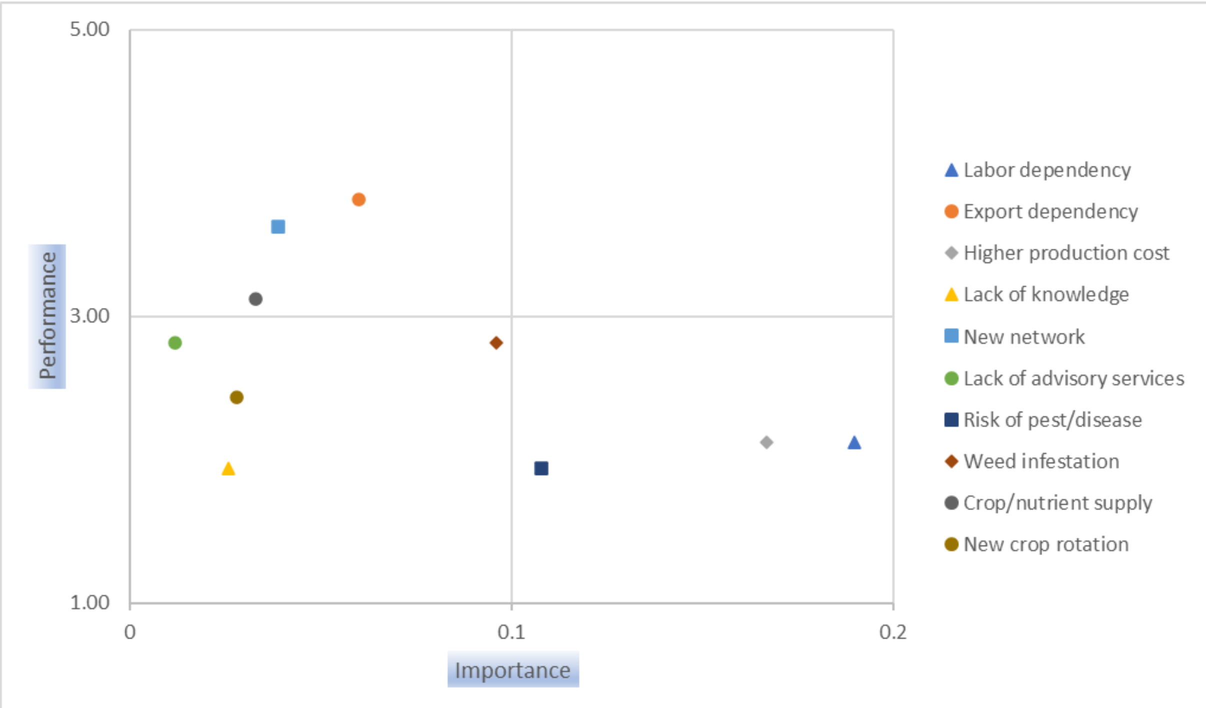

Figure 4: Importance/performance analysis of the selected sub-criteria

The results of the importance/performance analysis (Figure 4) show that the criteria are grouped in three different quadrants:

Quadrant A: The criteria with high importance and low performance are ‘labour dependency’, ‘higher production cost’ and ‘risk of pest and disease’.

Quadrant B: No criteria are grouped in the quadrant of high importance and high performance.

Quadrant C: The criteria with low importance and low performance are ‘lack of knowledge’, ‘lack of advisory services’, ‘crop rotation’ and ‘weed infestation’.

Quadrant D: The criteria with low importance and high performance are the ‘new network’, ‘export dependency’ and ‘crop/nutrient supply’.

Table 8: Levels of importance and performance of the sub-criteria

Sub criteria	**Importance**	**Performance**
Lack of knowledge	0.275	1.94
Lack of advisory service	0.128	2.81
New network	0.422	3.63
Higer cost price	0.335	2.13
Dependency on manual labour	0.388	2.13
Export dependency	0.123	3.81
Risk of pest/ disease	0.355	1.94
Weed pressure	0.315	2.81
Crop rotation	0.093	2.44
Crop/nutrient supply	0.108	3.13

5 Practical implications

The outcomes of this report may contribute to more effective policy making in stimulating the growth of organic arable farming in the Netherlands. The most important challenges of arable farmers switching to organic farming were found by identifying and ranking these challenges. For the economic criteria two essential challenges were found: higher production cost & dependency on manual labour. For the environmental criteria also two essential challenges were found: Risk of pest/disease and weed pressure. By specifically focusing on reducing these four challenges, a major step forward can be made in the further adoption of organic farming practices

Moreover, the outcomes of this report may contribute to finding relevant development areas of AI applications in organic farming. By initially identifying the potential of AI technologies and after measuring the current performance of AI technologies in organic farming, this approach gave insight in potential improvement areas for AI applications in the organic farming sector. The findings suggest that the development of new AI applications for the organic farming sector should mainly be focused on the economic criteria of lowering the production cost of organic farming and reducing the dependency on manual labour. Moreover, to reduce the risk of pests and diseases, AI applications should mainly be focused on early detection to play an important role in organic farming. Also for the less important challenges; 'lack of knowledge', 'lack of advisory services' and 'crop rotation' there is enough scope for development. These criteria can be improved if generative AI systems can become more reliable and valid over time. However, not all challenges might benefit from AI applications, as it was found that the potential of AI in finding a 'new network' and 'export dependency was rather low' and for these challenges, the role of human intervention should remain high.

6 Conclusion

This research aimed to investigate the mitigating effect that AI technologies can have on the most important challenges experienced by Dutch arable farmers switching to organic. After doing an extensive literature review which showed that the role of AI technologies in mitigating the challenges faced by arable farmers switching to organic is not investigated. The most accurate subdivision of the challenges was achieved, by using the Triple Bottom Line model as a way of categorizing the most important challenges (criteria). After doing this literature review and verification with two experts on organic farming, 10 sub-criteria were found. The final sub-criteria were; 'higher cost price', 'manual labour dependency', 'export dependency', 'risk of pest and disease', 'weed pressure', 'crop/nutrient supply', 'crop rotation', 'lack of knowledge', 'lack of advisory services' and 'new network' .The sub-criteria were further divided into the three main criteria economic, environment and social, the pillars of the Triple Bottom Line.

The importance of the criteria was determined by performing a linear BWM, which is an MCDM method that ranks criteria based on pairwise comparisons. By performing structured interviews with 16 experts on organic farming and AI technologies, it was possible to determine the importance of the main criteria and sub-criteria. The linear BWM results showed that economic criteria are the most significant challenges whereafter environmental challenges also form significant challenges. However, social criteria don't play a major in the challenges of arable farmers switching to organic. It was found that 'higher production cost', 'manual labour dependency' and 'risk of pest/disease' were identified as the most significant challenges.

Next to the importance of different criteria for switching to organic farming, the current performance of AI technologies in mitigating these challenges was measured. By asking the experts how they rate the current performance of AI technologies in mitigating the challenges of organic farmers it was possible to construct an importance/performance analysis. It was found that the most important challenges; 'higher production cost', 'manual labour dependency' and 'risk of pest/disease' currently have a low performance. However, experts specifically mentioned these challenges as having significant potential for solutions through AI technologies. Moreover, this study found in contrast to earlier literature on the potential of

AI technologies that the role of AI technologies in assisting in developing a 'new network' and reduce 'export dependency' is rather low. Regarding the criteria 'lack of knowledge', 'lack of advisory services' and 'crop rotation', experts currently assign a low performance rating due to the current unreliability of generative AI systems. If these generative AI-systems will become more reliable over time, there is significant potential for addressing these criteria effectively through AI technologies.

Nevertheless, this research has some limitations, it is therefore crucial to identify these limitations to be beneficial for future research. First of all, this study made use of the linear BWM, which is known for its efficiency and consistency. However, the linear BWM method does not account for any interaction between the criteria. When discussing the results it was found that some criteria may interact with each other. Especially the criteria 'dependency on manual labour' and 'weed pressure' are likely to interact. Therefore, follow-up research in defining the most important criteria in the switch to organic farming should use an MCDM method that accounts for interactions between criteria.

Secondly, this research relies on a relatively small sample size of (N=16) due to the relatively short time that was available. Therefore it might be possible that the results are not generalizable, so follow up research should increase the sample size to grasp a more reliable understanding of the role of AI technologies in solving the challenges of farmers switching to organic farming.

Thirdly, the challenges identified in this report should not be generalized for the full supply chain of organic agriculture. It therefore might also be interesting to identify the importance of the challenges for consumers in buying organic products. This is especially relevant because if the consumption of organic products remains low, further growth of organic farming adoption is hindered. A broader understanding of the factors that hinder the growth of organic agriculture can lead to more effective measures in mitigating these challenges. Eventually, by solving these barriers, the Netherlands may finally fulfil the goals set by the European Union on organic farming.

7 Literature

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7 Appendices

Interview Guide BWM Method & Importance-Performance Analysis

Permission for recording:

Ask for permission to record, still all given information will remain anonymously.

Introduction:

I am Thomas Bokdam, and I grew up on a organic arable farm in the Flevopolder, currently working on my thesis as part of my master in Sustainable Business and Innovation. This master's thesis focuses on the role of artificial intelligence in addressing the challenges faced by organic farmers and farmers in transition in comparison to conventional farmers. The research aims to identify the current performance of AI in addressing the challenges faced by organic farmers and aims to find improvement areas of AI in organic farming.

Numerous studies have explored the challenges and barriers experienced by organic arable farmers and farmers in transition, but these studies are not specific to Dutch arable farming, and they often are quite old. The purpose of this interview is to determine the level of importance of chosen challenges based on the Best Worst Method and find the current performance of AI in addressing these challenges.

Introduction questions:

1. Do you have any questions regarding the key concepts/ methods of this interview?
2. Do you have any other questions or unclarities before we start the interview?
3. Could you give a short introduction about your professional background?

Table 1: Challenges experienced by organic arable farmers/ farmers in transition to organic

Main areas / main criteria

Considering the main areas of the challenges in organic farming, choose the best (most important) and the worst (least important) area.

Compare the most important challenge with the least important challenge

Compare the most important improvement area with the remaining improvement areas, using a scale from 1 to 9 (where 1 is 'equally important' and 9 is 'extremely more important').

Compare the least important improvement area with the remaining improvement areas, using a scale from 1 to 9 (where 1 is ‘equally important’ and 9 is ‘extremely more important’).

Sub criteria (Economic)

Considering the economic challenges in organic farming, choose the best (most important) and the worst (least important) challenge.

Compare the most important challenge with the least important challenge

Compare the most important challenge with the remaining challenges, using a scale from 1 to 9 (where 1 is ‘equally important’ and 9 is ‘extremely more important’).

Compare the least important challenge with the remaining challenges, using a scale from 1 to 9 (where 1 is ‘equally important’ and 9 is ‘extremely more important’).

Social

Considering the social challenges in organic farming, choose the best (most important) and the worst (least important) challenge.

Compare the most important challenge with the least important challenge

Compare the most important challenge with the remaining challenges, using a scale from 1 to 9 (where 1 is ‘equally important’ and 9 is ‘extremely more important’).

Compare the least important challenge with the remaining challenges, using a scale from 1 to 9 (where 1 is ‘equally important’ and 9 is ‘extremely more important’).

Environmental

Considering the environmental challenges in organic farming, choose the best (most important) and the worst (least important) challenge.

Compare the most important challenge with the least important challenge

Compare the most important challenge with the remaining challenges, using a scale from 1 to 9 (where 1 is ‘equally important’ and 9 is ‘extremely more important’).

Compare the least important challenge with the remaining challenges, using a scale from 1 to 9 (where 1 is ‘equally important’ and 9 is ‘extremely more important’).

AI performance

Could you rate the current performance of AI in tackling the challenges in organic farming using a scale from 1 (very low) to 5 (very high) regarding their performance?

Closing questions + acknowledgment:

1. Do you think that the topics that we discussed during this interview are relevant for usage of AI in organic arable farming?

2. Are you interested in receiving the outcomes of my research by mail ?