



Examining the interplay between artificial intelligence and the agri-food industry

Abderahman Rejeb ^{a,*}, Karim Rejeb ^b, Suhaiza Zailani ^c, John G. Keogh ^d, Andrea Appolloni ^a

^a Department of Management and Law, Faculty of Economics, University of Rome Tor Vergata, Via Columbia, 2, Rome 00133, Italy

^b Faculty of Sciences of Bizerte, University of Carthage, Tunis, Tunisia

^c Department of Management, Faculty of Business and Economics, University Malaya, Kuala Lumpur, 50203, Malaysia

^d Henley Business School, University of Reading, Greenlands, Henley-on-Thames RG9 3AU, UK

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ABSTRACT

Artificial intelligence (AI) has advanced at an astounding rate and transformed numerous economic sectors. Nevertheless, a comprehensive understanding of how AI can improve the agri-food industry is lacking. In addition, there is a notable dearth of research on AI that investigates the influence of AI on agri-food resources and educates practitioners on the significance of knowledge-based and smart agriculture. We utilised bibliometric analysis to investigate the present state of the art and emerging trends in the relationship between AI and the agri-food industry. The research identified three distinct growth phases and the most prevalent AI strategies in the industry. In addition, we analysed key trends and offered researchers and practitioners insightful recommendations for future research. Using resource-based view (RBV) as the theoretical lens, this study established a framework emphasising the long-term effects of AI on various agri-food resources and proposed several research propositions. In addition, AI-related obstacles have been identified and categorised into four major categories. Lastly, the originality of the article lies in its numerous research suggestions and recommendations for advancing the AI field in the agri-food industry.

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* Corresponding author.

E-mail addresses: rjbrh01@uniroma2.it (A. Rejeb), karim.rejeb@fsb.ucar.tn (K. Rejeb), shmz@um.edu.my (S. Zailani), john@shantalla.org (J.G. Keogh), andrea.appolloni@uniroma2.it (A. Appolloni).

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1. Introduction

The agri-food industry constitutes one of the key contributors to any nation's economy and is vital for the well-being of nations' citizens (Abdollahi et al., 2021; Mithun Ali et al., 2019; Rejeb et al., 2022a). Moreover, the agri-food sector is of growing importance to developing and developed countries due to its role in supporting more sustainable production and consumption patterns, environmental protection, business competitiveness, social welfare, and economic growth (Del Borghi et al., 2014). Despite its importance, this sector faces several challenges driven by climate change, unprecedented technological innovation, and increased calls for sustainability, traceability, and transparency (Fait et al., 2019; Goodarzian et al., 2021). The notion of sustainability is becoming critically important in the agri-food industry due to increasing needs for food quality and safety, the effective utilisation and consumption of natural resources, and the balanced economic, ecological and societal performance of agri-food businesses (Mangla et al., 2018).

Agri-food businesses must eliminate supply chain inefficiencies and develop a more sustainable ecosystem (Rejeb et al., 2021a). One way to revolutionise the agri-food sector and increase sustainability is to leverage artificial intelligence (AI) applications. According to Holt (1978), AI is the science of programming computers to mimic the tasks of human behaviour that necessitate intelligence, judgement, and experience. Coupled with high-performance computing and big data technologies, AI techniques like deep learning, machine learning, and artificial neural networks present significant potential for data-intensive science in agriculture (Kamilaris and Prenafeta-Boldú, 2018; Liakos et al., 2018a; Rohit Sharma et al., 2020). For example, Patrício and Rieder (2018) investigate the combination of computer vision solutions and AI algorithms in precision agriculture and highlight several benefits of these technologies, including task automation, profitability, and increased food quality and safety.

Khoshnevisan et al. (2015) note that AI can assist greenhouse operators concerned with ecological performance in predicting the environmental effects of their cultivation systems and justifying claims about their products. Similarly, Pantazi et al. (2016) posit that AI can be applied to understand yield response to soil variables, identify the factors responsible for yield and quality variation, and determine target yields. AI pushes the conventional agricultural practices and methods toward smart farming, a sustainable approach that helps to reduce the waste of resources (e.g., fertilisers, pesticides) and achieves sustainable development (Fan et al., 2018). Pydipati et al. (2006) highlight that combining AI and machine vision helps achieve smart farming. These technologies facilitate the early detection of plant diseases, proper plant control, and minimise losses. Several AI models can process data generated from agriculture internet of things (IoT) and sensors to provide accurate and precise farming for soil fertility, diseases, irrigation, and pest regulations (Lin et al., 2019). AI also makes robots well equipped to optimise productivity (Brogårdh, 2007), improve work efficiency, and enhance the quality of fresh produce (Bechar and Vigneault, 2016). The use of data can enhance farming practices and operations as agri-food businesses can create value from it, relying on the ability of AI to manage data sharing and access control (Spanaki et al., 2021). Therefore, AI can address the knowledge needs of farming businesses and increase their ability to identify diseases, monitor irrigation, reduce human efforts, and maximise yield production.

Many academics have extensively studied the use of AI in agricultural activities in recent years. Research content involves various aspects, such as the state-of-the-art of AI, its applications, and promises for agri-food businesses. For example, Kollia et al. (2021) review AI-enabled food supply chains. They find that AI methodologies predict plant growth and yield, optimise energy consumption across an extensive network of food refrigeration systems, and automate the inspection of retail packaged food. Liakos et al. (2018a) thoroughly review the possibilities of machine learning and reveal that this AI technique supports crop management and the reliable analysis of data generated from IoT sensors. According to the authors, machine learning has been employed mainly in some crops and animals, including maize, wheat, cattle, and sheep. Moreover, Saleem et al. (2019) summarise the literature surrounding the use of automation in agriculture through machine and deep learning tools and argue that these technologies bring human-level precision in diverse agriculture applications such as plant recognition, fruit counting, plant disease detection and classification, land cover classification, and weed/crop discrimination. Shine and Murphy (2022) conduct a mapping study to aggregate and evaluate journal articles and conference papers, which employ machine learning algorithms in farming-related issues to detect patterns in the geographical sources of data, algorithms, features, assessment metrics, and methodologies applied. Hassoun et al. (2022) review the most critical food Industry 4.0 technologies, including AI, the IoT, big data analytics, and blockchain. Chen and Yu (2021) summarise the recent developments in reliable, precise, and cost-effective remote tools in the food industry, such as AI-based techniques, image processing systems, and sensors for quality evaluation. According to the authors, image processing systems and AI can be utilized for different objectives such as product classification based on shape and size, detection of product defects and microbes, and food quality grading. Qazi et al. (2022) review the literature pertaining to the applications, challenges, and future trends of IoT technologies and AI techniques in smart agriculture. Finally, Tripodi et al. (2022) study the contributions of AI and machine learning to data analysis and their use in next-generation breeding.

While these studies provide valuable insights into AI applications in the agri-food sector, a bibliometric analysis is still needed to analyse the interplay between AI and the agri-food sector and consolidate the literature. In general, when a research field observes a significant rise in the number of published works, as in AI research (Ruchika Sharma et al., 2022; Singh et al., 2021), there is a need for organised and systematic reviews that employ quantitative methodologies to study the knowledge landscape and structure of the AI field in the agri-food industry (Rejeb et al., 2020; Rejeb et al., 2022b). Although traditional reviews mainly aim to summarise the current literature based on authors' opinions and judgments, which may be prone to numerous forms of biases (A. A. Qazi and Appolloni, 2022), bibliometric analyses add rigour thanks to their quantitative and structured literature investigations. Indeed, this rigour can be viewed as the fundamental contribution of the technique (Piwowar-Sulej et al., 2021). Moreover, the main advantage of bibliometrics, compared to conventional traditional review methodologies, is that it facilitates the construction of objective, reliable, detailed, and comprehensive knowledge visualisations (Rejeb et al., 2022d,e). Such visualisations constitute analytical representations of linkages between scientific entities (L. Zhang et al., 2019). The merits of scientific mapping also include studying large datasets and

generating memorable, rich, and interpretable visuals. Consequently, applying bibliometrics provides timely, unbiased, and visual techniques to trace the growth of scholarly activities and evaluate the intellectual structure of a particular research field (Rejeb et al., 2022e). It enables understanding of the historical development of a discipline and allows identifying research trends and hotspots from micro and macro perspectives (Rejeb et al., 2021b).

Therefore, we argue that the increasing body of knowledge related to AI requires a bibliometric approach to comprehend the knowledge structure of this field. Since AI research matures and becomes increasingly complex, it is crucial to provide a retrospective evaluation of the publications accumulated to reveal new contributions, capture research trends, and identify prospective areas for future investigation. Overall, the aims of the study are driven by the four research questions below:

- What are the research trends on the nexus of AI and the agri-food sector?
- How is AI being utilised in the agri-food sector?
- What are the important research hotspots in AI and the agri-food sector?
- What are the key challenges to AI application in the agri-food sector?

The findings of the bibliometric analysis show a significant rise in the scholarly works examining the potential of AI for the agri-food industry. Several bibliometric indicators, including the most relevant journals, the most cited countries, and the most publications, are also identified. The keyword analysis demonstrates the prevalence of some AI techniques in the agri-food context, including deep learning, convolutional neural network, and artificial neural networks. Furthermore, the trend topics analysis shows an earlier focus on using AI-powered robots in agriculture and an emerging tendency toward different technologies and AI techniques, including big data, the IoT, deep learning, machine learning, and fuzzy logic. The keyword co-occurrence network analysis aids in unravelling the research hotspots of AI, suggesting that AI techniques contribute to food safety and the development of smart farming practices (e.g., smart crop, soil, water, and livestock management). However, AI's benefits cannot be realised unless the technology's social, technical, ethical, and organisational issues are addressed. The overall findings of the review have been integrated into a unified and sound theoretical framework to underscore the long-term impact of AI on various agri-food resources and advance future studies on the technology. In terms of contributions, no prior bibliometric analysis of AI research in the agri-food context is as extensive, systematic, and timely as ours. By doing a bibliometric study of this subject, we offer in-depth understanding and enrich the knowledge field by highlighting key AI applications employed in the agri-food industry and the potential and constraints of AI for agri-food businesses. Moreover, intriguing research possibilities are offered for researchers, professionals, and policymakers wishing to understand AI and its role in attaining sustainability in the agri-food industry. Furthermore, this study's novelty resides in the useful conceptual framework for practitioners and researchers who want to grasp AI's influence on agri-food resources. Further, various research propositions developed from the framework may be experimentally confirmed by academics in the future.

After the introduction, we describe the bibliometric technique and research procedure employed. Next, we analyse the main results, including the yearly distribution of publications, the most productive journals and nations, the most influential publications, and the research hotspots. In Section 4, we discuss the findings and highlight research contributions, research agenda, and shortcomings. In Section 5, the study finishes with short reflections and conclusions.

2. Bibliometric method

Multiple indicators can be utilised in a bibliometric study to analyse a specific academic subject (Kapoor et al., 2018; Mishra et al., 2017;

Rejeb et al., 2020; Rejeb et al., 2021a). We utilised best practices and recommendations to conduct a dependable and insightful bibliometric analysis (Beydoun et al., 2019; Fahimnia et al., 2015; Mostafa, 2020) of the interplay between AI and the agri-food sector. As a first step, we consulted one of the leading and trustworthy scientific databases, Web of Science (WoS) (Caulfield et al., 2012; da Silva et al., 2017; Treiblmaier et al., 2020). While a few scholars have utilised Scopus to conduct similar analyses (Faruk et al., 2021; Herrera-Franco et al., 2020; Mishra et al., 2021), recent works have identified that the bulk of bibliometric studies use the WoS databases (Alnajem et al., 2021; Escamilla-Fajardo et al., 2020; González-Serrano et al., 2019; B. Wang et al., 2014). Bartol and Mackiewicz-Talarczyk (2015) argue that, unlike other scientific databases, the records extracted from the WoS database are more standardised and consistent. WoS enables the straightforward retrieval of publications, author names, sources, and cited references. Moreover, WoS represents the most renowned database and has been internationally utilised to assess academic performances (L. Zhang et al., 2019). The search strategy applied to extract the data on AI research in the agri-food context is as follows. Following Fosso Wamba and Queiroz (2021), “artificial intelligence” OR “machine learning” OR “deep learning” OR “robot” were used and combined with “food” OR “agriculture*” OR “agri-food” OR “agro-food” in the title, abstract, and keywords fields to extract the publications (see Fig. 1). WoS Core Collection, including Science Citation Index Expanded (Sci-Expanded), Social Sciences Citation Index (SSCI), Arts & Humanities Citation Index (A&HCI), and Emerging Sources Citation Index (ESCI), was used to conduct the research. Even though there were no restrictions on the time span, the first two papers selected were published in 1992. Non-English language publications and publications with incomplete bibliographic data (e.g., keywords) were excluded. The initial search query returned 4869 documents. The returned publications were evaluated against the inclusion criteria, assuring publications were English-language speaking, with complete bibliographic data, and relevant to the research topic. Moreover, two reviewers were involved in the careful reading of the titles and abstracts of the returned documents to minimise bias and guarantee the validity and reliability of the findings (Thomé et al., 2016). The application of these filters and the manual screening of the documents led to the exclusion of 708 documents, either non-English documents with incomplete bibliographic data or irrelevant. To analyse the findings, we used the visualisation tool VOSviewer (Rejeb et al., 2022c; van Eck and Waltman, 2011, 2014) and the statistical software package Biblioshiny (Shonhe, 2020). These software tools are specialised in data mining and quantitative analysis. Finally, the publications were coded according to the publication year, most productive journals, most cited countries, and influential publications. Keywords analysis, abstract analysis, trend topic analysis, and keyword co-occurrence analysis were also conducted to depict the dynamics, trends, and avenues for future research opportunities in the AI field.

3. Results from the bibliometric analysis

Our analysis did not restrict the time period and noted that the first two extracted publications appeared in 1992 (see Table 1). 589 of the 4750 papers retrieved contain insufficient data for bibliometric analysis. Consequently, we evaluated 4161 papers written by 14,779 authors. A single author wrote only 4.49% (187 out of 4161 total papers). Moreover, the authors employed a large number (12375) of keywords.

3.1. Annual distribution of publications

Fig. 2 depicts the evolution of AI research in the context of the agri-food industry based on the annual distribution of a sample of papers. There are three distinct growth stages visible. In the first phase, from 1992 to 2000, the maximum number of papers published per year was fifteen (in 1997); in the second phase, from 2001 to 2010, the

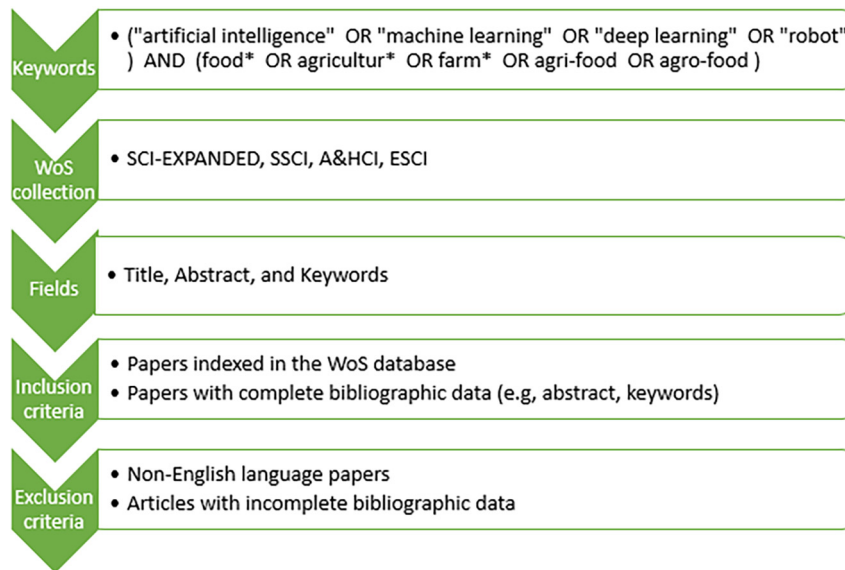


Fig. 1. The review protocol.

maximum was thirty. We can observe slow and inconsistent growth, surpassing thirty published documents in 2010. The last three years have witnessed unprecedented growth in the third phase (2011 to 2020). During this period, AI applications in the agri-food industry received great attention, as evidenced by the sharp increase in publications. In 2020, scholarly output more than doubled from 2019, surpassing 1700 documents, suggesting that the proliferation and prevalence of various AI approaches and applications in the agri-food industry can explain this dramatic increase.

3.2. Top 20 most relevant journals

Regarding the most relevant journals based on the number of articles published, Table 2 lists the top 20 and reveals that Computers and Electronics in Agriculture is the only outlet to surpass 300 publications. In addition, we can see that information technology and environmental science journals dominate the list. Surprisingly, no business, management, or operations research journals were ranked among the top 20.

Table 1
Main information regarding data collection.

Description	Results
Main information about data	
Timespan	1992:2021
Sources (e.g., Journals, Books)	1264
Documents	4161
Average years from publication	3.54
Average citations per document	14.99
Average citations per year per doc	3.31
Document contents	
Keywords plus (ID)	7150
Author's keywords (DE)	12,375
Authors	
Authors	14,779
Author appearances	18,988
Authors of single-authored documents	187
Authors of multi-authored documents	14,592
Author's collaboration	
Single-authored documents	207
Documents per Author	0.282
Authors per Document	3.55
Co-Authors per Documents	4.56
Collaboration index	3.69

This suggests that the dominant journals focus on the technical aspects of AI research in the agri-food sector, necessitating knowledge from various disciplines and sources.

3.3. Top 20 most cited nations

Table 3 lists the top 20 countries by total citations regarding the most cited nations. Only the United States and China received over nine thousand citations. Followed by Spain (3219), the United Kingdom (3010), and Australia (2771). Consequently, the average number of citations per article in China was lower than in all countries listed. This result may suggest that Chinese researchers need to improve the calibre of their published work. In addition, most cited articles originated from developed nations, reflecting the technological advancements made in the AI field and the availability of advanced research labs. Although the United States dominated the list, Europe, Asia (China, India, Japan, and Korea), and Oceania (Australia) are well represented. Latin American and African nations did not appear in the ranking, except Brazil. Switzerland ranked first (44.92 average citations per article), followed by Ireland (39.85), Greece (34.52), Sweden (31.14), and the Netherlands (24.79).

3.4. Top 20 most cited publications

Table 4 includes the authors, titles, sources, citations, and citations per year for the most cited publications. We can see that two of the top 20 papers were published in 2012. The most cited articles incorporate AI techniques into the agri-food industry. Algorithms (regression) and deep learning are the most frequently used AI techniques in the top five AI-related publications. Overall, regression, deep learning, machine learning, and optimisation applications in the agri-food industry received considerable attention. Recent articles by Kamilaris and Prenafeta-Boldú (2018), Bioucas-Dias et al. (2012), and Wolfert et al. (2017) were the three most cited according to the total citations per year (TCY). The authors of the most-cited paper examined applications of deep learning in agriculture and received a significant number of citations per year (153.75). In the second most-cited paper, AI algorithms were useful for supporting hyperspectral cameras and facilitating several agri-food activities, including remote sensing of farms and food safety. The third most-cited paper examined big data applications in smart agriculture and how their deployment can provide new opportunities for data-intensive science in the agri-food industry. Other cited

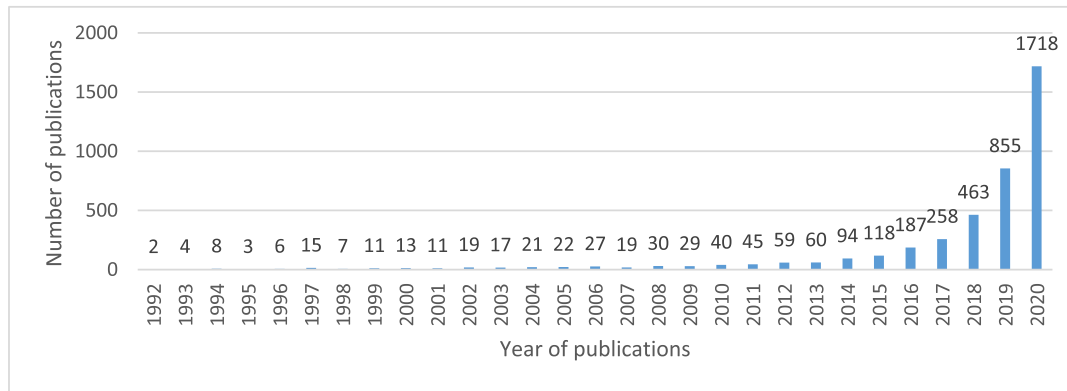


Fig. 2. The annual distribution of publications.

publications from 2018 emphasise the significance of AI techniques for agriculture and farming. Lastly, we observe that Huaizhi Wang is the primary author of two papers and that computer science journals are the leaders in AI research in the agri-food industry Table 4.

3.5. Keywords analysis: Authors versus keywords plus

We extracted both the authors and keywords plus from WoS to examine keywords dynamics (see Table 5). The former set of keywords is provided by the authors themselves, while the second is generated regardless of the title or author keywords, reflecting the paper's contents with profound depth and variety (Garfield, 1990; Rejeb et al., 2022d). The analysis of author keywords and keywords plus could overcome limitations like the uncomplete meaning and the small number of author keywords. Since the keywords used in the search query were “artificial intelligence”, “machine learning”, “deep learning”, “food”, and “agriculture”, it is evident that they appeared in the first ranks on the authors' keywords' side. Nevertheless, it should be mentioned that the keyword “machine learning” exceeded four times the occurrences of “artificial intelligence”. Moreover, we can see the high frequency of other AI techniques such as deep learning, convolutional neural networks, and artificial neural networks. Other keywords also held a high position, such as “remote sensing”, “computer vision”, “image processing”, “big data”, and “internet of things”. These technologies constitute enablers for precision agriculture strategies. They can optimise crop production,

reduce the environmental impacts of agricultural activities, and ensure reliable sensing of different variables (e.g., soil properties, water management, weather, topography) for large crop fields. As per the keywords plus, terms such as “classification”, “system”, “model”, “prediction”, and “identification” appeared in the top 10, thus informing the keywords supplied by the authors. In addition, some other essential topics emerge from the keywords plus list, including “regression”, “optimisation”, and “segmentation”. In this vein, this collection of keywords has an important association with AI approaches since they reflect some AI capabilities in agri-food management, among other things, prediction and optimisation of crop yield, plant segmentation, and forecasting of environmental variables. Therefore, keywords plus advocate the potential of AI for the realisation of increased value within the agri-food sector.

3.5.1. Treemap based on abstracts

To supplement the analysis of the keyword's dynamics, we extracted the most frequent terms from abstracts. In Fig. 3, the rectangle size reflects the occurrence of the term. On the left side, we can see that the popular terms are “data”, “learning”, “machine”, “model”, “system”, “food”, and “accuracy”. Besides, there is a clear appearance of main AI tasks such as “classification”, “analysis”, “prediction”, and “detection”. As a result, this bolsters the argument that AI is a game-changing technology that can contribute to the sustainability of the agri-food sector by enhancing current agricultural systems and food value chains.

Table 2
Top 20 most relevant journals.

Rank	Sources	Articles
1	Computers and Electronics in Agriculture	333
2	Remote Sensing	199
3	Sensors	137
4	IEEE Access	129
5	Biosystems Engineering	66
6	Applied Sciences	57
7	Science of the Total Environment	46
8	Frontiers in Plant Science	41
9	Remote Sensing of Environment	41
10	Sustainability	40
11	Agronomy	39
12	Journal of Dairy Science	37
13	Energies	36
14	The International Journal of Robotics Research and Application	28
15	IEEE Robotics and Automation Letters	25
16	International Journal of Agricultural and Biological Engineering	23
17	International Journal of Advanced Computer Science and Applications	22
18	Journal of Field Robotics	22
19	Precision Agriculture	22
20	Geoderma	21

Table 3
Top 20 most cited countries.

Country	Total citations	Average article citations
USA	12,864	19.49
China	9193	12.39
Spain	3219	19.51
United Kingdom	3010	16.72
Australia	2771	17.76
Germany	2075	14.12
Canada	1942	19.62
Iran	1899	14.61
Netherlands	1810	24.79
France	1698	20.71
Italy	1674	14.56
Greece	1657	34.52
India	1624	7.77
Brazil	1345	9.89
Japan	1268	10.06
Israel	1201	23.55
Korea	1190	9.67
Switzerland	1123	44.92
Ireland	1076	39.85
Sweden	872	31.14

Table 4
Most globally cited articles.

Rank	AU	TI	SO	TC	TCY
1	(Bioucas-Dias et al., 2012)	Hyperspectral Unmixing Overview: Geometrical, Statistical, and Sparse Regression-Based Approaches	IEEE JOURNAL OF SELECTED TOPICS IN APPLIED EARTH OBSERVATIONS AND REMOTE SENSING	1536	153.6
2	(Foley et al., 2012)	Current methods and advances in forecasting of wind power generation	RENEWABLE ENERGY	630	63
3	(Kamilaris and Prenafeta-Boldú, 2018)	Deep learning in agriculture: A survey	COMPUTERS AND ELECTRONICS IN AGRICULTURE	615	153.75
4	(Mohanty et al., 2016)	Using Deep Learning for Image-Based Plant Disease Detection	FRONTIERS IN PLANT SCIENCE	512	85.3333
5	(Wolfert et al., 2017)	Big Data in Smart Farming - A review	AGRICULTURAL SYSTEMS	497	99.4
6	(Duro et al., 2012)	A comparison of pixel-based and object-based image analysis with selected machine learning algorithms for the classification of agricultural landscapes using SPOT-5 HRG imagery	REMOTE SENSING OF ENVIRONMENT	490	49
7	(Kussul et al., 2017)	Deep Learning Classification of Land Cover and Crop Types Using Remote Sensing Data	IEEE GEOSCIENCE AND REMOTE SENSING LETTERS	443	88.6
8	(Mitchell et al., 2004)	Learning to decode cognitive states from brain images	MACHINE LEARNING	432	24
9	(Slaughter et al., 2008)	Autonomous robotic weed control systems: A review	COMPUTERS AND ELECTRONICS IN AGRICULTURE	358	25.5714
10	(Bell and McMullen, 2004)	Ant colony optimisation techniques for the vehicle routing problem	ADVANCED ENGINEERING INFORMATICS	357	19.8333
11	(Sideratos and Hatzigiorgiou, 2007)	An advanced statistical method for wind power forecasting	IEEE TRANSACTIONS ON POWER SYSTEMS	329	21.9333
12	(Ma et al., 2017)	A review of supervised object-based land-cover image classification	ISPRS JOURNAL OF PHOTOGRAMMETRY AND REMOTE SENSING	309	61.8
13	(Scott et al., 2006)	Data analysis for electronic nose systems	MICROCHIMICA ACTA	299	18.6875
14	(Zhong et al., 2018)	Spectral-Spatial Residual Network for Hyperspectral Image Classification: A 3-D Deep Learning Framework	IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING	285	71.25
15	(Liakos et al., 2018b)	Machine Learning in Agriculture: A Review	SENSORS	272	68
16	(Antcheva et al., 2009)	ROOT - A C++ framework for petabyte data storage, statistical analysis, and visualisation	COMPUTER PHYSICS COMMUNICATIONS	264	20.3077
17	(H. Wang et al., 2017)	Deep learning-based ensemble approach for probabilistic wind power forecasting	APPLIED ENERGY	261	52.2
18	(H. Z. Wang et al., 2016)	Deep belief network based deterministic and probabilistic wind speed forecasting approach	APPLIED ENERGY	225	37.5
19	(Du and Sun, 2006)	Learning techniques used in computer vision for food quality evaluation: a review	JOURNAL OF FOOD ENGINEERING	223	13.9375
20	(Liu et al., 2018)	A New Deep Learning-Based Food Recognition System for Dietary Assessment on An Edge Computing Service Infrastructure	IEEE TRANSACTIONS ON SERVICES COMPUTING	222	55.5

Note: AU = Authors; T = Title; SO = Source; TC = Total of citations; TCY = Total of citations per year.

3.6. Trend topics

To identify emerging topics at the intersection of AI and the agri-food industry, we generated Fig. 4, which depicts research hotspots and log-frequency-based research trends. Accordingly, the organisation of AI topics reveals that robots, algorithms (i.e., the Kalmar filter),

Table 5
Top 20 most frequent keywords (authors keywords vs. keywords plus).

Rank	Authors keywords	Occurrences	Keywords plus	Occurrences
1	machine learning	1025	classification	406
2	deep learning	514	system	296
3	artificial intelligence	287	model	256
4	convolutional neural network	198	prediction	250
5	precision agriculture	197	identification	157
6	random forest	182	neural networks	145
7	agriculture	181	performance	134
8	remote sensing	142	regression	133
9	artificial neural network	126	agriculture	124
10	classification	122	algorithm	124
11	computer vision	101	management	124
12	image processing	89	design	122
13	support vector machine	78	systems	119
14	big data	68	neural network	105
15	robotics	68	models	102
16	prediction	61	yield	94
17	internet of things	59	quality	91
18	machine vision	58	food	85
19	feature extraction	47	optimization	85
20	transfer learning	47	segmentation	82

automation, and expert systems were popularised and revitalised in the early years of the field (2002–2006). The dominant themes between 2007 and 2016 were the integration of AI-powered robots and agricultural mechanisation. Emerging topics such as “mobile robot,” “autonomous vehicle,” “agriculture vehicles,” and “parallel robot” could be supported by AI capabilities to automate human tasks, optimise operational efficiency, and increase output. Commonly, these robots employ AI to enhance their situational awareness and sensing capabilities during agricultural tasks. Since 2017, the focus has been on various technologies and AI techniques, including big data, the IoT, convolutional neural networks, deep learning, machine learning, and fuzzy logic. Combining these innovations is essential for the transition to precision agriculture, which provides agri-food companies with options to optimise their production, reduce resource consumption, and improve the quality of agricultural products. In conclusion, the results indicate that, at the time this analysis was conducted, precision agriculture and AI techniques were key concepts and current trends.

3.7. Cluster analysis

To better understand the research hotspots, we conducted a keyword co-occurrence network to identify topics with common features (Kapoor et al., 2018; Rejeb et al., 2020). As a result, we set the parameters mentioned in Table 6. According to Fig. 5, four clusters were generated for the keywords supplied during the study period (1992–2020). The first cluster (red) is the most significant, consisting of terms like “Machine Learning”, “Random Forest”, “Support Vector Machine”, “Remote Sensing”, and “Classification”. Besides, the keyword “Food Security” belongs to this cluster, and it represents a critical driver for AI implementation and further technological innovations. As a

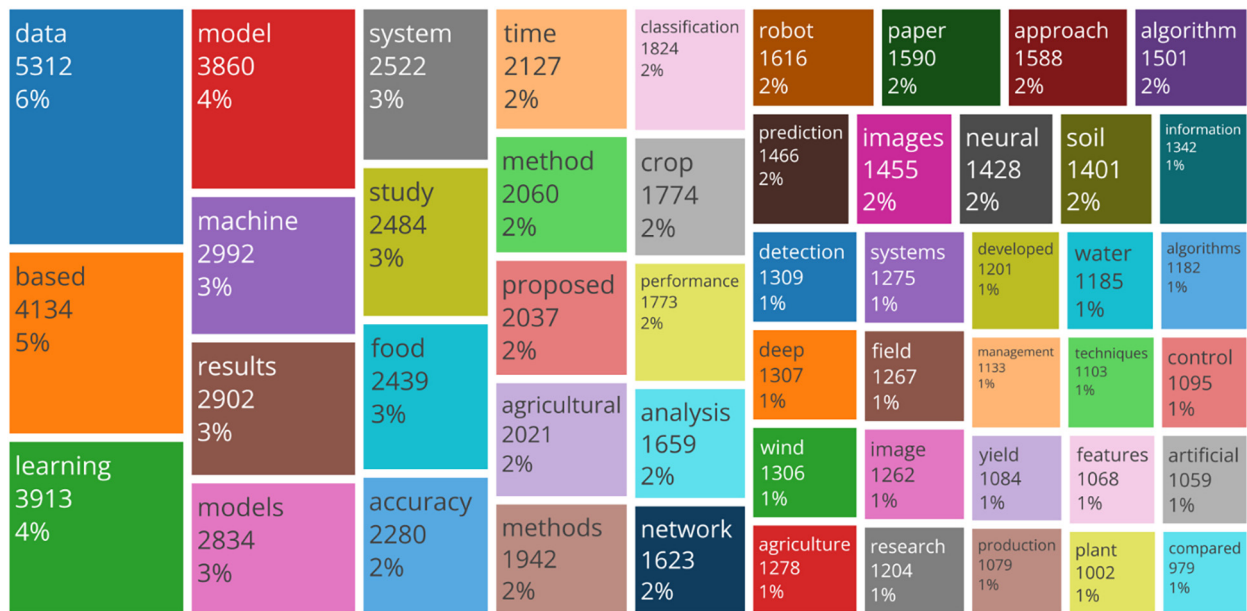


Fig. 3. Treemap based on abstracts.

solution for food security issues, AI techniques help create smart farming, promote sustainable agriculture, and transform subsistence farming into competitive and profitable agri-food businesses. In the second cluster (green), other AI techniques were highlighted, such as “Deep

Learning”, “Convolutional Neural Networks”, “Image Classification”, and “Recurrent Neural Network”. Another keyword that received increasing attention is “UAV” (unmanned aerial vehicles), which implies that this technology also supports the rise of digitalisation in agriculture

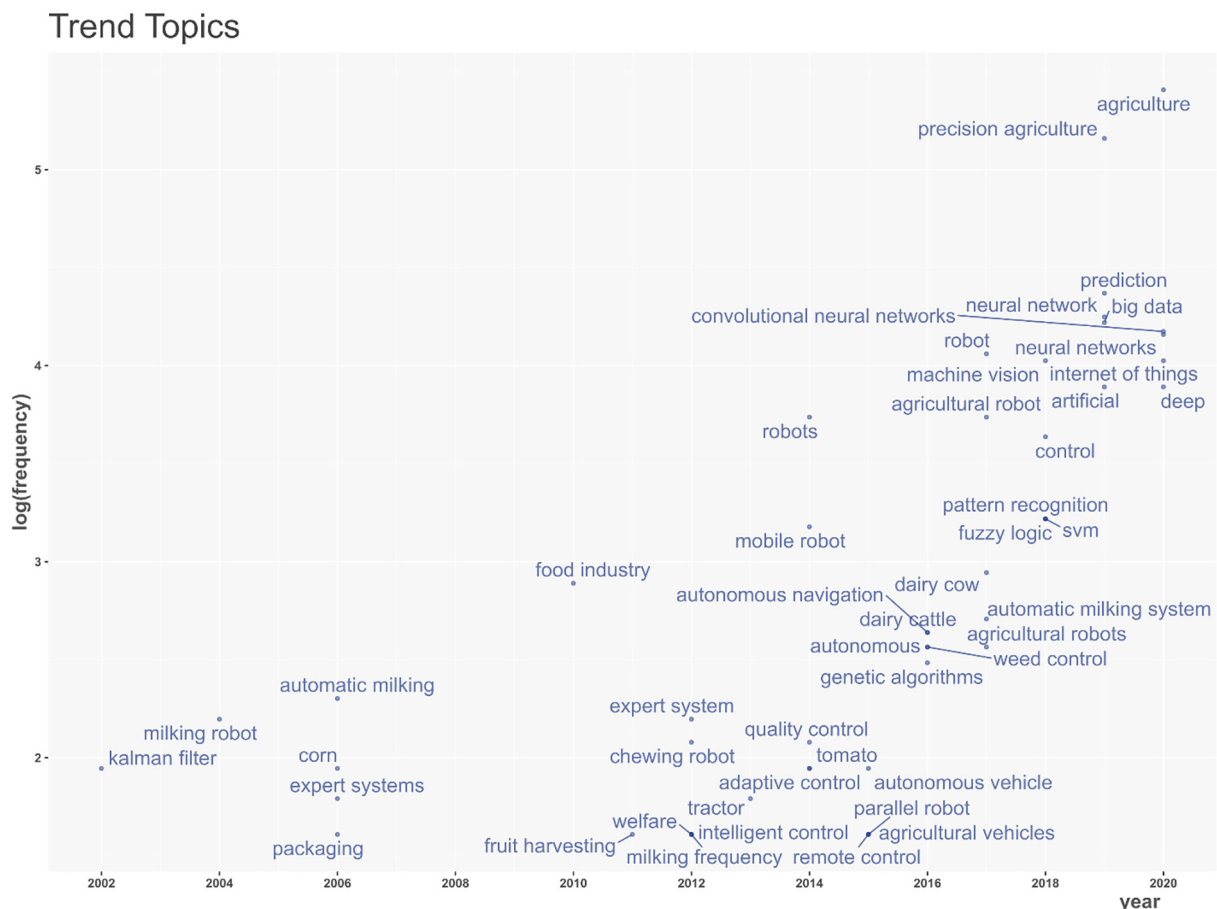


Fig. 4. Trend topics.

Table 6
Keyword clustering parameters.

Type of analysis	Keyword co-occurrence
Unit of analysis	Author keywords
Counting method	Full counting
Minimum number of a keyword	20
Threshold	88
Number of clusters	4

due to its ability in spraying, crop monitoring, field surveying, identification of drought spots and harmful weeds, and surveillance. The next cluster (blue) was predominated by keywords like “Agriculture”, “Agricultural Robot”, “Internet of Things”, and “Robotics”. Combined with AI, these technologies can inform more intelligent agri-food decisions by controlling crop behaviour, monitoring livestock, crop growth, and supporting the efficient use of manpower. Therefore, these technological advancements play a critical role in developing a more data-driven and knowledge-intensive agri-food sector. In the last cluster (yellow), we see the predominance of “Artificial intelligence”, “Artificial Neural Networks”, “Modelling”, “Genetic Algorithm”, and “Optimisation” - all are innovative and reliable solutions for current agri-food challenges.

In general, the findings from the keyword co-occurrence clustering suggest that AI techniques such as machine learning, deep learning, and artificial neural networks were the most common approaches in agri-food systems and thus, accelerated the sector's digitalisation. Additionally, robots, the IoT, wireless sensor networks, and UAVs are popular technologies integrated with AI to modernise farming practices. Nevertheless, other adjacent technologies like blockchain, 3D printing, augmented reality, and virtual reality did not appear in the visualisation.

This finding suggests a lack of studies examining the fusion of these emerging technologies and AI to support precision agriculture, increase the integrity of the agri-food value chain, and achieve sustainability.

4. Discussion

In this paper, we analysed the relationship between AI and the agri-food industry and AI's role in accelerating the shift to precision and cognitive agriculture. In contrast to previous reviews on AI and agri-food systems (e.g., [Jha et al., 2019](#); [Patrício and Rieder, 2018](#)), our findings are novel and insightful because this is one of the few investigations to use a comprehensive sample of research papers that were published over nearly three decades. Consequently, the following sections provide an in-depth examination of AI and agri-food industry developments ([Liakos et al., 2018b](#); [Sharma et al., 2020](#)).

4.1. Theoretical contributions

4.1.1. What are the research dynamics on the interplay between AI and the Agri-food sector?

By addressing the first research question, our bibliometric review analyses the key productivity measures of the field. According to the sample we analysed, the earliest publications were published in 1992. In addition, the analysis depicted the dynamics of scholarly production throughout three major stages. The initial period of publication ran from 1992 to 2000, and during this period, only a few publications were produced annually. In the second stage, between 2001 and 2010, the field grew steadily, reaching 40 publications for the first time in 2010. This was due to the unprecedented advances in computer science during this period. In the third stage, between 2011 and 2020, AI techniques

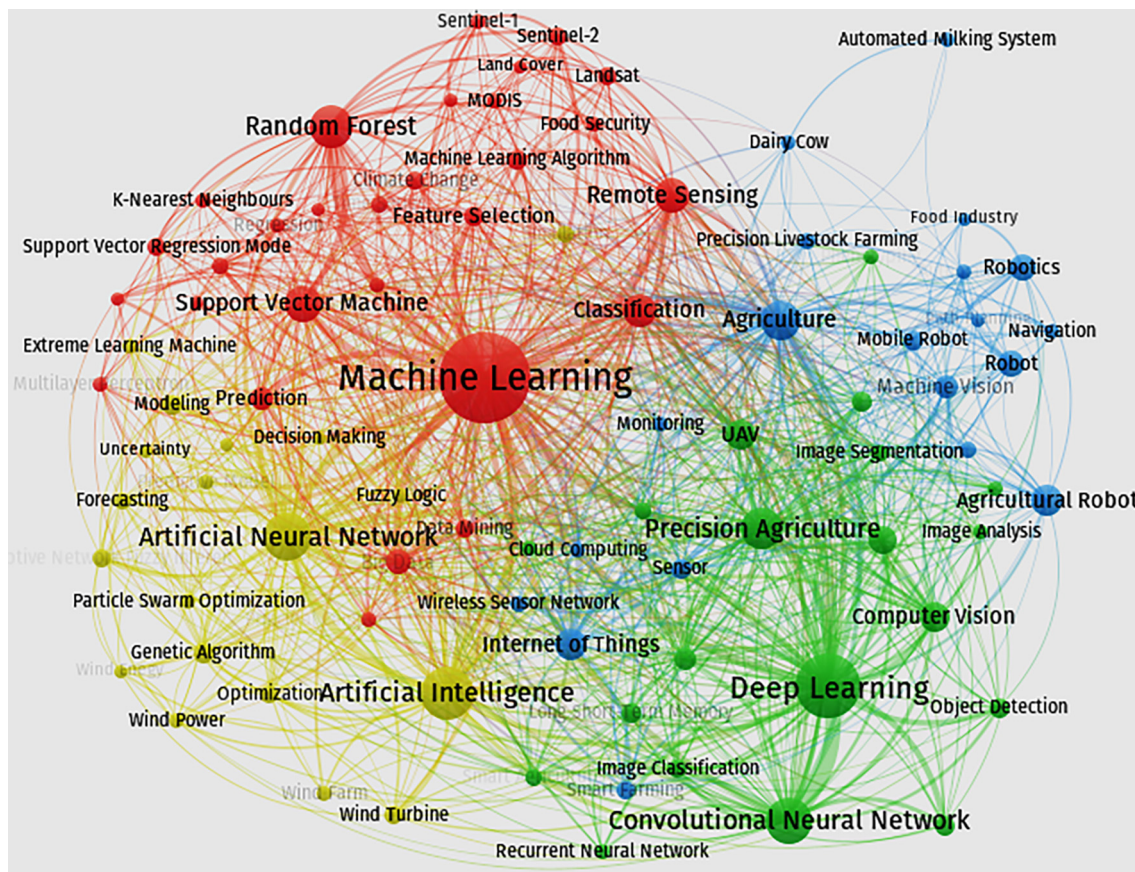


Fig. 5. Keyword co-occurrence network.

exhibited phenomenal performance due to their large data storage capacity and high computational power. The number of publications has reached its peak, surpassing 1700 papers for the first time in 2020.

In addition, our research identified the most pertinent sources. Computers and Electronics in Agriculture, a leading journal, dominate the AI literature in the agri-food industry in this regard. On the one hand, computer science and engineering journals were the most prolific and ranked highly. In contrast, this ranking did not include business, management, operations research, and decision science-focused publications. According to the number of citations received, the United States dominated the list, while European and Asian countries occupied significant positions. In the top 20 most influential nations, no contributions from Latin America and Africa were relevant. This suggests that the scientific outcome on a global scale was more concentrated and predominantly represented by developed nations.

The current academic literature describes the role of AI in the modernisation of agriculture and the transition from unsustainable farming practices to more data-driven precision agriculture. Several thought-provoking issues arise in this vein. For instance, almost all the literature on integrating AI techniques in the agri-food industry was published within the last five years (2015–2020). This expansion coincides with the transition to agriculture 4.0, in which precision agriculture is supported by AI techniques, the IoT, robots, and smart food systems. In information technology-related journals, applications of AI in the agri-food industry dominated the discussion. It is expected that the flagship journals of AI research will accommodate the evolving nature of the AI field by incorporating this crucial topic into their editorial strategies. Finally, it is suggested that academic institutions from underdeveloped regions of the world engage in AI research by forming partnerships with research labs, universities, and governments in developed nations..

4.1.2. How is AI being used in the Agri-food sector?

Based on the results, our study can draw several important conclusions about how agri-food systems use AI to facilitate agricultural operations (Liakos et al., 2018b; Mohanty et al., 2016; Pantazi et al., 2016). From this perspective, we identified the publications with the highest global citations (see Table 4). According to these publications, AI algorithms, deep learning, and machine learning are advancing the creation of a sustainable agri-food industry and promoting precision agriculture. AI techniques attracted a great deal of interest. They gained momentum due to their capacity to enhance farmers' awareness of potentially hazardous weather conditions, crop health conditions, and resource utilisation, which would otherwise be difficult to detect. Utilising robots to automate field operations, increase agricultural productivity, improve food safety and quality, reduce fuel consumption, and promote sustainability is another intriguing strategy (Bechar and Vigneault, 2016; Wolfert et al., 2017; X. Zhang et al., 2020; Zhao et al., 2016). As a result, these technologies provide solutions that reduce the reliance on human labour, increase the global competitiveness of agri-food businesses, and increase their overall profitability (Lenain et al., 2006; Slaughter et al., 2008; Valente et al., 2011; Wolfert et al., 2017; Xiong et al., 2017).

Moreover, by analysing the keyword dynamics, our study revealed that “machine learning” and “deep learning” are among the most investigated AI techniques in agriculture. Artificial and convolutional neural networks are crucial enablers for precision agriculture due to their capacity to analyse produce images and determine its condition (damaged or healthy), support decision making, and predict climate (Deo and Şahin, 2015). Big data, robots, and the IoT are key drivers of developing smarter and more autonomous agri-food value chain practices, which are advantageous to farmers and consumers. In addition to “remote sensing,” “classification,” “image processing,” and “transfer learning,” there are several other noteworthy topics. According to the keywords provided in the abstracts, the most popular research topics are “data,” “learning,” “models,” “classification,” “robot,” “prediction,” “detection,” and “neural”. In addition to reflecting the breadth and velocity of digital

transformations, these topics demonstrate that the agri-food industry is increasingly seeking AI implementations. Despite the abundance of research on AI, it is essential to emphasise the paucity of research examining the combination of AI and other emerging technologies, such as 5G telecommunications, 3D printing, blockchain, and bioinformatics, in the development of sustainable agri-food supply chains. Integrating these technologies enables farmers to work more creatively and effectively; however, the real question lies in comprehending the adverse side effects of AI-assisted agriculture. Consequently, our findings emphasise the urgent need for more research on how responsible AI can redefine farming practices and achieve holistic sustainability in the agri-food sector (Abdella et al., 2020; Camaréna, 2020).

4.1.3. What are the trend topics pertaining to AI and the Agri-food sector?

We can observe that machine learning, deep learning, artificial neural networks, fuzzy logic, genetic algorithms, and expert systems are the most popular AI approaches supporting the agri-food industry in major trend topics. Moreover, emerging technologies such as AI-assisted robots, the IoT, and big data are linked to the digitalisation of agriculture and precision farming, which is expected to become one of the most prominent trends in the agri-food industry (Kamilaris and Prenafeta-Boldú, 2018; Wolfert et al., 2017).

By examining the activities that AI techniques can facilitate, it becomes clear that they can be applied to various fields, including crop performance analysis, livestock monitoring, disease detection, yield prediction, and production optimisation, among others. In addition, AI affords additional opportunities in other agri-food activities, such as automatic recognition, remote sensing, plant classification, smart irrigation, soil management, cultivation, phenotyping, yield mapping, field scouting, and weed management.

4.1.4. What are the main challenges of AI in the Agri-food sector?

To respond to this question, four categories of obstacles were highlighted. First, AI in the agri-food industry exacerbates social concerns, such as replacing human labour with automation and machines (Lezoche et al., 2020). Despite requiring expensive specialised equipment and labour, Bechar and Vigneault (2016) note that investments in robotics and automation can be profitable because the required workforce typically decreases enough to offset the high investment costs. As a result, minimising human intervention will pose a major problem for employment standards. The second class relates to the technological constraints of AI, such as connectivity, power supply, bandwidth, security, data validation and integrity, network latency, response time, flexibility, and the need for big data in training AI models (Eli-Chukwu, 2019; Guillén et al., 2021; Wolfert et al., 2017). The third class relates to privacy and ethical issues, such as the absence of privacy norms in AI-based agri-food systems, liability for decisions made by AI, and regulations regarding data processing and analysis (Beydoun et al., 2019; Camaréna, 2020; Udendhran and Balamurugan, 2021; Villa-Henriksen et al., 2020). Ethical considerations, fairness, accessibility, and transparency are a few trade-offs and repercussions raised by AI that require urgent discussion (Camaréna, 2020). The fourth category relates to organisational barriers to AI adoption, such as reluctance to adopt new technologies (Fountas et al., 2020), cultural and bureaucratic issues (Chatterjee and Hussain, 2021), upgrade of organisational processes, skill and knowledge requirements (Balducci et al., 2018; Lezoche et al., 2020), investment cost (Wolfert et al., 2017), and organisational uncertainty. Therefore, these findings suggest that agri-food companies should work diligently to overcome the obstacles to AI integration and employee adaptability to the new AI-based business model (Bar et al., 2016). Businesses in the agri-food industry should develop the organisational capabilities required to reconfigure and integrate existing resources and adapt to the changing conditions of AI-enabled agri-food processes.

4.2. Theoretical implications

Fig. 6 presents a categorisation framework comprising four main elements considering the significant findings regarding AI applications in the agri-food industry. AI techniques and related technologies, application areas, AI benefits, and adoption barriers are discussed.

Machine learning, deep learning, and artificial neural networks are the most studied approaches to AI techniques and other technologies (Balducci et al., 2018; Kamilaris and Prenafeta-Boldú, 2018). Various agricultural activities, such as crop cultivation, livestock farming, disease diagnosis, crop image classification, plant identification and segmentation, and resource (e.g., soil, water) management, could employ these AI techniques. In addition, we discovered that crop yield prediction, irrigation, consumer behaviour analysis, disaster (e.g., drought, flood) prediction, and food traceability are the most prevalent AI applications in the agri-food industry. The benefits of automation of farming practices, increased accuracy and rapidity of plant diagnosis (Sharma et al., 2020; Shendryk et al., 2021), cost savings, efficient energy consumption, and improved product quality are the results of utilising AI technologies (Smetana et al., 2021). In addition, AI techniques can enhance agricultural production, reduce greenhouse gas emissions, ensure animal welfare, improve field navigation, and boost the performance of agricultural robots (Afonso et al., 2020; Hemming et al., 2020; Kamilaris and Prenafeta-Boldú, 2018; Sharma et al., 2020).

To achieve more beneficial and responsible AI implementations in the agri-food sector, it is necessary to overcome several obstacles. For example, the literature acknowledges social issues of AI, such as robots replacing humans in the workforce and unemployment (Ampatzidis et al., 2017; Rose and Chilvers, 2018). AI is hampered by lack of connectivity, security attacks, limited computation resources, and low network bandwidth (Liu et al., 2018). Therefore, effective AI algorithms and systems must be designed and developed to improve their task performance (Liu et al., 2018). Other concerns include data privacy and ethics; as a result, agri-food businesses are required to implement and enforce stringent measures and policies to safeguard their data and comply with the applicable regulations. In addition, organisational barriers, such as resistance to change, the need for new skills and capabilities, and prohibitive investment costs, create uncertainty about the value of AI in the agri-food industry.

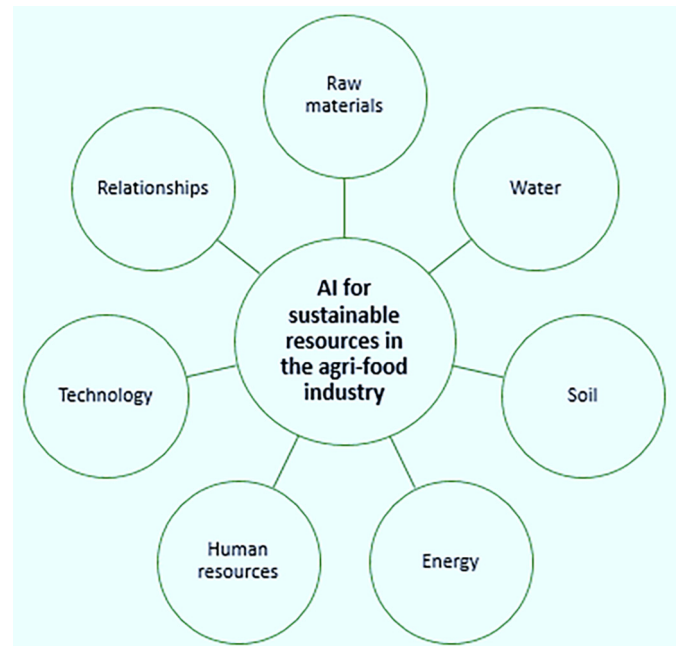


Fig. 7. RBV-based framework for the interplay between AI and agri-food resources.

4.2.1. From framework to research propositions

Considering the proposed categorisation framework, a set of research propositions are derived using the Resource-Based View (RBV) to provide a foundation for future research on AI applications in the agri-food industry. RBV is based on the idea that a company's competitive position is determined by its unique resources and capabilities and their interrelationships (Barney, 1991; Farooq and O'Brien, 2015). In this context, the interaction between AI and the agri-food industry must be rooted in resources, including raw materials, water, soil, energy, human resources, technology, and relationships (see Fig. 7). For each resource, we provide several insightful and recommended research propositions.

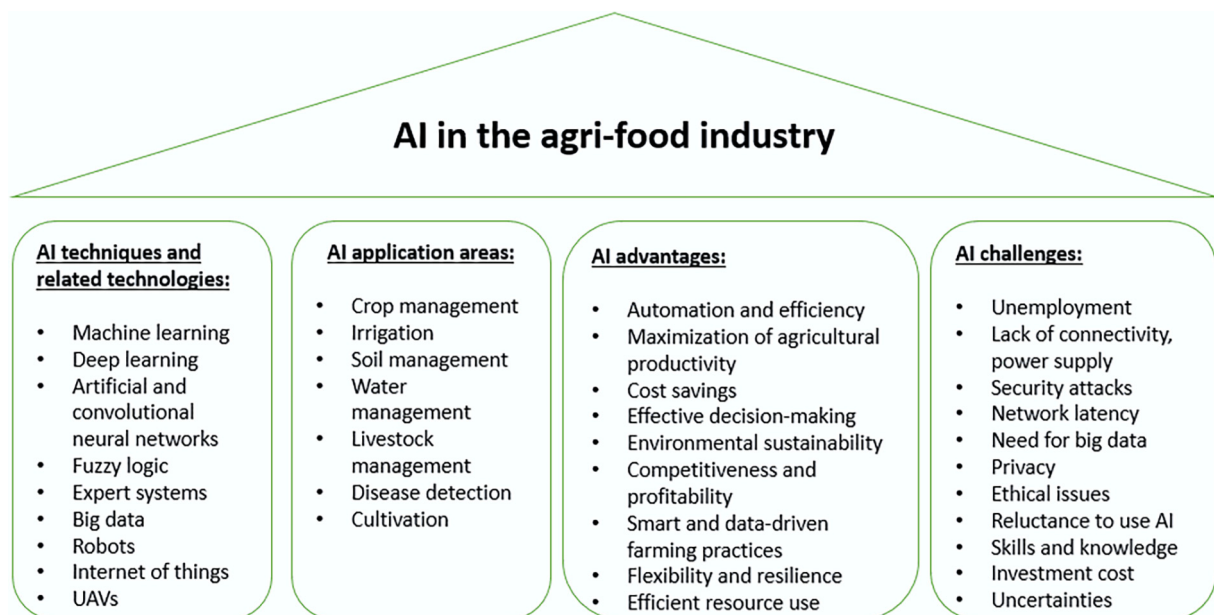


Fig. 6. The framework of the study findings.

4.2.1.1. Raw materials. In the agri-food sector, raw materials are vital for product quality and safety. They include seeds, nutrients, fertilisers, and chemicals. By deploying AI techniques, farmers could understand several agricultural-related issues such as seed identification, herbicide use, classification, and identification of raw materials quality (Kamilaris and Prenafeta-Boldú, 2018). Furthermore, AI technologies enable farmers to understand their crops at a micro-scale, enabling the early detection of diseases in seeds (Patrício and Rieder, 2018) and maintaining precise fertigation (Bechar and Vigneault, 2016). Therefore, the following research propositions emerge:

- RP1–1: AI enables agri-food businesses to improve their production processes and deliver high-quality products because of its ability to control the quality of raw materials used.
- RP1–2: AI aids in protecting seed and crop damage from herbicides, viruses, and insects.
- RP1–3: AI aids agricultural raw materials tolerance to environmental stresses like floods and drought and plays a role in improved taste and nutrition benefits.

4.2.1.2. Water. Since water represents the vital resource consumed by agri-food businesses, there is a need to reduce the pressure on this resource and reinforce water stewardship in the agri-food sector. AI can save the excess use of water and support the development of adequate water and agricultural policies (Sánchez et al., 2020). The big data generated by smart farming sensors can be processed using machine learning to improve the management of smart farming, gain crop insights, elevate productivity, and optimise water resources (Freeman et al., 2019; Navarro et al., 2020). Based on this, we suggest that:

- RP2–1: AI facilitates the use and processing of large datasets to control crop status and optimise sustainable water use.
- RP2–2: AI aids in reducing water consumption in agriculture while maintaining product quality and yield.

4.2.1.3. Soil. Soil is an essential non-renewable resource in the agri-food industry, and its preservation is crucial. Because destruction and erosion pose a threat to soil, there is an opportunity to unlock the value of AI and ensure the preservation of this precious resource. For example, machine learning can help predict and identify soil properties such as drying, temperature, and moisture content (Liakos et al., 2018b). AI tools automate the acquisition of knowledge and the analysis of large data sets concerning soil health, condition, and hydrology (Benke et al., 2020; Kuzmanovski et al., 2015). Consequently, we derive the following research propositions:

- RP3–1: AI provides more insights into soil properties, temperature, and moisture, increasing farmers' understanding of ecosystem dynamics and impingements in the agri-food sector.
- RP3–2: AI aids the selection of the most optimal soil characteristics utilised in crop yield prediction.
- RP3–3: AI positively impacts soil fertility and productivity.

4.2.1.4. Energy. Arguably, an enormous amount of energy is imperative for the production, storage, and distribution of food products (Paulikienė et al., 2020). To ensure more efficient energy use, farmers could leverage AI to reduce energy consumption and cost through predictive process parameter optimisation (Smetana et al., 2021). Furthermore, machine learning could develop models for the effective management of energy systems in the agri-food sector (Cubric, 2020). Therefore, AI supports energy conservation and ultimately reduces energy waste thanks to its ability to forecast energy demand based on operational usage, historical demands, or current weather (Bokade et al., 2021). In light of this, we propose that:

- RP4–1: AI aids in optimising energy consumption during planting, irrigation, harvesting, processing, packaging, transportation, and distribution of food products.
- RP4–2: AI aids the use of renewable energies to power agricultural operations.
- RP4–3: AI facilitates the recycling of food waste and the development of more sustainable energy options such as bio-refinery products (e.g., biofuels).

4.2.1.5. Human resources. Innovation in human resources represents a primary source of improved sustainable performance in the agri-food sector (Brofman Epelbaum and García Martínez, 2014). Human resources are vital for agri-food businesses, requiring significant attention due to their impact on production, financial, marketing, and management decisions (Alreshidi, 2019). To optimise their utilisation, agri-food businesses can integrate AI to develop more skilful and flexible workers. With the support of AI-assisted robots, agricultural workers would no longer need to perform manual tasks (e.g., hand weeding of organic crops), thus avoiding several health risks such as musculoskeletal disorders and chronic diseases (Pérez-Ruiz et al., 2014). The synergy between AI and human workers can improve the applicability of several agricultural activities such as harvesting (Zhao et al., 2016) and create a safer and less stressful working environment. However, agri-food businesses must reskill and upskill their human resources to be a source of differentiation and better adapt to changing industrial requirements. The scarcity of human resources with analytical skills may negatively influence the adoption of AI techniques. Therefore, organisations are incentivised to develop skill-building programs for farmers and other actors in the agri-food supply chain (Sharma et al., 2020). Therefore, we present the following research propositions:

- RP5–1: AI augments the analytical capabilities of human resources in the agri-food sector.
- RP5–2: AI aids the safety and convenience of the working environment in the agri-food sector.
- RP5–3: AI increases the flexibility, agility, adaptability, responsiveness, and resilience of farmers.
- RP5.4: How human resources are managed in AI-assisted agriculture impacts agri-food businesses' performance.

4.2.1.6. Technology. Technological progress contributes to the automation of agri-food activities, agricultural productivity, efficiency, reliability, and precision (Bechar and Vigneault, 2016). The smart reform of agri-food systems necessitates the implementation of innovative practices and technology-driven processes. This calls for agri-food organisations to adopt AI to fortify their technological infrastructure. As such, the combination of AI and other technologies like the IoT, edge computing, blockchain, and augmented reality is considered a promising solution for pest identification, safety traceability of agricultural products, and environmental pollution caused by the use of fertilisers and pesticides (Zhang et al., 2020). Furthermore, AI augments the utility of data analytics to improve crop production and assist farmers in selecting the best breed according to their location and climate (Lova Raju and Vijayaraghavan, 2020), monitoring livestock in real-time (Taneja et al., 2020), and predicting frost events (Diedrichs et al., 2018). Therefore, the following research propositions can be investigated:

- RP6–1: The fusion of AI techniques and other technologies (e.g., the IoT, computing technologies, blockchain, big data analytics, robotics, virtual/augmented reality) ushers in an interconnected digital ecosystem that turns existing farming practices into knowledge-based agriculture and maximises production levels and product quality.
- RP6–2: The integration of AI and other advanced technologies brings significant economic, environmental, and social benefits to the agri-food sector.

- RP6–3: Through AI and data analytics, agri-food firms would be able to develop sustainable and responsible business models and build synergies and collaboration with other agri-food ecosystems.
- RP6–4: AI techniques, in combination with other technologies, can help improve agri-food product packaging, handling optimisation, customisation, and to mitigate the risk of food fraud and other opportunistic behaviour.

4.2.1.7. Relationships. Closer strategic relationships with customers and suppliers are crucial for business learning and adaptation (Lezoche et al., 2020). AI provides a cooperative mechanism that improves collaborative activities and value co-creation with the agri-food sector stakeholders to empower relationships. For example, machine learning algorithms can ensure the optimal use of resources through the agri-food supply chain and create a novel dimension of symbiosis in this sector (Sharma et al., 2020). AI techniques can aid farmers in identifying the most demanded food products, shortage and supply, and most suitable suppliers. AI can turn customer data into actionable insights and insightful knowledge that can be leveraged to strengthen customer relationship management and gain a significant business value (Fiore et al., 2017). The use of AI can lead to more precise prediction of future demand and accurate targeting of potential customers, thereby maximising the profitability of agri-food businesses. However, a major issue of AI applications and related technologies is that they necessitate collaboration between multiple stakeholders playing different roles in the agri-food value chain (Wolfert et al., 2017). As a result, new organisational connections and modes of collaboration need to be developed in the supply chain to accelerate the transition toward AI-assisted agriculture and farming. Therefore, AI can create more robust and closer linkages with suppliers and customers, achieving higher levels of trust and loyalty. Based on the prior discussion, the following research propositions are suggested:

- RP7–1: The use of AI stimulates collaboration, coordination, and value co-creation among the agri-food sector stakeholders.
- RP7–2: The impact of AI-enabled collaborative relationships on the performance of agri-food businesses.
- RP7–3: AI helps to coordinate the pace of information sharing, prevent excess inventory, and reduce inefficiencies.

4.2.2. Agenda for future research

As a critical resource for the growth of plants (Zakir et al., 2021), soil can significantly benefit from AI implementations. As such, AI and machine learning applications can assist farmers in understanding soil conditions, including PH level, nitrogen, nutrients, and moisture content. Farmers can leverage AI techniques to predict soil water content and select the most suitable crops to maximise yields (Yu et al., 2021). As a result, the real-time prediction of soil parameters can contribute to more sustained land resource management and irrigation practices. Future research can investigate the utility and performance of different AI techniques to ensure accurate estimations of soil conditions (Ge et al., 2018). Since the modelling of soil water content is a challenging task due to plant growth dynamics, climate changes, and soil content variations, there is a need for efficient, reliable, and accurate AI algorithms to facilitate the processing and analysis of soil water data. This is crucial as it helps design an adequate watering schedule and lessening the effect of drought situations (Adeyemi et al., 2018).

The agri-food industry represents the major consumer of water on a worldwide scale since crops largely depend on water availability. Considering the significant depletion rate of water resources, there is a need for effective water management to conserve this resource and establish sustainable agricultural production. The effective use of water can be conducive to significant improvements in water quality and a decrease in health issues and pollution (Neupane and Guo, 2019). In this vein, recent research on AI demonstrates the technology's ability to

improve water management by monitoring water levels, scheduling water runs, and regulating water amounts needed by individual crops. Even though AI offers several tangible advantages to water management, Kamarudin et al. (2021) state that AI applications in plant water assessments are still under-studied. Future research should examine how AI techniques can increase water productivity and enhance water management practices in low water productivity areas (Virnodkar et al., 2020). Other opportunities for future studies include exploring AI's role in water erosion assessment (Kamilaris and Prenafeta-Boldú, 2018) and supporting precision agriculture systems to ensure water resources' stability (Ganeshkumar et al., 2021).

The deployment of AI in farming activities can improve energy management (Cubric, 2020). AI allows for the modelling of energy needed in farming activities, thus contributing to energy saving and the delivery of green and clean agricultural products (Bolandnazar et al., 2020). The adoption of AI and the shift to smart agriculture can motivate more farmers to utilise green energy sources (Ragazou et al., 2022). AI plays a critical role in mitigating the carbon footprints caused by agriculture, farming, and food production. The agri-food industry can capitalise on AI to optimise energy consumption and produce more with fewer energy resources (Mor et al., 2021). Related to this theme, future research should attempt to develop efficient AI models to predict the optimal amount of energy necessary for agricultural activities (Nabavi-Pelesaraei et al., 2018). In addition, researchers are recommended to assess the energy efficiency achieved by AI use at different levels of the agri-food supply chain. Another topic of interest is examining the support of AI to agricultural activities, which are based on sustainable energies such as wind energy, solar energy, biomass, and geothermal energy (Escamilla-García et al., 2020). The development of new AI-enabled systems to minimise the energy use of greenhouses is also an intriguing research direction that needs further attention since AI can offer automated, data-driven, and actionable insights to reshape greenhouse crop farming.

Increasing agricultural production at least costs while protecting the environment represents one of the main objectives of the agri-food industry. Timely detection and control of issues related to crop management can help boost production and profits. In recent years, AI is utilised to increase crop output and productivity from effective agricultural resource utilisation based on remote sensing of field-based information (Zhou et al., 2021). Farmers can connect with applications and respond to fast change requests for processes and raw materials such as inputs, seed stock, soil moisture, temperature and light for crops, and crop growth components. As a result, plants can easily be controlled to meet requirements (Manogaran et al., 2021). In this regard, Chlingaryan et al. (2018) argue that machine learning techniques have helped achieve precise yield predictions for different crops, quantify nitrogen status, and model expert knowledge for crop management. AI can establish in-season crop management systems that make real-time decisions regarding the amount, location, and timing to apply optimal inputs and optimise profitability in agriculture production (Weiss et al., 2020). Other beneficial AI applications in agriculture also include rapid plant disease detection, plant phenotyping, efficient use of agrochemicals, and support for workers with location-relevant agromonic advice (Tzachor et al., 2022). Like crop management, AI offers accurate and reliable estimation and prediction of farming parameters to maximise the production of livestock systems and achieve substantial economic benefits (Liakos et al., 2018a). For example, weight forecasting systems can anticipate the future weights of cattle before slaughter, enabling farmers to change feeds and livestock conditions accordingly. Similarly, AI techniques and models can be used to estimate the growth of animals, forecast their yield, assess their water needs, and prevent diseases from occurring based on past observations (Kamilaris and Prenafeta-Boldú, 2018). Overall, future crop and livestock management studies may involve questions about how AI can support farmers in predicting crop varieties and their performance in different environments, thereby increasing food safety (Kugler, 2022). Of additional

interest is an exploration of the role of AI in identifying crop yield objectives to be reached according to resources available and climate conditions (Le Bars and Attonaty, 2001). The development of AI-powered spray systems to analyse plants' colour, shape, and size and deliver accurate amounts of herbicides is recommended to facilitate precision targeting, prevent collateral damage to plants, and support precision agriculture. To advance the understanding of AI applications in livestock management, future studies are required to examine how AI can contribute to reducing greenhouse emissions caused by livestock farming. Research may also provide further insights into AI's role in genomics and how this can support farmers' understanding of animals' metabolisms and facilitate selective breeding (Eastwood et al., 2021). Finally, AI applications like facial recognition for animals and image classification should be investigated in detail to allow the individual monitoring of animals and their behaviour (Jung et al., 2021; Xu et al., 2021).

With the support of AI, farmers can reduce manual labour and increase task accuracy and performance. Bechar and Vigneault (2016) state that the problems associated with workforce shortage can be mitigated with the incorporation of AI since the technology helps increase agricultural productivity and compensate for the higher investment cost due to the significant decline in the required workforce. Moreover, AI-powered robots can perform risky tasks and farming operations under harsh conditions (Bechar and Vigneault, 2016), thus contributing to workers' safety and job satisfaction. This can also allow farmworkers to save time and energy for more strategic farming activities requiring

human intelligence. Nevertheless, the convenience brought by AI can yield the substitution of farmworkers with robots, resulting in job losses. Therefore, future studies need to examine how AI influences rural and farming communities. In addition, researchers must look into the positive and negative impacts of AI on human resources management from the perspective of ethics, social sustainability, and equality (Wolfert et al., 2017). Related to sustainable business relationships, it is expected that AI will provide suppliers and customers with the information required to make more informed decisions about agricultural products and foods. By integrating AI into agricultural activities, farmers can meet consumers' needs for sustainable agricultural products since AI allows compliance with increasing pesticide use regulations (Slaughter et al., 2008). Accordingly, a contribution opportunity from future research would be to examine how AI can help agricultural producers establish new markets and effectively satisfy the desires of their existing customers. Despite the abundance of AI applications, there is still a paucity of studies examining AI's potential for supplier selection in the agri-food industry (Zavala-Alcívar et al., 2020). Collaborative approaches between the agri-food industry stakeholders (e.g., farmers, suppliers, buyers, and regulators) using AI are another promising research area that should be explored in the future.

Since consumers are increasingly becoming aware of sustainability, food authenticity, production methods, and labour exploitation, there is a need to achieve greater traceability of agricultural products along the agri-food supply chain (Lillford and Hermansson, 2021). In the era

Table 7
Agenda for future research on AI applications in the agri-food sector.

Main topics	Directions for future research	Related literature
AI for sustainable soil management	<ul style="list-style-type: none"> • Exploration of AI techniques to improve soil fertility, salinity, texture, moisture, and productivity • Investigation of AI techniques for soil segmentation from remotely sensed data • Examination of the role of AI in countering the challenges caused by water scarcity and extreme climatic conditions 	(Dong et al., 2019; Heggemann et al., 2017; Ünal, 2020)
AI for sustainable water management	<ul style="list-style-type: none"> • Use of AI techniques in irrigation scheduling and waste management • The importance of AI in achieving water self-sufficiency and resilience in harsh environments 	(Cavazza et al., 2020; Jimenez et al., 2020; Xavier et al., 2020)
AI for sustainable energy management	<ul style="list-style-type: none"> • Exploration of the role of AI in reducing the negative impacts of energy consumption on the environment and ensuring food security • Identification of the benefits and limitations of AI in supporting the use of renewable energy sources in the agri-food sector 	(Benites-Lazaro et al., 2018; Díaz et al., 2020; Khoshnevisan et al., 2015; Syed Ahmed Kabir et al., 2020)
AI for sustainable crop management	<ul style="list-style-type: none"> • Exploring how AI can facilitate precision crop management • Utilisation of AI in robotics to account for crop requirements • Investigation of AI capabilities to protect crops and predict pest's behaviour • The contribution of AI to animal welfare 	(Balducci et al., 2018; Kamilaris and Prenafeta-Boldú, 2018; Kollia et al., 2021; Lezoche et al., 2020; Rohit Sharma et al., 2020)
AI for sustainable livestock management	<ul style="list-style-type: none"> • Investigation of AI to reduce the carbon footprint of livestock management • Potential of AI techniques for improving the farming conditions of livestock and facilitating the interaction of farmers with the animals • Investigation of the main ergonomics need for users of AI in the agri-food sector 	(García et al., 2020; Kamilaris and Prenafeta-Boldú, 2018; Kling-Eveillard et al., 2020; Marvin et al., 2020)
AI for sustainable human resources management	<ul style="list-style-type: none"> • The role of AI in developing a safe and ethical workforce for agriculture and farming • Exploration of AI in supporting several human resources activities in the agri-food sector, including recruiting, training, and job performance evaluation • The impact of AI on customer satisfaction • The role of AI in supplier selection, supplier development, and supplier integration 	(Bar et al., 2016; Kling-Eveillard et al., 2020; Pérez-Ruiz et al., 2014; Sharma et al., 2020; Slaughter et al., 2008)
AI for sustainable business relationships	<ul style="list-style-type: none"> • Examination of the potential of AI for agri-food supply chain coordination, customer and supplier involvement, and reduction of transaction costs in the sector • Investigation of AI techniques' ability to ensure end-to-end supply chain traceability 	(Abdella et al., 2020; Lezoche et al., 2020; Saggi and Jain, 2018; Sharma et al., 2020)
AI for sustainable traceability	<ul style="list-style-type: none"> • The role of AI to prevent food fraud, product recalls and provide effective enhancements for traceability performance in food processing 	(Alfian et al., 2020; Milan et al., 2019; Qian et al., 2020; Yingjie et al., 2018; X. Zhang et al., 2020)
AI for sustainable waste management	<ul style="list-style-type: none"> • Exploration of how AI techniques support behavioural changes in food waste • Role of AI to foster eco-efficiency, reduce food waste and food miles • The opportunities of AI to manage waste in circular agri-food supply chains • The role of AI to develop more sustainable and socially responsible business models in the agri-food sector 	(Barrett and Rose, 2020; Camaréna, 2020; Navarro et al., 2020)
AI for sustainable business models	<ul style="list-style-type: none"> • Investigation of AI-enabled business models to achieve optimal consumption and production levels in farming and agriculture • The use of AI in the formation of innovative bio-based business models and social innovation 	(Govindan and Al-Ansari, 2019; Rose and Chilvers, 2018; Sharma et al., 2020; Tsolakis et al., 2019)

of traceability and precision agriculture, future research must scrutinise how AI techniques for agricultural production can offer practical solutions in developing end-to-end agri-food supply chain traceability. Integrating AI with other emerging technologies such as the IoT, blockchain, and augmented reality should be explored to find out how AI can bring increased visibility and transparency to all stages of the agri-food supply chain and prevent social non-compliances. Additionally, future studies should investigate the role of AI techniques to integrate all the agri-food stakeholders and reinforce commitments for traceable and sustainable food products. As AI can provide access to sophisticated analytical tools, farmers must improve farming operations and minimise waste in food production while reducing the negative impacts on the environment. Future studies need to explore how AI can be leveraged in land suitability analyses to reduce fertiliser and water consumption (Xiong et al., 2017). Furthermore, AI applications for transforming organic materials and wastes and biomass energy generation are another promising avenue for future research (Senocak and Guner Goren, 2022). By restoring to AI-based machines, there is an increased interest in examining the potential of AI to increase environmental sustainability, reduce carbon footprint, and achieve systematic waste management (Wiangkham et al., 2022). Finally, the investigation of how AI tools can introduce novel disruptive business models in the agri-food industry is encouraged in future studies. The automated information processing and extraction through AI are expected to promote smart business models. Given the paucity of agriculture research on business models, it is recommended to study the impacts of AI-enabled agricultural systems on sustainability's economic, environmental, and social dimensions. The shift from current agricultural practices to AI-enabled agriculture is far from easy; hence, the implementation of AI and the related technologies and routines are expected to bring more complexity and other challenges, which need to be explored in future research. Overall, Table 7 presents the proposed agenda to guide and advance AI research in the agri-food sector.

4.3. Practical implication

The bibliometric analysis in this study resulted in several conclusions. We identified the most prevalent AI techniques and related technologies (e.g., robots, the IoT, big data, UAVs) and their applications in the agri-food industry. This may assist practitioners in determining which AI-supporting methodologies to employ. Second, utilising RBV theory, we developed a framework to assist practitioners in determining which AI deployments may impact agri-food resources. When applying AI to agri-food activities, the seven resource categories (raw materials, water, soil, energy, human resources, technology, and relationships) must be evaluated. In addition, practitioners should carefully consider the economic and technical viability of incorporating AI while emphasising the technology's ethical and socially responsible dimensions.

4.4. Study limitations

Our study has limitations. This review began by performing a keyword search against a single database, Web of Science-WoS. Consequently, relevant publications may be omitted, especially those not indexed in the WoS database. The authors' keywords may also introduce bias into the analysis. To circumvent these issues, future studies may utilise multiple databases (e.g., Scopus, Google Scholar), include additional keywords, and employ additional analysis methods (e.g., meta-analysis, main path analysis).

5. Conclusion

This paper conducted a bibliometric analysis to examine the relationship between AI and the agri-food industry. We evaluated the papers by addressing four research issues: the dynamics underlying

the relationship between AI and agri-food systems, how farmers use AI techniques to modernise agriculture, the major trends in AI integration in agri-food businesses, and the challenges and concerns associated with leveraging AI in the digitalisation of agriculture and farming activities. AI has the potential to be an indispensable tool at every level of the intricate agri-food supply ecosystem. In addition to physical product ecosystems, its role can extend from primary production to processing, distribution, and retail, encompassing agricultural assurance and logistics service ecosystems.

In terms of scholarly output, we identified three distinct phases of AI in the agriculture and food industry. We observed that exponential growth began in 2015 due to advances in computational sciences and the emergence of innovative technologies. Unsurprisingly, AI research is published in computer science journals. The United States, China, and Spain were the top three most influential nations in terms of citations per country. Latin American and African nations contribute negligibly to AI research in the agri-food industry. In addition, robotics, the IoT, and unmanned aerial vehicles (UAVs) were identified as significant technologies that could benefit from AI techniques such as machine learning, deep learning, artificial neural networks, convolutional neural networks, and fuzzy logic. In addition, we identified machine learning and deep learning as recent trending topics. On the other hand, integrating AI with blockchain technology, virtual and augmented reality, 3D printing, and bioinformatics have received little attention. Therefore, future research should concentrate on how AI can enhance these technologies' capacity to manage soil, water, energy, crops, and livestock. In addition, the barriers to AI adoption were analysed and categorised into four broad groups: social concerns, technical concerns, privacy and ethical concerns, and organisational concerns.

Our research contributes to the expanding body of knowledge regarding AI applications in the agri-food industry. The primary findings, along with the RBV-based framework and research propositions, are instructive for scholars and practitioners interested in the AI potential of the agri-food industry. AI will be useful for forecasting weather and other agricultural conditions, and accurate forecasting will alleviate the concerns of many farmers. The future of agriculture depends on creating a resilient and sustainable farming system. Consequently, the recommendations for future research may motivate scholars to pursue additional AI research projects and contribute to the consolidation of this body of knowledge. Most propositions are valid and empirically testable. In addition, the research agenda outlined in this paper contributes to the current body of knowledge regarding AI applications in several agri-food industry domains. In conclusion, the key takeaways from this research suggest that practitioners and actors in the agri-food industry should closely monitor the effect of AI on their performance. Practitioners can use the proposed framework, which provides a comprehensive perspective for assessing the impact of AI on agri-food sustainability, as a point of reference. However, AI's potential can only be realised if practitioners work to overcome the obstacles preventing its integration into the industry. We identified several obstacles that must be addressed when integrating AI into the agri-food industry, including unemployment, ethics, and privacy. Lastly, our research aimed to bridge the gap between theory and practice regarding AI applications in the agri-food industry.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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