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Artificial Intelligence in Extended Agri-Food Supply Chain: A Short Review Based on Bibliometric Analysis

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Abstract

Climate change and population growth are triggering a digital transformation in agriculture. Consequently, agri-food supply chains are becoming more intelligent, producing vast amounts of data and pushing the boundaries of the traditional food lifecycle. However, artificial intelligence (AI) for the extended agri-food supply chain is only beginning to emerge. This paper presents a short literature review of eighteen papers on the intelligent agri-food supply chain. The bibliometric analysis reveals key research clusters and current trends in the AI-enabled stages of food production, distribution, and sustainable consumption. The important advances of AI in traditional stages of production need to be expanded with intelligent planning for demand uncertainty and personalized needs of end-customers, storage optimization, waste reduction in the post-production phase (e.g., distribution and recycling), and boundary-spanning analytics. For theory, this work highlights mature areas for AI adoption in agri-food and identifies opportunities for future research in the extended agri-food supply chain. For practice, the review findings can inspire startups interested in extended agri-food ecosystems and incumbents in their pilot projects for the intelligent and sustainable digital transformation of agri-food. AI techniques can contribute to close the loop of sustainable agri-food supply chains.

Keywords: Artificial Intelligence; Extended Agri-Food Supply Chain; Agriculture 4.0; State of the Art.

1. Introduction

The agricultural sector faces numerous challenges such as sustainability, digitalization, food safety, and the crucial need for more efficient agri-food supply chains [1,2]. This problem is exacerbated if we bear in mind that by

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2050 a further one-third of the world's population is expected to grow [3]. Therefore, academia, governments, and industry suggest that the integration of Industry 4.0 technologies into Agriculture is a possible answer to this trend [4–6], promoting a profound digital transformation [7].

Industry 4.0 is a technological initiative that aims to revolutionize manufacturing through the digital transformation of processes and products [8,9]. As a result, the entire industrial supply chain is expected to evolve, becoming more autonomous and intelligent [1]. Agri-food supply chains are facing similar pressures for technology adoption that may involve the Internet of Things (IoT), robotics, artificial intelligence (AI), big data and analytics, or blockchain [1]. However, among these critical cross-industry technologies, AI is one of the less market-ready [5], and the challenges for smarter agri-food are significant: "*hard to find single standard solution; gap between farmers and AI researchers; distributed secure machine learning;* [and] *technical and social issues with big data*" [1].

The agri-food supply chain includes different stages from "farm to fork". The traditional perspective involves decisions in physical and informational flows through production, harvest, storage, and distribution [10]. More recently, the vision of an extended agri-food supply chain also includes contextual information, consumption, and food waste reduction [11,12], putting sustainability and circular economy on the top of the agenda of food lifecycles.

The need to understand how AI is explored in the extended agri-food supply chain has inspired the formulation of the following research objectives (RO):

- *RO1: Identify research clusters of intelligent agri-food.*
- *RO2: Understand the role of AI in the extended agri-food supply chain.*

This literature review offers a novel systematized outlook on the importance of AI in the extended agri-food supply chain, presenting consolidated and newly deployed solutions and pointing to future research paths in a rapidly growing area.

The remainder of this paper is organized as follows. The following section explains the literature survey methodology, namely, bibliometric analysis and a short literature review. Subsequently, relevant clusters of intelligent agri-food are depicted in two bibliometric networks (RO1). Afterward, a classification and content analysis of eighteen papers are presented (RO2). Finally, the paper closes by stating the main conclusions, the study limitations, and future work opportunities.

2. Research Approach

This systematic literature review follows the key steps presented by [13]. Moreover, the study is based on a bibliometric analysis using VOSviewer [14] to identify research clusters (RO1) and assist in the selection of manuscripts for content analysis (RO2). Web of Science (WoS), Scopus, and Google Scholar (GS) were selected because they are "*the three major bibliometric databases*" [15]. VOSviewer [14] was used to identify research clusters in the form of network-based maps. This software developed at the Leiden University enables the creation, visualization, and analysis of bibliometric data networks extracted from bibliographic database files (including WoS and Scopus). Moreover, it can be used to evaluate the papers' co-authorship, co-occurrence, citation, bibliographic coupling, and co-citation relationships [14]. Bibliometric networks have attracted researchers' attention since it allows a straightforward approach to conceive an overview of a topic before its careful analysis (e.g., [16–18]).

Our work started in December 2020, focusing on AI-enabled agri-food supply chains. Since we could not find studies using the keyword ("intelligent system" OR "artificial intelligence") AND "extended agri-food supply chain", different tests were done to evaluate alternatives. Our purpose was to combine our research (AI) technological focus and the context of agri-food supply chains. Therefore, the following combination was used for the three databases: ("intelligent system" OR "artificial intelligence") AND ((("agri-food" OR "agro-food" OR "agrifood" OR "agrofood") AND "supply chain") OR "precision agriculture"). The term "precision agriculture" was later included because several AI-related papers adopted it. The topics search performed in the WoS was limited to its Core Collection database, while the Scopus search was within the article title, abstract, and keywords. In the GS search, we excluded citations and patents. A total of 2414 papers were identified.

Three exclusion criteria (EC) are determined. The first exclusion criterion (EC1) delimits the studies indexed in more than one database (i.e., the manuscripts that belong to the set (GS ∩ Scopus) ∪ (Scopus ∩ WoS) ∪ (GS ∩ WoS)) aiming to obtain a sample of research papers simultaneously indexed in top scientific databases. From the application of EC1, 91 articles remained. As a result of our exploratory analysis using bibliometric networks, the second exclusion criterion (EC2) selected publications with ten or more citations, or studies revealing total strength of bibliographic coupling link (calculated by VOSviewer based on the connections between documents, sources, authors, organizations, and countries) greater or equal than twenty. This number was chosen to include all the top-cited papers and extend the sample with at least 50% of more recent studies (possibly with fewer citations) closely related to the former. A total of 49 publications passed to the next step. Finally, EC3 involved screening the title and abstract. Preference was given to publications on the design and development of case studies or field studies in the extended agri-food supply chain context. Eighteen articles remained for full-text reading. Complementarily, we compared the findings with an earlier literature review [19] to understand how the topic is evolving.

Fig. 1 summarizes this search process.

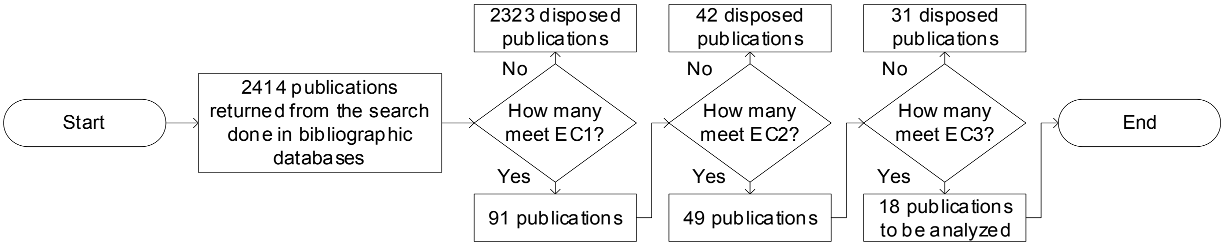

Fig. 1. Literature review search process.

The next section details the results of the bibliometric analysis, revealing meaningful research clusters of AI-enabled agri-food supply chains.

3. Insights from the Bibliometric Networks

A total of 2414 papers were obtained according to the distribution presented in Fig. 2.

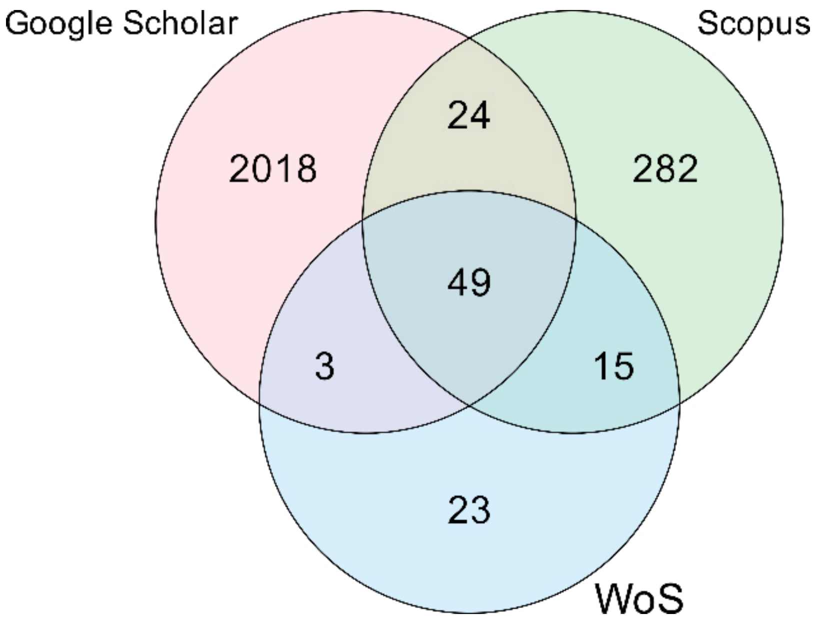

Fig. 2. Distribution of the number of publications returned by the scientific search engines used.

Google Scholar returned the highest number of results (2094 publications, excluding patents and citations), as expected, due to its broader scope. Scopus with 370 hits and WoS with 90 completed the set of papers. Interestingly, almost 40% of the documents found in Google Scholar were published in the past two years, revealing the significant interest in this recent topic and the exponential number of publications available.

The bibliometric analysis with VOSviewer used two different datasets: one with the data obtained from WoS (Fig. 3) and containing the manuscripts that belong to the set (WoS ∩ GS) ∪ (WoS ∩ Scopus); and another with the data obtained from Scopus (Fig. 4) and containing the articles that belong to the set (Scopus ∩ GS) ∪ (Scopus ∩ WoS). Both databases allow direct export of records to VOSviewer.

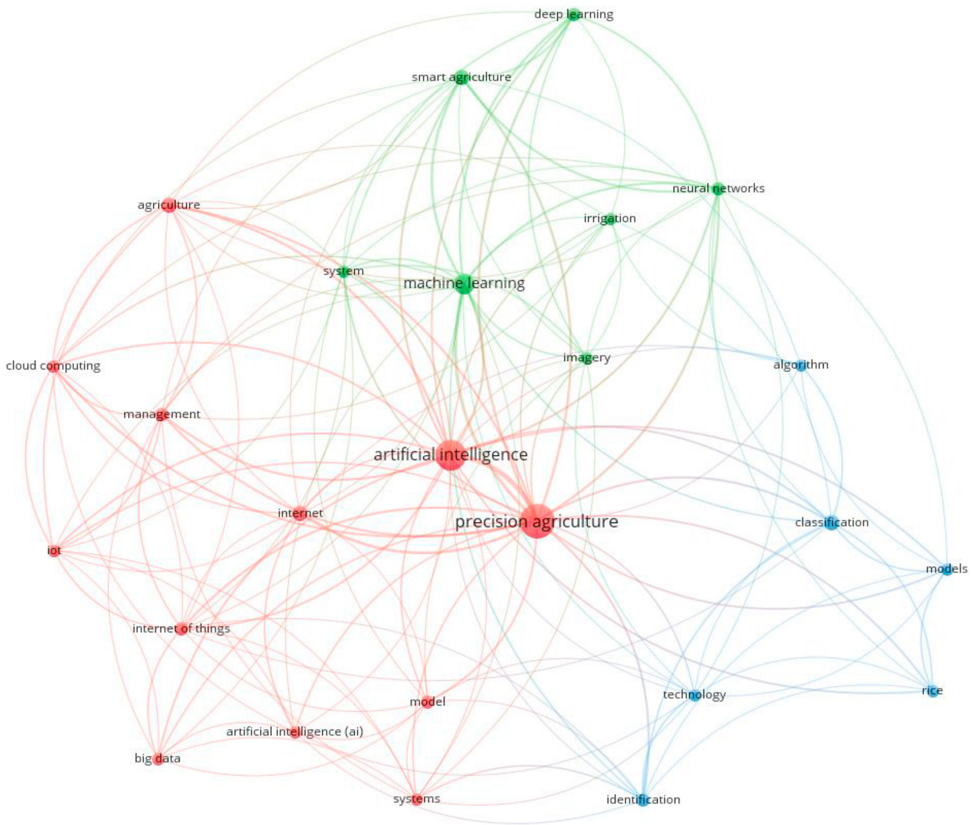

Fig. 3. Bibliometric analysis in WoS: intelligent agri-food supply chains (co-occurrence of all keywords; at least five occurrences).

Three main clusters emerge in WoS publications (Fig. 3, analyzing 67 studies). The red cluster (on the left) focusing the adoption of Industry 4.0 in Agriculture (Agriculture 4.0) and its enabling infrastructure (e.g., cloud, big data). The blue cluster (on the right) details studies using images (e.g., classification and identification), and the green cluster highlights concepts of deep learning, machine learning, or neural networks.

Scopus results (Fig. 4) are most diffuse due to the high number of papers in the sample (88). However, it is possible to emphasize AI-related studies and precision agriculture in the red cluster.

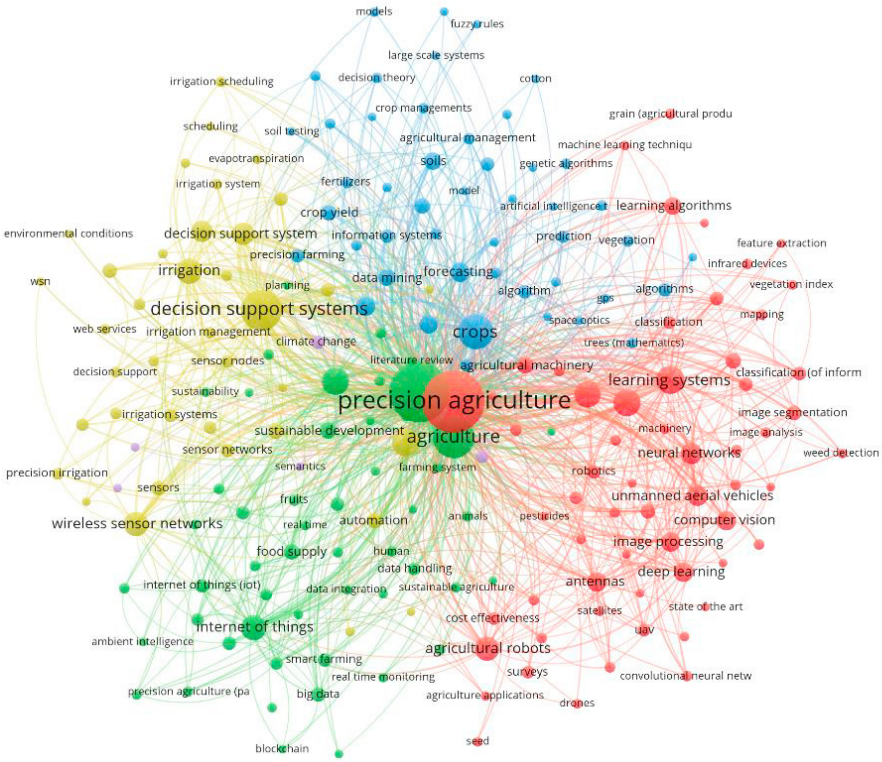

Fig. 4. Bibliometric analysis in Scopus: intelligent agri-food supply chains.

This phase of our research was mainly exploratory to guide the review. The next section details the eighteen papers selected for content analysis.

4. Towards an Extended Agri-Food Supply Chain Driven by AI

Table 1 systematizes the objectives, main results, AI techniques employed, AI discipline, and the scope of the agri-food supply chain addressed in each of the eighteen papers. Our classification of AI techniques includes methods and models, following the differentiation presented by [20]: "*AI is a science, ML* [Machine Learning] *is the most mainstream AI implementation, and deep learning is a branch of ML and the most popular ML*". The classification of "AI disciplines" (fifth column) follows [21]'s proposal, namely, natural language processing (NLP), knowledge representation (KR), automated reasoning (AR), machine learning (ML), computer vision (CV), and robotics. Finally, the scope is classified according to the traditional supply chain steps ("*production, harvest, storage, and distribution*" [10]) and the extended supply chain contextual elements inspired in [11], including sustainability and circular economy [12].

Table 1. Review and classification of the literature.

Ref.	**Objectives**	**Main results**	**AI techniques employed**	**AI discipline**	**Scope**
[22]	Develop a technique for data acquisition and image processing to evaluate the phenotypic characteristics of citrus crops.	Detect and count citrus trees in a grove of 4931 trees: accuracy of 99.9% and 99.7%, respectively; estimate their canopy size with an overall accuracy of 85.5% and detect, count, and geolocate tree gaps.	Deep learning – convolutional neural network (DL-CNN).	Machine learning (ML). Computer vision (CV).	Product monitoring – production.

Ref.	Objectives	Main results	AI techniques employed	AI discipline	Scope
[23]	Design and implement a cyber-physical intelligent agent for horticultural crops irrigation.	Reduction of 65% of water consumed and 31% of the costs associated with irrigation than a conventional system (i.e., non-automated irrigation).	Belief-desire-intention (BDI).	Knowledge representation (KR). Automated reasoning (AR).	Sustainability – production.
[24]	Design and develop a smart sprayer to distinguish target weeds from non-target objects (e.g., vegetables) and spray on the desired target.	The overall precision of 71% and recall of 78% for plant detection and target spraying accuracy.	DL-CNN.	AR. ML. CV.	Sustainability – production.
[25]	Develop a hybrid method to classify fruits and their diseases.	Accuracy of up 99.6% was achieved.	Convolutional neural network (CNN).	ML. CV.	Product monitoring – production.
[26]	Develop and test automatic methods for creating crop type maps in settings without field-level data.	GMM achieves over 85% accuracy in states with low crop diversity, but performance may be affected when high crop diversity interferes with clustering.	Gaussian mixture model (GMM).	ML. CV.	Product monitoring – production.
[27]	Develop a remote-sensing rice mapping framework by leveraging spatial, spectral, and temporal information of satellite images.	The empirical evaluations highlight that the technique developed outperforms baselines with over 0.93 F1-score.	Deep neural network (DNN).	ML. CV.	Product monitoring – production.
[28]	Develop a hybridized fuzzy model with a firefly algorithm for predicting daily reference evapotranspiration over the Burkina Faso region.	The hybrid ANFIS-FA model outperformed the classical ANFIS-based model for all three stations. Climatic data gave the best results with full inputs.	Adaptative neuron fuzzy inference system with firefly algorithm (ANFIS-FA).	ML. CV.	Context data – context-awareness.
[29]	Develop an image-processing and AI-based system using multi-class detection with instance-wise segmentation of fruits (tomato) in an image capable of estimate their dimensions and mass.	Detection and segmentation results show an average mask intersection over a union of 96.05%, mean average precision of 92.28%, the detection accuracy of 99.02%, and precision of 99.7%.	CNN.	ML. CV.	Product monitoring – production and harvesting.
[30]	Develop a fully unsupervised framework based on image processing and the DL method for plant detection. Uses high-resolution drone remote sensing.	Average counting accuracy of 90.9%. Average object detection location error of 11px. Mean precision, recall, and F1 for plant detection were 0.868, 0.849, and 0.855, respectively.	CNN.	ML. CV.	Product monitoring – production and harvesting.
[31]	Develop a model for monitoring plant phosphorus (P) dynamics across the different developmental stages of wild celery, strawberry, and sugar beet crops under different P fertilizations using hyperspectral reflectance.	The lowest prediction accuracy was obtained for the early stages of plant development. There are correlations between leaf biochemical constituents, P fertilization, and the mass of the leaf/roots of the plants.	ML.	ML.	Production monitoring – production.
[32]	Identification algorithm in orchard conditions using video processing and majority voting based on different hybrid artificial neural networks (ANN).	The accuracy of the majority voting method in the best execution and 500 executions was 98.01% and 97.20%, respectively.	Hybrids ANN.	ML. CV.	Product monitoring – production.
[33]	Design a low-power sensing system to perform seed recognition and germination detection.	Achieved 83% of average intersection over union (IoU) score and 97% of seeds recognition accuracy.	CNN.	ML. CV.	Product monitoring – production.

Ref.	Objectives	Main results	AI techniques employed	AI discipline	Scope
[34]	Develop an automatic synchronous system to identify dairy cows using image data and pressure data.	The recognition of 2160 images in 30 videos shows that the recognition rate of a single image is 90.55%, and in the video segment is 93.33%.	CNN.	ML. CV.	Product monitoring – production.
[35]	Develop an approach to detect weeds in the middle of soybean fields using histograms on color indices.	The overall accuracy of 96.601% for BPNN and 95.078% for SVM.	Back-propagation neural network (BPNN). Support vector machine (SVM).	ML. CV.	Product monitoring – production.
[36]	Develop a monitoring system that provides a prediction of plant growth dynamics.	The error of prediction within four days is less than 5%.	ML.	ML. CV.	Product monitoring – production.
[37]	Translate satellite imagery for precision agriculture and agroindustry using CNN and GA.	Most individuals in the initially generated population still spread randomly, and the number of non-dominated individuals is still smaller than the dominated individual. The population moves intelligently to the optimum position at the end.	CNN. Genetic algorithm (GA).	ML. CV.	Context data – context-awareness.
[38]	Develop an Android-based mobile application to predict plant photosynthetic pigment contents (chlorophyll, carotenoid, and anthocyanin) from the leaf images.	The prediction error for anthocyanin was ±2.93µg/g (in the range of 0-245.45 µg/g), for carotenoid ±2.14µg/g (0-211.30µg/g) and chlorophyll ±5.75µg/g (0-892.25µg/g).	CNN.	ML. CV.	Product monitoring – production.
[39]	Develop a system for vine disease detection using multispectral UAV images.	The overall accuracy of 93.72% was achieved.	CNN.	ML. CV.	Product monitoring – production.

The evaluation and continuous monitoring of product characteristics (e.g., phenotypic) is a mature field of research. For example, tree strength (e.g., by selecting those less affected by diseases or pests, or those with fewer resources) and fruit production (e.g., production volume, shelf time, or refining size). Another example is the introduction of unmanned aerial vehicles (UAVs) [39], combined with image processing. For example, multispectral imagining and deep learning convolutional neural networks [22] reduces the effort required for data collection and improves knowledge extraction. Moreover, new relationships can be established between producers or biotech experts [40]. There are also possibilities to the extended agri-food supply chain. For example, extending the work presented in [22] to other physical flow stages. Technology is essential for the extended agri-food supply chain of the future, "*exploring the ecosystem that represents the key locus of innovation to face the grand challenges connected to sustainability and CE in the agri-food industry, which is represented by the 'extended' agri-food supply chain, in which technology providers are integral parts*" [41].

Traceability and transparency are pillars of modern food quality and safety. However, AI adoption is scarce in this area, considering our sample. Additional field studies could deploy intelligent IoT-enabled monitoring systems using RFID [42] or extend the increasing adoption of blockchain in agri-food [41,43] with AI capabilities. Nevertheless, there is a shortcoming of studies incorporating (extended) data related to the market or the consumer. For example, identifying customer segments more suitable for a particular product, meteorological forecasting to predict irrigation, or detecting food demand fluctuation (accelerate or delay production). Furthermore, the COVID-19 pandemic scenario reinforced the need to improve product traceability throughout the supply chain [44], from the early stages of raw material purchase to after-sale.

The majority of papers (94%) adopt two or more AI disciplines. Machine learning and computer vision are the most popular. These AI disciplines are combined in 83% of the cases, evidencing a significant inter-relationship between the use of images and automatic analysis. This observation is aligned with the results obtained in Fig. 4 (red cluster), integrating the "unmanned aerial vehicles", "computer vision", or "learning systems".

Detection, classification, and prediction of plant and soil conditions account for almost two-thirds of the articles analyzed. Thus, monitoring agri-food emerges as the main priority, while a few studies focus on control, such as irrigation (11%) or dealing with plant diseases and pests (22%). However, the extended supply chain will require more contributions for storage improvement (e.g., intelligent warehousing, energy efficiency in food conservation), flexible distribution (e.g., demand prediction, reducing carbon footprint in food transportation), and algorithms to close the loop in agri-food supply chains (e.g., reduce food waste, support food quality assessment and traceability by consumers). Fig. 5 summarizes the classification of the AI discipline (a), scope (b), and year of publication (c).

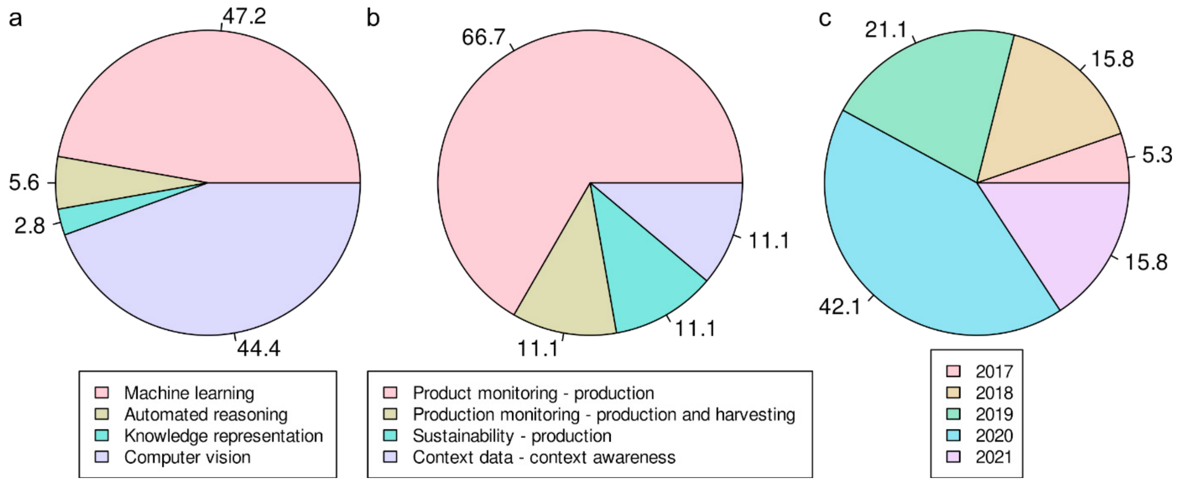

Fig. 5. (a) AI discipline; (b) scope; (c) publication year.

Machine learning and computer vision are, by far, the most popular disciplines addressed in our sample (Fig. 5a). These results align with the green cluster of WoS (Fig. 3) and the more AI-related red cluster in Scopus (Fig. 4) revealed by the network-based maps (e.g., "machine learning", "neural networks", "learning systems", or "image processing"). Most papers included address the traditional agri-food supply chain [10]. Fig. 5b shows that 77.8% of the studies fall in the product/production monitoring phase. This observation is confirmed in other related surveys (e.g., [19]). Therefore, the "extended phases" of food consumption and waste reduction are underrepresented. The rightmost chart in Fig. 5 (c) confirms the novelty of this line of research: 100% of the papers analyzed were published in the past five years, and 57.9% since 2020.

Comparing our results with prior literature review, we found some similarities with the work of [19]. These authors found that crop management is the top application domain for machine learning in agricultural systems (61%), which was also verified and strengthened in our study (78%). Moreover, artificial and deep neural networks are the most widely used AI techniques, corresponding to 55% in [19] and 72.2% in our analysis. However, our sample proportionally includes more studies about crop quality (22%) when comparing to [19] with 8%.

5. Conclusion

This paper presents a review of recent literature on AI-enabled extended agri-food supply chains. The results support the increasing impact of AI on food production and the need to integrate the contributions in the entire supply chain. Many studies focus on the production stages and the traditional process stakeholders (e.g., producers), mainly using images to optimize the process. The vision on an extended agri-food supply chain involving more stakeholders and the entire supply chain lifecycle will need additional contributions that take advantage of multiple data sources. In addition, the extended AI support to agri-food needs to increase the use of contextual information, food consumption, and food waste reduction, closing the loop in sustainable agri-food.

Some limitations must be stated. The first is related to the small number of studies that have been analyzed in detail. AI in the extended agri-food supply chain is growing at an accelerated pace. Second, the databases and keywords selected create a natural limitation. Other databases may be considered, and relevant studies may adopt different keywords. However, these papers' choice sought to highlight the most visible studies with implementation in real scenarios. Third, it was possible to identify the predominant focus in the production stages. However, this study is exploratory, and the recommendations to the future intelligent and extended agri-food supply chain will need more field intervention to prove its benefits.

The opportunities for future research are significant. First, the need for additional research addressing the traditional supply chain stages of storage (e.g., optimizing warehouses and synchronizing related supply chain steps of harvesting and distribution) and distribution (critical in the case of the perishable product). Second, aiming the extended agri-food supply chain [11] new AI solutions to explore the connection with retailers, consumers, and the circular economy [12]. Third, the extended agri-food supply chain requires flexibility, AI integration between members of the business ecosystem, operational alignment, coordinated planning, and collaborative relationships [10]. This vision for "extension" will need AI solutions that (1) integrate data from multiple stages of the agri-food supply chain, (2) use internal and external data sources, which require new partnerships with governments, business associations, and IT companies, and (3) develop end-to-end AI solutions with the input of producers, partners, governments, end-customers, and other organizations operating in the area. The intelligent extension of the agri-food supply chain is technological and societal and is only now beginning.

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References

[1] Liu, Y., Ma, X., Shu, L., Hancke, G.P., and Abu-Mahfouz, A.M. (2021) From Industry 4.0 to Agriculture 4.0: Current Status, Enabling Technologies, and Research Challenges. *IEEE Transactions on Industrial Informatics*. 17 (6), 4322–4334.

[2] Lezoche, M., Hernandez, J.E., Alemany Díaz, M. del M.E., Panetto, H., and Kacprzyk, J. (2020) Agri-food 4.0: A survey of the supply chains and technologies for the future agriculture. *Computers in Industry*. 117 103187.

[3] FAO (2018) The future of food and agriculture - Alternative pathways to 2050. Rome.

[4] Bonneau, V., Copigneaux, B., Probst, L., and Pedersen, B. (2017) Industry 4.0 in Agriculture: Focus on IoT aspects. .

[5] De Clercq, M., Vats, A., and Biel, A. (2018) Agriculture 4.0: The Future of Farming Technology. Dubai.

[6] Deloitte (2020) Transforming Agriculture through Digital Technologies. .

[7] Rose, D.C. and Chilvers, J. (2018) Agriculture 4.0: Broadening Responsible Innovation in an Era of Smart Farming. *Frontiers in Sustainable Food Systems*. 2 87.

[8] Rojko, A. (2017) Industry 4.0 concept: Background and overview. *International Journal of Interactive Mobile Technologies*. 11 (5), 77–90.

[9] Vaidya, S., Ambad, P., and Bhosle, S. (2018) Industry 4.0 – A Glimpse. *Procedia Manufacturing*. 20 233–238.

[10] Ahumada, O. and Villalobos, J.R. (2009) Application of planning models in the agri-food supply chain: A review. *European Journal of Operational Research*. 196 (1), 1–20.

[11] Edwards, P., Peters, M., and Sharman, G. (2001) The effectiveness of information systems in supporting the extended supply chain. *Journal of Business Logistics*. 22 (1), 1–27.

[12] Ciccullo, F., Cagliano, R., Bartezzaghi, G., and Perego, A. (2021) Implementing the circular economy paradigm in the agri-food supply chain: The role of food waste prevention technologies. *Resources, Conservation and Recycling*. 164 105114.

[13] Kitchenham, B. (2004) Procedures for Performing Systematic Literature Reviews. *Joint Technical Report, Keele University TR/SE-0401 and NICTA TR-0400011T.1*. 33 (2004), 33.

[14] Jan van Eck, N. and Waltman, L. (2018) VOSviewer Manual. .

[15] Harzing, A.-W. and Alakangas, S. (2016) Google Scholar, Scopus and the Web of Science: a longitudinal and cross-disciplinary comparison. *Scientometrics*. 106 (2), 787–804.

[16] Wang, B., Tao, F., Fang, X., Liu, C., Liu, Y., and Freiheit, T. (2020) Smart Manufacturing and Intelligent Manufacturing: A Comparative Review. *Engineering*.

[17] Siderska, J. and Jadaan, K.S. (2018) Cloud manufacturing: a service-oriented manufacturing paradigm. A review paper. *Engineering Management in Production and Services*. 10 (1), 22–31.

[18] Teniwut, W.A. and Hasyim, C.L. (2020) Decision support system in supply chain: A systematic literature review. *Uncertain Supply Chain*

Management. 8 (1), 131–148.

[19] Liakos, K., Busato, P., Moshou, D., Pearson, S., and Bochtis, D. (2018) Machine Learning in Agriculture: A Review. *Sensors*. 18 (8), 2674.

[20] Lu, Y. (2019) Artificial intelligence: a survey on evolution, models, applications and future trends. *Journal of Management Analytics*. 6 (1), 1–29.

[21] Russell, S. and Norvig, P. (2020) Artificial Intelligence: A Modern Approach (4th Edition). Pearson, .

[22] Ampatzidis, Y. and Partel, V. (2019) UAV-Based High Throughput Phenotyping in Citrus Utilizing Multispectral Imaging and Artificial Intelligence. *Remote Sensing*. 11 (4), 410.

[23] Jimenez, A.-F., Cardenas, P.-F., Jimenez, F., Ruiz-Canales, A., and López, A. (2020) A cyber-physical intelligent agent for irrigation scheduling in horticultural crops. *Computers and Electronics in Agriculture*. 178 105777.

[24] Partel, V., Charan Kakarla, S., and Ampatzidis, Y. (2019) Development and evaluation of a low-cost and smart technology for precision weed management utilizing artificial intelligence. *Computers and Electronics in Agriculture*. 157 339–350.

[25] Mashood Nasir, I., Bibi, A., Hussain Shah, J., Attique Khan, M., Sharif, M., Iqbal, K., et al. (2021) Deep Learning-based Classification of Fruit Diseases: An Application for Precision Agriculture. *Computers, Materials & Continua*. 66 (2), 1949–1962.

[26] Wang, S., Azzari, G., and Lobell, D.B. (2019) Crop type mapping without field-level labels: Random forest transfer and unsupervised clustering techniques. *Remote Sensing of Environment*. 222 303–317.

[27] Nguyen, T.T., Hoang, T.D., Pham, M.T., Vu, T.T., Nguyen, T.H., Huynh, Q.-T., et al. (2020) Monitoring agriculture areas with satellite images and deep learning. *Applied Soft Computing*. 95 106565.

[28] Tao, H., Diop, L., Bodian, A., Djaman, K., Ndiaye, P.M., and Yaseen, Z.M. (2018) Reference evapotranspiration prediction using hybridized fuzzy model with firefly algorithm: Regional case study in Burkina Faso. *Agricultural Water Management*. 208 140–151.

[29] Lee, J., Nazki, H., Baek, J., Hong, Y., and Lee, M. (2020) Artificial Intelligence Approach for Tomato Detection and Mass Estimation in Precision Agriculture. *Sustainability*. 12 (21), 9138.

[30] Hosseiny, B., Rastiveis, H., and Homayouni, S. (2020) An Automated Framework for Plant Detection Based on Deep Simulated Learning from Drone Imagery. *Remote Sensing*. 12 (21), 3521.

[31] Siedliska, A., Baranowski, P., Pastuszka-Woźniak, J., Zubik, M., and Krzyszczak, J. (2021) Identification of plant leaf phosphorus content at different growth stages based on hyperspectral reflectance. *BMC Plant Biology*. 21 (1), 28.

[32] Sabzi, S., Pourdarbani, R., Kalantari, D., and Panagopoulos, T. (2020) Designing a Fruit Identification Algorithm in Orchard Conditions to Develop Robots Using Video Processing and Majority Voting Based on Hybrid Artificial Neural Network. *Applied Sciences*. 10 (1), 383.

[33] Shadrin, D., Menshchikov, A., Ermilov, D., and Somov, A. (2019) Designing Future Precision Agriculture: Detection of Seeds Germination Using Artificial Intelligence on a Low-Power Embedded System. *IEEE Sensors Journal*. 19 (23), 11573–11582.

[34] Li, Z., Ge, C., Shen, S., and Li, X. (2018) Cow Individual Identification Based on Convolutional Neural Network. in: Proc. 2018 Int. Conf. Algorithms, Comput. Artif. Intell., ACM, New York, NY, USApp. 1–5.

[35] Abouzahir, S., Sadik, M., and Sabir, E. (2018) Enhanced Approach for Weeds Species Detection Using Machine Vision. in: 2018 Int. Conf. Electron. Control. Optim. Comput. Sci., IEEE, pp. 1–6.

[36] Nesteruk, S., Shadrin, D., Kovalenko, V., Rodriguez-Sanchez, A., and Somov, A. (2020) Plant Growth Prediction through Intelligent Embedded Sensing. in: 2020 IEEE 29th Int. Symp. Ind. Electron., IEEE, pp. 411–416.

[37] Firdaus, Arkeman, Y., Buono, A., and Hermadi, I. (2017) Satellite image processing for precision agriculture and agroindustry using convolutional neural network and genetic algorithm. *IOP Conference Series: Earth and Environmental Science*. 54 012102.

[38] Prilianti, K.R., Anam, S., Brotosudarmo, T.H.P., and Suryanto, A. (2020) Real-time assessment of plant photosynthetic pigment contents with an artificial intelligence approach in a mobile application. *Journal of Agricultural Engineering*. 51 (4), 220–228.

[39] Kerkech, M., Hafiane, A., and Canals, R. (2020) VddNet: Vine Disease Detection Network Based on Multispectral Images and Depth Map. *Remote Sensing*. 12 (20), 3305.

[40] Tong, H. and Nikoloski, Z. (2021) Machine learning approaches for crop improvement: Leveraging phenotypic and genotypic big data. *Journal of Plant Physiology*. 257 153354.

[41] Biswas, K., Muthukkumarasamy, V., and Tan, W.L. (2017) Blockchain Based Wine Supply Chain Traceability System. in: Proc. 2017 Futur. Technol. Conf., The Science and Information Organization, Vancouver, Canadapp. 56–62.

[42] Corallo, A., Paiano, R., Guido, A.L., Pandurino, A., Latino, M.E., and Menegoli, M. (2018) Intelligent monitoring Internet of Things based system for agri-food value chain traceability and transparency: A framework proposed. in: 2018 IEEE Work. Environ. Energy, Struct. Monit. Syst., IEEE, pp. 1–6.

[43] Caro, M.P., Ali, M.S., Vecchio, M., and Giaffreda, R. (2018) Blockchain-based traceability in Agri-Food supply chain management: A practical implementation. in: 2018 IoT Vert. Top. Summit Agric. - Tuscany (IOT Tuscany), IEEE, pp. 1–4.

[44] Di Vaio, A., Boccia, F., Landriani, L., and Palladino, R. (2020) Artificial Intelligence in the Agri-Food System: Rethinking Sustainable Business Models in the COVID-19 Scenario. *Sustainability*. 12 (12), 4851.