Review article

A systematic review of trends, applications, and challenges of emerging technologies in the agricultural industry

Una revisión sistemática sobre tendencias, aplicaciones y desafíos de las Tecnologías Emergentes en la Industria Agrícola

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Received: October 30, 2025; Accepted: February 21, 2026
https://doi.org/10.15446/rfnam.v79.122666

ABSTRACT
The use of smart technologies for the automation and management of the agricultural sector has become a strategic area of research and development, as traditional methods are insufficient to meet the growing global food demand. In this context, this study analyzes, through a systematic literature review, how emerging technologies, particularly Artificial Intelligence and the Internet of Things (IoT), can contribute to the improvement, application, and evolution of smart practices in the agricultural sector. This paper presents a characterization of the concepts of precision agriculture and smart agriculture, along with the main digital tools that have driven their adoption. It also identifies the most relevant applications of these technologies within the agricultural supply chain, based on an analysis of scientific literature published between 2008 and 2025 using advanced search strategies supported by Boolean operators and processed with the Bibliometrix tool. As a result, the authors identify trends and lines of research that are grouped into three main areas: a) technological innovation, b) application scenarios, and c) business and commercialization. These latter areas, although fundamental to the consolidation of smart agriculture, have received less attention than technological developments. Therefore, a model-oriented, decision-making framework for intelligent management in the agricultural sector is proposed, based on a five-layer IoT architecture. These elements constitute strategic areas for future research to promote the digital transformation and sustainability of the agricultural industry.

KEYWORDS: Artificial intelligence, Digital transformation, Internet of things, Smart agriculture, Supply chain, Systematic review

CITATION: Araujo Alonso CE, Padilla-Medina JA, Contreras Medina DI, Jiménez García JA and Guerrero Campanur A (2026) A systematic review of trends, applications, and challenges of emerging technologies in the agricultural industry, Revista Facultad Nacional de Agronomía Medellín 79: e122666. doi: https://doi.org/10.15446/rfnam.v79.122666

RESUMEN
El uso de tecnologías inteligentes para la automatización y gestión del sector agrícola se ha consolidado como un área estratégica de investigación y desarrollo, debido a que los métodos tradicionales resultan insuficientes para satisfacer la creciente demanda alimentaria mundial. En este contexto, el presente estudio analiza, mediante una revisión sistemática de la literatura, la manera en cómo las tecnologías emergentes,

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particularmente la Inteligencia Artificial y el Internet de las Cosas (IoT), pueden contribuir al progreso, aplicación y evolución de prácticas inteligentes en el sector agrícola. Este trabajo presenta una caracterización de los conceptos de agricultura de precisión y agricultura inteligente, así como de las principales herramientas digitales que han impulsado su adopción. Asimismo, se identifican las aplicaciones más relevantes de estas tecnologías dentro de la cadena de suministro agrícola, a partir del análisis de literatura científica publicada en el periodo comprendido entre 2008 y 2025 mediante estrategias de búsqueda avanzada apoyadas en operadores booleanos y procesadas con la herramienta Bibliometrix. Como resultado, se identifican tendencias y líneas de investigación agrupadas en tres áreas principales: a) innovación tecnológica, b) escenarios de aplicación y c) negocios y comercialización. Estas últimas, aunque fundamentales para la consolidación de la agricultura inteligente, han recibido menor atención en comparación con los desarrollos tecnológicos. Por lo que se propone un modelo orientado a la gestión inteligente para la toma de decisiones en el sector agrícola, sustentado en una arquitectura IoT de cinco capas. Dichos elementos constituyen áreas estratégicas para futuras investigaciones destinadas a impulsar la transformación digital y la sostenibilidad de la industria agrícola.

PALABRAS CLAVE: Inteligencia artificial, Transformación digital, Internet de las cosas, Agricultura inteligente, Cadena de suministro, Revisión sistemática

INTRODUCTION

Importance of the agricultural sector and its challenges

The agricultural sector is one of the fundamental pillars of the global economy and food security. The Food and Agriculture Organization of the United Nations (FAO) indicates that more than 60% of the world's population depends, directly or indirectly, on agriculture for their livelihoods, and that approximately 12% of the Earth's land surface is used for agricultural activities. However, demographic projections indicate that by 2050, the world population will reach 9.6 billion people, requiring an approximate 70% increase in food production (FAO 2021).

This scenario presents a structural challenge: the expansion of agricultural production must occur in a context marked by reduced arable land due to urbanization, climatic constraints, soil degradation, and environmental variability. Furthermore, although the agricultural sector contributes significantly to Gross Domestic Product (GDP) growth and plays a key role in reducing hunger and poverty (Khan et al. 2020), it also accounts for a significant share of greenhouse gas emissions due to the intensive use of fertilizers, biomass, and fossil-fuel-based machinery.

In this context, traditional agricultural production methods are insufficient to simultaneously address the challenges of productivity, sustainability, and climate resilience. The increasing complexity of the agricultural environment demands solutions that optimize resources, improve operational efficiency, and strengthen decision-making processes. It is precisely at this point those smart digital technologies emerge as a strategic alternative for transforming the agricultural industry.

Role of emerging technologies

Smart and precision agriculture are consolidating as approaches that integrate digital tools for automation, monitoring, and the efficient management of production systems. Technologies such as the Internet of Things (IoT) and Artificial Intelligence (AI) have demonstrated their potential across applications in crop monitoring, yield prediction, and resource use optimization (Tzounis et al. 2017). Furthermore, the incorporation of big agricultural data allows for the generation of predictive scenarios that support the sustainability and resilience of the agri-food system (Ait Issad et al. 2019).

The literature shows that the adoption of smart technologies has had a significant impact on the productivity and sustainability of the agricultural sector internationally. In Taiwan, the implementation of controlled-environment production systems has increased the yield of various vegetables by five to 10 times compared to traditional methods. In Spain, predictions of parameters associated with greenhouse tomato crops have been achieved with accuracy levels exceeding 90%. Meanwhile, in Ireland, the adoption of smart technologies has contributed to a 10% reduction in greenhouse gas emissions, a 21% reduction in agricultural management costs, and a 47% improvement in soil fertility. Similarly, in Brazil, arugula crop size has increased by 17.9% and weight by 14.29% following the adoption of smart applications. Finally, in India, the implementation of IoT-based systems has reduced water consumption by 30%, resulting in yield increases of between 15 and 20%.

These results confirm the potential of smart technologies to optimize productive and environmental efficiency in different agricultural contexts (Araújo et al. 2021). However, despite the growing number of studies on technological applications in agriculture, most have focused on developing prototypes, sensors, and algorithms primarily aimed at improving crop productivity (Bhat and Huang 2021). Few works systematically integrate the joint contributions of AI and IoT not only from a technical perspective but also in terms of their impact on administrative management, strategic decision-making, and the comprehensive transformation of the agricultural supply chain (Wang et al. 2024).

Consequently, there is a gap in the literature regarding the limited integration of technological advances into agricultural management and decision-making, which are fundamental to consolidating the digital transformation of the sector.

Contributions

In this context, this study aims to analyze, through a systematic literature review, the impact of emerging technologies, particularly Artificial Intelligence and the Internet of Things (IoT), on the agricultural sector, identifying their trends, applications, and areas of opportunity, with an emphasis on their contribution to smart management. Consequently, the following research question is proposed: How do emerging technologies, particularly Artificial Intelligence and IoT, contribute to the development, application, and evolution of smart practices in the agricultural sector?

As an additional contribution, a five-layer IoT architecture is proposed to facilitate the adoption and integration of digital technologies, thereby improving the management and efficiency of production systems. In this way, the work not only systematizes existing knowledge but also offers an integrated vision to guide future research and strengthen the sustainable digital transformation of the agricultural industry.

MATERIALS AND METHODS

This review is a comprehensive analysis of trends and challenges in the development of smart and precision agriculture based on technologies from Artificial Intelligence and the Internet of Things (IoT), as well as their various applications within the agricultural supply chain. It also reveals various digital tools that will need to be studied in the future to achieve the transformation of the agricultural industry. A systematic review was carried out based on the PRISMA methodology. The research methodological process developed is divided into three stages, as shown in Figure 1.

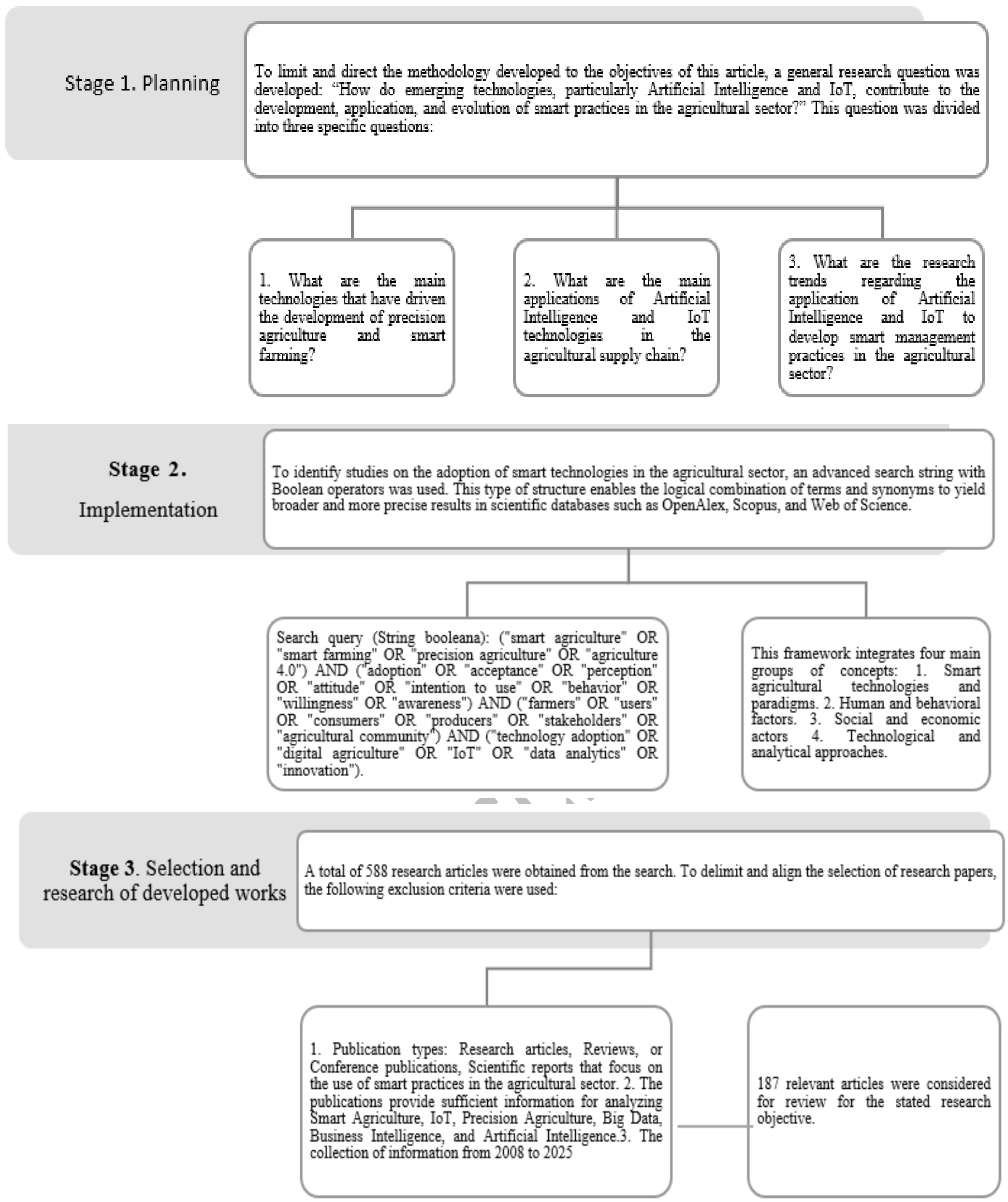

Figure 1. Research methodological process.

RESULTS AND DISCUSSION

The literature reports various agricultural techniques and methods, including aeroponic and hydroponic soilless plant cultivation systems, as well as urban agriculture. These modern and innovative techniques could help solve current food problems. However, the contribution of this article focuses on the description of two types of agriculture, the precision one and the smart one, which can be adapted by any agricultural technique or method and enhance its innovation, fully benefiting traditional and modern agricultural practices and in this way driving present and future solutions related to food health problems worldwide, in addition to promoting the development of the agricultural sector.

Agriculture technologies

The constant evolution of digital tools and the dynamic development of emerging technologies derived from Artificial Intelligence and IoT represent areas of opportunity for innovation in the agricultural sector, providing new concepts such as Agriculture 4.0. This term enables the combination of different fields of research, such as precision agriculture and smart agriculture, driven by scientific advances in information and communication technologies (ICT) (Araújo et al. 2021, 2023).

The automation and decision-making process in agriculture requires different technologies at each stage of information acquisition and transmission. Data is collected through IoT sensors and transferred to different servers, where, through AI-based algorithms, the decision support systems store, analyze and process the information, which will provide the resources for farmers to have a perspective of all the processes in progress, understand the real conditions, make predictions based on the various data obtained and produce early warnings about the dangers that may threaten crops and in this way take actions for their optimization (Araújo et al. 2021, 2023).

Figure 2 illustrates the main technologies used in agriculture, categorized into two application groups: precision agriculture, which encompasses physical mechanisms such as sensors, robots, and communication devices, and smart agriculture, which incorporates intelligent digital tools for information analysis and decision-making.

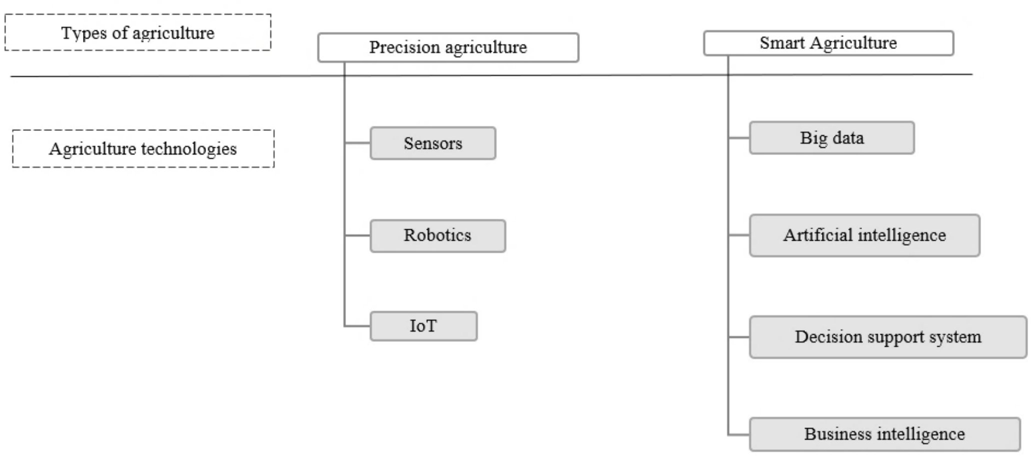

Figure 2. The main technologies used in agriculture, categorized into two application groups: precision agriculture and smart agriculture.

Precision agriculture

Precision Agriculture integrates sensors, monitoring and control systems, field actuators, and management mechanisms to optimize agricultural production by considering variability and uncertainty by adapting conventional agricultural techniques to the specific conditions of each crop. It provides a method for monitoring the food supply chain and managing the quantity and quality of products and processes in the agricultural sector. Precision agriculture can be divided into three stages: 1) Determination stage. It focuses on identifying and grouping the crop's characteristics and variables by area. 2) Information gathering stage. Information and control systems compile and process information. 3) Launch stage. The mechanisms and actuators respond to the signals sent in the previous stages (Zhang et al. 2002).

IoT

The "Internet of Things" encompasses the connection of sensors and/or actuators that are addressable and accessible via the Internet without requiring human intervention. Currently, the integration of IoT technology in the agricultural sector enables the convergence of traditional and data-driven agriculture, facilitating real-time decision-making and proposing solutions to current agricultural challenges, such as droughts, land suitability, reducing environmental impact, detecting pests and diseases, and providing climate and soil monitoring alerts. In addition to facilitating the optimization of renewable and non-renewable resources, the monitoring and recording of production traceability (Kamilaris and Prenafeta-Boldu 2018) are crucial. Figure 3 provides a summary of the most notable works on the integration of IoT technology in the agricultural sector.

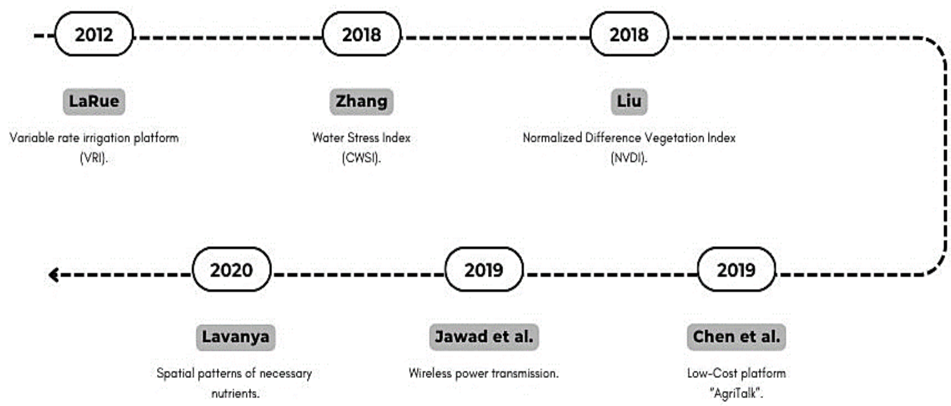

Figure 3. Summary of the most outstanding works that show the results of using IoT technology in the agricultural sector.

Currently, there is no universal design for an IoT-based system in the agricultural field. Various authors suggest different types of architecture with different degrees of technological application. Although the classification of the layers may have slight variations, several researchers converge that three layers can base a generalized IoT architecture: a) perception layer, integrated by sensors responsible for collecting and detecting parameters and attributes of the agricultural environment; b) network layer integrated by communication protocols to transmit data from the sensors to the application layer; c) application layer (mechanisms and actuators), which includes a server to store, process, visualize and analyze information (Ferrández-Pastor et al. 2016; Sagar and Birje 2025; Miller et al. 2025; Ahmed and Shakoor 2025).

Although the architecture of this technology is in a state of evolution where it is not yet possible to determine its total structure, this review raises the possibility of adding two additional layers described in the reviewed literature: d) business layer that includes all the information on environmental, geographic and business management data; to monitor traceability variables throughout the entire agricultural supply chain, including information on environmental, geographic and business parameters and in this way design timely strategies for agricultural decision-making and e) user layer made up of the access and information transmission security system, this layer can safeguard all the information immersed in each of the phases of the agricultural supply chain through security methods for access, storage and data transmission and in this way promote a healthy environment between devices and users (Farooq et al. 2019; Araújo et al. 2021). Figure 4 illustrates the five layers proposed for modeling an IoT-based architecture. Figure 5 presents the schematic of the proposed IoT architecture.

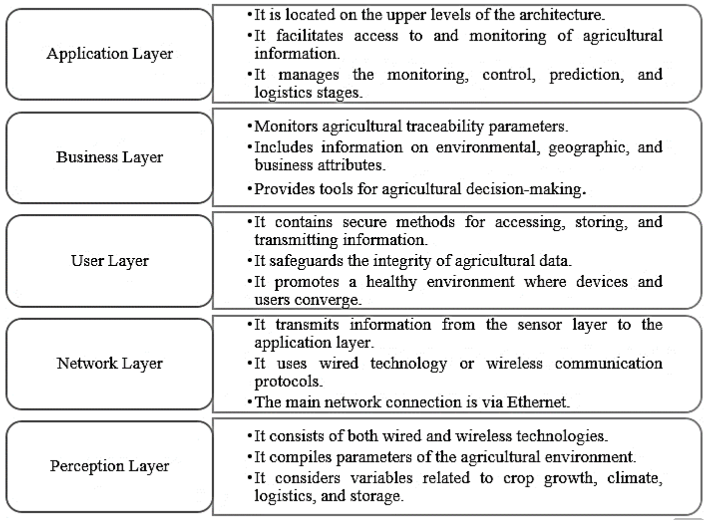

Figure 4. IoT architecture based on five layers. Adapted from Ferrández-Pastor et al. (2016), Farooq et al. (2019), Araújo et al. (2021), Sagar and Birje (2025), Miller et al. (2025) and Ahmed and Shakoor (2025).

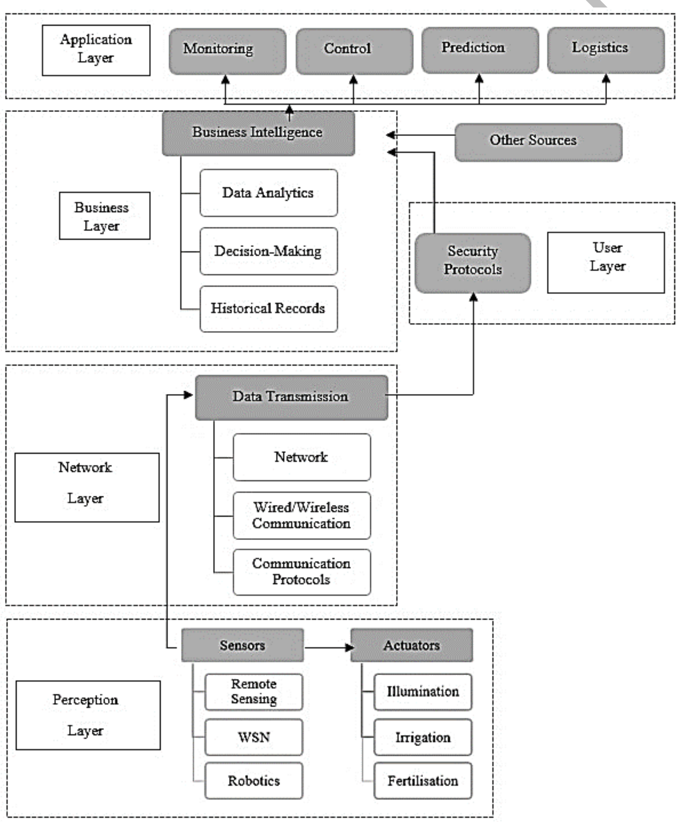

Figure 5. Proposed IoT architecture. Adapted from Ferrández-Pastor et al. (2016), Farooq et al. (2019), Araújo et al. (2021), Sagar and Birje (2025), Miller et al. (2025), and Ahmed and Shakoor (2025).

Sensors

In recent decades, the use of wired and wireless sensors has increased significantly in the agricultural sector (Tzounis et al. 2017), as they provide valuable information about crops and the environment, thereby constituting an essential technology for implementing IoT in agriculture.

Sensor networks allow for the analysis of multiple parameters in real-time, such as water properties, soil conditions, or climatic characteristics, allowing for take actions at that instant at the field level (Musa et al. 2024) in this way it is possible to optimize agricultural resources, thus increasing efficiency in crop production and at the same time enhancing environmental sustainability. In recent decades, the use of wired and wireless sensors has increased significantly in the agricultural sector (Tzounis et al. 2017), as they provide valuable information about crops and the environment, thereby constituting an essential technology for implementing IoT in agriculture.

The designs of sensors are specifically tailored to support traceability in the agricultural sector, as they enable the collection, storage, and processing of spatial and temporal variables that significantly influence agricultural production (Zhang et al. 2002). These variables are managed primarily through two approaches: a map-based approach and a sensor-based approach, both of which are used in monitoring, control, and decision-making within the agricultural production process. Figure 6 summarizes the most notable studies on the use of sensors in the agricultural sector.

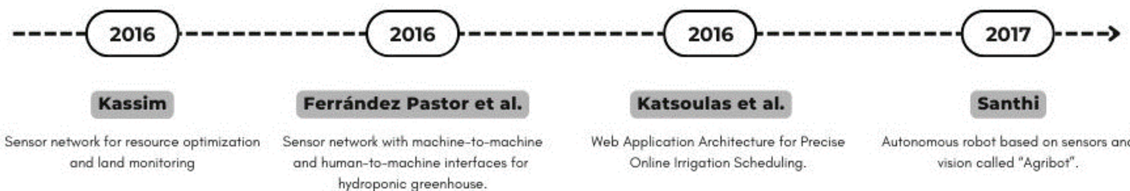

Figure 6. Summary of the most notable works demonstrating the application of sensors in the agricultural sector.

To determine the classification of the most widely used sensors in agriculture (Figure 7), a review of various literature compilation works was conducted, which provided the types of sensors and their applications in the agricultural field. Hassan et al. (2021) analyzed a total of 114 articles. In Araújo et al. (2021), a semi-automated approach based on NLP enabled the analysis of 8,485 works. In Farooq et al. (2019) reviewed 304 documents. Soussi et al. (2024) achieved a summary of 1,282 papers. Prakash et al. (2023) analyzed a total of 973 articles.

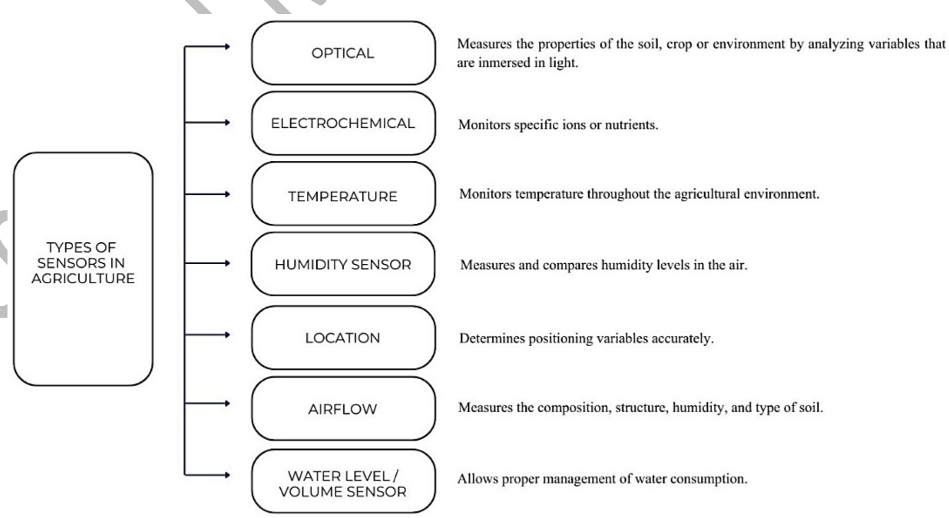

Figure 7. Most used sensor types in agriculture. Adapted from Elijah et al. (2018), Farooq et al. (2019), Hassan et al. (2021), Araújo et al. (2021), Prakash et al. (2023), and Soussi et al. (2024).

Good sensor coupling enables greater efficiency in agricultural activities; however, each sensor has specific technical characteristics that depend on the IoT communication protocols and technologies used. Fundamental wireless technologies are categorized into several groups (Figure 8) and various types of communication protocols in the IoT field. Table 1 compares the attributes of the most commonly used wireless protocols in agriculture.

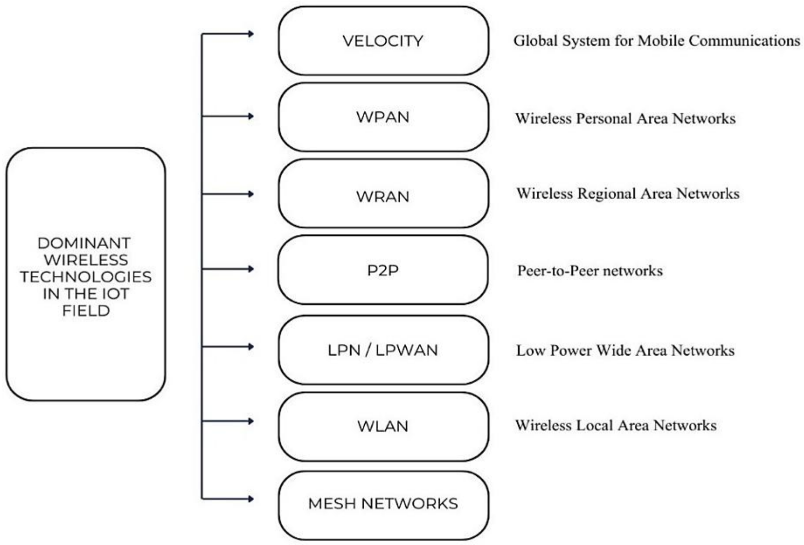

Figure 8. Dominant wireless technologies in the IoT field. Adapted from Tzounis et al. (2017), Elijah et al. (2018), Jawad et al. (2019), Farooq et al. (2019), Shi et al. (2019), Araújo et al. (2021), Soussi et al. (2024), and Prakash et al. (2023).

Table 1. Types of communication protocols most used in agriculture and their basic characteristics.

Protocol Type	Wireless Standard	Frequency Band	Data Range	Transmission Range	Energy Consumption	Cost
Bluetooth	IEEE 802.15.1	2.4 GHz	1 – 24 Mb/s	8-100 m	0.1-1 W	Low
LoRaWAN	LoRaWAN	Various	0.3 – 50 Kb/s	<30 km	100 mW	High
NFC	ISO/IEC 13157	13.56 MHz	424 Kb/s	0.1 m	1-2 mW	Low
Mobile communication	2G-GSM, 3GUMTS, 4GLTE	868/915 MHz, 2.4 GHz	2G: 50 – 100 kbs/s 3G: 200 kb/s 4G:0.1 – 1Gb/s	Entire mobile Area	1 W	Medium
RFID	ISO 18000-6C	860-960 MHz	40 to 423 kb/s	1-5 m	1 mW	Low
Sigfox	SigFox	2400 – 2483.5 MHz	100 – 1000 bit/s	30-50 km	122 mW	Low
Wi-Fi	IEEE 802.11 a/c/b/d/g/n	5 GHz - 60 GHz	1 Mb/s – 7 Gb/s	20-100 m	1 W	Low
ZigBee	IEEE 802.15.4	2.4 GHz	20 – 250 Kb/s	10-20 m	1 mW	Low

Adapted from Tzounis et al. (2017), Elijah et al. (2018), Jawad et al. (2019), Farooq et al. (2019), Shi et al. (2019), Araújo et al. (2021), Soussi et al. (2024), and Prakash et al. (2023).

Robotics

In the agricultural sector, robots are designed to perform basic repetitive tasks; however, they can also perform more specific tasks to provide farmers with information about the soil, temperature, humidity, agricultural equipment, and the crop, allowing them to optimize the use of chemical inputs, machinery, and natural resources (Cheng et al. 2023).

In agriculture, mobile robots are considered a significant breakthrough in enhancing agricultural management. Their development and application have the potential to impact every stage of the agricultural production cycle, from crop establishment to monitoring, environmental control, tracking, supply, and treatment, as well as pest and disease detection, through to the harvest of the final product (Hernández et al. 2025). They do not require the integration of additional components or the use of a decision support system; however, their application is often combined with IoT and sensor-related technologies. There are two primary types of robots: unmanned ground vehicles and unmanned aerial vehicles, which have enabled various agricultural applications. Table 2 presents the definitions and main applications of the two most used classes of robots in agriculture.

Table 2. Summary of robot categories and their main applications in agriculture.

Robotics Categories	*Unmanned Ground Vehicles (UGVs)* As the agricultural industry expanded, rural labor resources began to be affected, prompting the development of automated heavy machinery to become an important factor in agriculture. An average unmanned ground vehicle offers significantly greater speed, precision, resource optimization, and time efficiency than traditional agricultural labor.	***Applications***	Crop Health Irrigation Monitoring assessment of crops
	Unmanned Aerial Vehicle (UAVs) Drones can be defined as unmanned aerial vehicles used in agriculture to enhance various farming practices. These devices can be controlled remotely by manual control or programmed to perform tasks automatically. They facilitate crop health analysis using geographic information system mapping. Their implementation is primarily based on large crop areas where monitoring and control activities are strenuous to perform accurately and regularly.		Crop spraying Planting Analysis of soil field

Adapted from Farooq et al. (2019), Cheng et al. (2023), and Hernández et al. (2025).

Smart agriculture

Smart agriculture is perceived as one of the most effective adaptation strategies to achieve food security while mitigating the impact of climate change by conserving natural resources. Therefore, it promotes sustainability and increased agricultural productivity by addressing climatic implications and, consequently, a balanced food supply (FAO 2021). It incorporates digital tools for the application and management of Information and Communication Technologies (ICT) and allows their integration throughout the agricultural supply chain. It is updated in real-time, thus providing improved performance for precision agriculture solutions and a more intelligent management approach (Ait Issad et al. 2019).

Big data

Big data represents a system of convergence of structured and unstructured data sets from diverse sources, which, through digital tools such as data mining, artificial intelligence, predictive analytics, and natural language processing, can be extracted and analyzed. Several authors have classified and categorized big data into five dimensions: volume, velocity, variety, value, and veracity; however, some scholars agree that big data might not satisfy all five dimensions depending on the specifications required by its application, generalizing the concept to only three aspects: volume, variety, and velocity (Rodriguez et al. 2017). Figure 9 illustrates the three fundamental dimensions of big data, along with their general definitions.

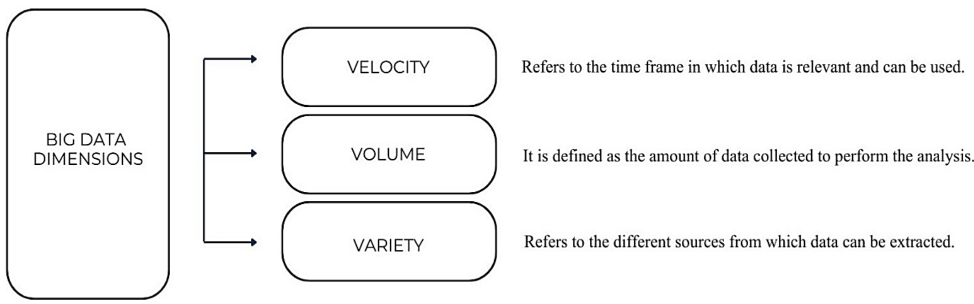

Figure 9. Fundamental dimensions of big data. Adapted from Rodriguez et al. (2017).

Big data analysis requires technological techniques and tools that enable the transformation of large amounts of structured, semi-structured, and unstructured data into a format that is accessible and understandable for analytical processes. The algorithms used in these analytical tasks must be able to detect patterns, trends, and correlations in the shortest possible time. Data mining stands out as one of the most outstanding solutions in this field, as it provides the extraction of valuable information from vast sample spaces and the discovery of unknown or hidden patterns or correlations within the data that may be relevant to solving various problems. Currently, the development of agriculture has benefited from the adoption of these techniques and digital tools (Zhang et al. 2002). Various authors classify data mining techniques into four categories: classification, clustering, association, and prediction (Kamilaris and Prenafeta-Boldu 2018; Rehman et al. 2019; Ait Issad et al. 2019). Table 3 shows the classification and description of data mining techniques.

Table 3. Classification and description of data mining techniques.

Categories	Description	Techniques
Classification	It is a supervised learning process that consists of mapping selected data into a predefined set of classes and assigning a class label to each element.	Bayesian Networks. Decision Trees. Support Vector Machine. Neural Networks. Random Forests. K-Nearest Neighbors. Deep Learning.
Clustering	It is an unsupervised learning process that involves grouping objects based on patterns of similarity and relationships between elements. Clustering techniques can be categorized into five main types: partitioning methods, hierarchical methods, density-based methods, grid-based methods, and model-based methods.	Partition Methods: K-Means; PAM. Hierarchical Methods: CHAMELEON; BIRCH. Density-based Methods: DBSCAN; DENCLUE; OPTICS. Grid-based methods: STING; CLIQUE. Model-Based Methods: COBWEB; CLASSIT.

Association	Exploring meaningful relationships between objects in a large dataset involves identifying associations or patterns within the most common groups of elements.	Apriori. AprioriTid. Dic. Eclat. FP-growth.
Prediction	It is the analysis of patterns that can lead to reasonable conclusions for predicting events using sequences of data observed over time.	Regression analysis. Linear regression. Neural Networks. Support Vector Machine. Decision Tree. Random Forest.

Adapted from Kamilaris and Prenafeta-Boldu 2018, Rehman et al. 2019, and Ait Issad et al. 2019.

In the agricultural sector, big data has proven to be a valuable alternative for addressing some of the challenges faced by agriculture, including diagnosing soil quality, predicting diseases and pests, weather forecasting, determining optimal crop harvesting times, and managing the consumption of natural and material resources. This technology directly benefits the quality and quantity of agricultural production (Bhat and Huang 2021). It is not limited solely to the field or production; it also encompasses the stages of food transportation, storage, sale, and consumption, significantly improving the agricultural supply chain and reducing the challenges facing food security. Consequently, it is considered an important driver of environmental conservation (Kayacan and Vardar 2025).

Several authors predict that big data analytics will transform both the organizational structure and the way agricultural decisions are made, managed, and implemented. Figure 10 shows a summary of the main contributions of big data to the agricultural sector.

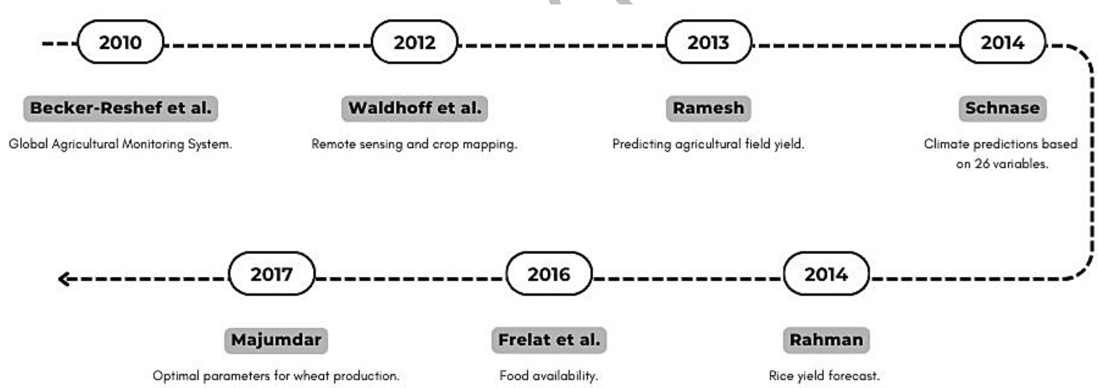

Figure 10. Summary of the most outstanding works that show the main contributions of big data in the agricultural sector.

Artificial intelligence

Artificial Intelligence (AI) is defined as the ability of a machine to intelligently understand the variables that interact within its environment. It involves the use of computational systems for pattern recognition, reasoning, learning, and understanding behaviors from experience, as well as the acquisition and preservation of knowledge and the development of various inference techniques that provide optimal or exact solutions to problems arising in the decision-making process. Its purpose is to understand the phenomenon of human intelligence and the design of systems that allow emulating human behavior patterns, creating relevant knowledge for problem-solving. It has had various successful applications in areas such as robotics, machine learning, data mining, neural networks, genetic algorithms, and expert systems (Kaplan and Haenlein 2019).

Several authors agree that artificial intelligence is a broad domain that includes machine learning and deep learning as two interrelated subsets. Table 4 summarizes the definition of these two subsets and defines the most widely used models and methods in the literature.

Table 4. Definition of machine learning and deep learning.

			Artificial Intelligence Models	
Artificial Intelligence	Machine learning	Machine learning can learn patterns from models based on data analysis without the need to define them beforehand. Its applications can progressively improve as behaviors are discovered in the information, that is, as it "learns" about the data being processed. Machine learning encompasses the stages of information input, processing, and output.	Supervised Machine Learning	It is used for categorizing and processing information based on the mapping of input and output data through artificial intelligence algorithms.
			Unsupervised Machine Learning	Analyzes the relationship or correlation of input information, extracting inferences from data sets that do not have defined attributes, that is, they have not been categorized or labeled.
			Semisupervised Machine Learning	A two-stage process in which one of the previous models is used as a preprocessing phase to use the next model, thus employing both types of learning.
			Artificial Intelligence Methods	
	Deep Learning	Deep learning is considered a subset of machine learning, where various mathematical methods are used to process information. Therefore, artificial intelligence can be defined as a superset of machine learning, implying the relationship between the two.	Artificial Neural Networks	A theoretical mathematical model based on the behavior of the human brain. It consists of a series of linear or nonlinear processes called nodes, which are interconnected to form a network of connections.
			Fuzzy Logic	A set of mathematical principles based on an alternative approach to classical logic. It analyzes and conceptualizes information that presents a certain degree of ambiguity. This model is based on linguistic parameters, which approximate a function using different values within the interval [0, 1].
			Expert Systems	The name of this concept derives from the term "knowledge-based expert system," which is a mathematical model based on the collection of user knowledge and experience, imitating the reasoning process that experts use to solve specific problems.

Adapted from Kaplan and Haenlein (2019), Shi et al. (2019), Paschen et al. (2020), and Hassan et al. (2021).

Some authors have shown that the use of Artificial Intelligence tools can reduce poverty and malnutrition. Furthermore, it is an application that enhances efficiency and production levels in the agricultural sector while also compensating for the shortage of human resources and mitigating the environmental footprint associated with traditional agri-food operating systems. Therefore, a significant shift is presented for business models, whose purpose is also to address the challenges posed by environmental and social sustainability issues (Asolo et al. 2024). Furthermore, various studies demonstrate that AI is a fundamental pillar for companies seeking to design strategies that enable them to dominate their competitive sector due to its ability to extract information from large datasets suitable for management and decision-making. Thus, for the agri-food sector, the use of AI is aimed at enhancing the competitiveness of agricultural companies by mitigating the negative environmental impacts (Sharifmousavi et al. 2024).

The reviewed literature presents significant agricultural advances through the adoption of emerging technologies; however, most of the reviewed works have provided new tools for the digitalization and automation of systems, mechanisms, techniques, and prototypes that offer various opportunities for monitoring and controlling crop growth and development from pre-harvest to post-harvest. Therefore, an area of opportunity for study is perceived, a system where all these advances in the agricultural sector can converge, with the adoption of emerging technologies in the administrative and decision-making areas within the agricultural supply chain so that this system enables complete automation, scalability, monitoring and control of the entire ASC at any time and in any place, this provides the ability to detect and predict problems at the field level accurately and therefore, faster and more timely decision-making, improving the resilience and sustainability of the agricultural sector. Therefore, farmers could begin to establish channels of communication and understanding of their crops at a microscale through emerging technologies. It enables more intelligent management of the agricultural supply chain, significantly impacting food safety objectives. It also promotes traceability of food origin, strengthens relationships between stakeholders, and ensures consumer confidence in the high quality of food. Within the literature, studies have focused on agricultural management systems that enable the convergence of technological tools and agricultural administration, which are discussed below.

Farm management information system

Agricultural information management systems play a fundamental role in the development of smart agriculture by allowing the convergence of all users, processes, methodologies, machinery, and devices involved in agronomy to manage all the information coming from the different entities and in the different stages of the agricultural supply chain, and in this way designing intelligent strategies for agricultural decision-making (AlJafa and Várallyai 2023).

Each FMIS (Farm Management Information System) can be designed for various general or specific functions within the stages of the agricultural supply chain, such as production management or financial management, or it can even focus on one or more domains of the agricultural sector, for example, livestock or agriculture (Müller et al. 2025).

One of the critical components for developing an agricultural information management system is the design of its digital architecture which must include, among its benefits, a communication channel between interested parties and the evaluation of the system (Mansoor et al. 2025).

Two digital architectures are reported in the literature, capable of managing all information from the agricultural sector in an accessible manner using flexible and adaptable platforms within each domain and at every stage of the agricultural supply chain: Decision Support Systems and Business Intelligence. Figure 11 defines the characteristics of these platforms.

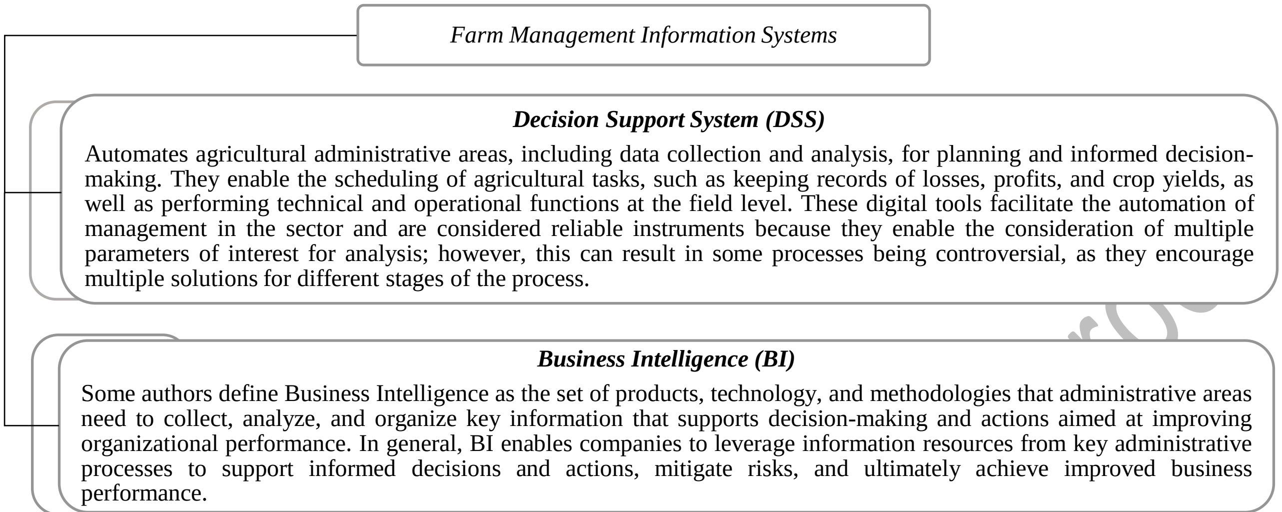

Figure 11. Definition of the most prominent agricultural management systems. Adapted from Mikalef et al. (2017), Bhat and Huang (2021), Munazza et al. (2023), Lamolinara et al. (2024), and Müller et al. (2025).

Agriculture applications

This section outlines the status of technology adoption in the agricultural sector. It identifies the primary application domains, categorizing them into four main categories: monitoring, control, prediction, and logistics, as well as their relevance to the agricultural supply chain.

Agri-food supply chain

The term Agri-Food Supply Chain (AFSC) is used to describe the processes involved in the production of the agricultural sector and its distribution to the consumer. It is comprised of various entities responsible for the production, processing, distribution, and marketing of agricultural products.

Like other supply chains, AFSC can be defined as a network of organizations working in synchrony within the processes, activities, and stages of production to provide products and services that can satisfy customer demands. However, what differentiates AFSC from other supply chains is the relevance of food quality and safety variables and variations related to climate change. Other important particularities of agricultural products include their limited shelf life, demand, and market volatility, which makes AFSC more complex to manage than supply chains in any other sector (Aramyan and van Iwaarden 2024).

It is possible to identify opportunities for innovation offered by technologies throughout the agricultural supply chain. According to Talavera et al. (2017), these fields of application can be classified into four categories: Monitoring, Control, Prediction, and Logistics, as illustrated in Figure 12.

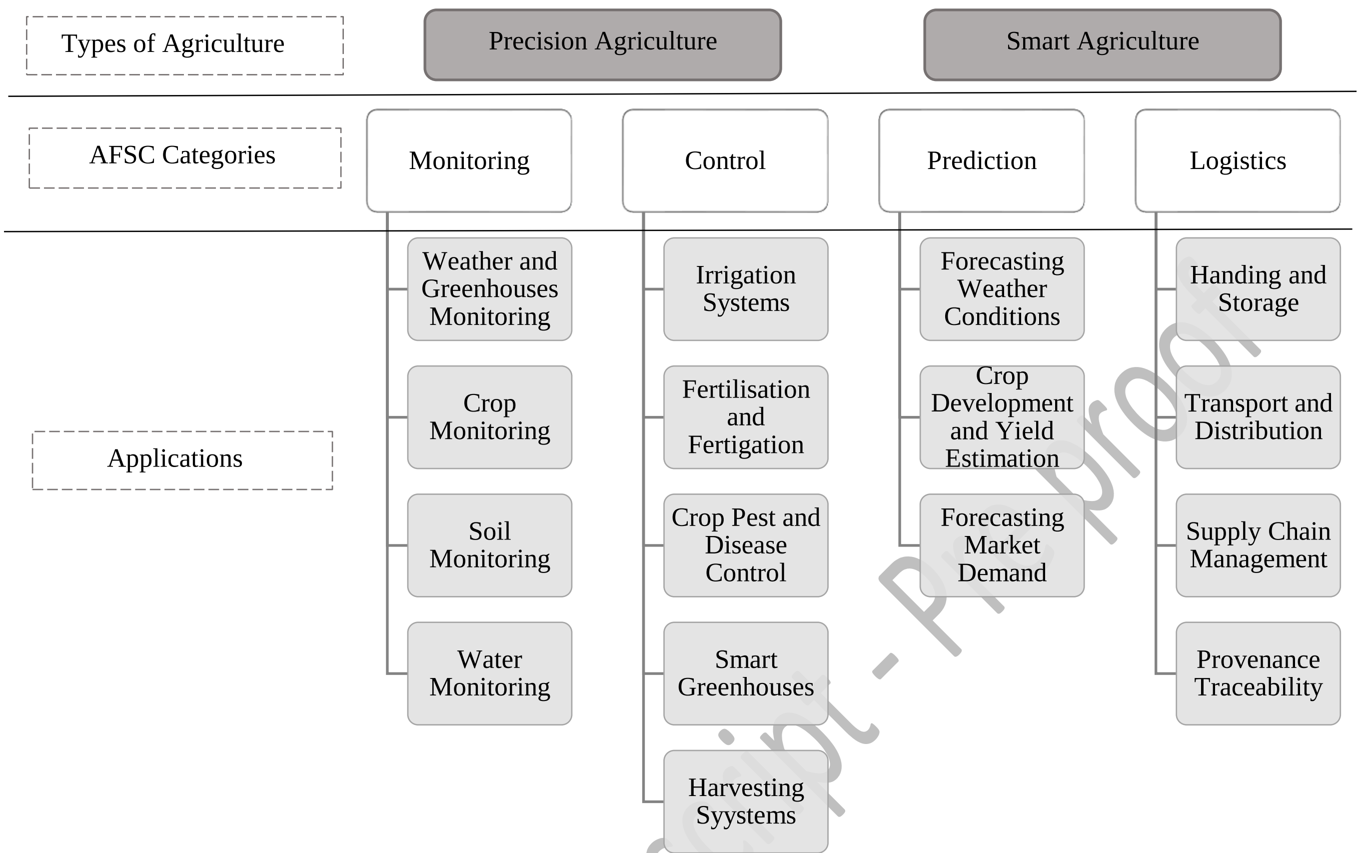

Figure 12. Fields of application of technologies in the agricultural supply chain. Adapted from Talavera et al. (2017).

Monitoring

It is defined as the continuous evaluation of parameters against a standard established by users. In the agricultural sector, the use of digital tools can be seen as an alternative or complement to traditional approaches. Therefore, the proper application of monitoring systems offers the possibility of successful agricultural management due to the collection of essential field data in real-time and its analysis through the different available technologies. These intelligent architectures enable farmers to make informed decisions and implement preventive measures that enhance agricultural productivity, minimize waste, reduce costs, and ultimately preserve the environment (Araújo et al. 2021, 2023). Figure 13 shows a summary of the most outstanding works in the application of agricultural monitoring.

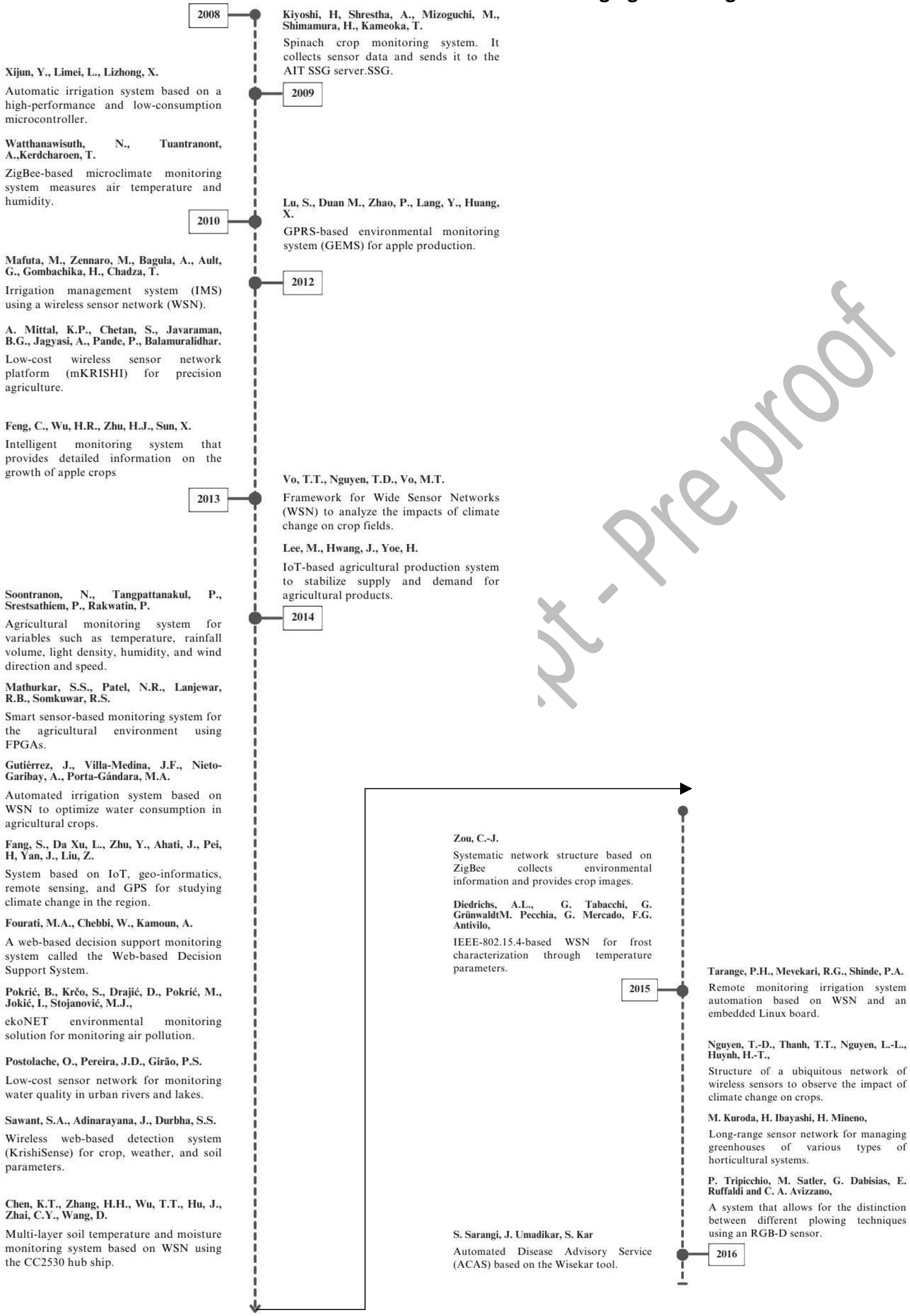

Figure 13. Summary of the most outstanding works showing results of the use of digital technologies in the agricultural sector.

Control

In the context of agriculture, control is the ability to manage inputs according to crop attributes and deficits, avoiding waste and mitigating the effects of potential disturbances or uncertainties, both environmental and human, ensuring optimal crop development. The adoption of advanced control techniques in an agricultural system enables the precise application of inputs at optimal times, resulting in high resource efficiency. It enables higher yields, energy, and labor savings, as well as the optimization of agricultural technology and equipment use. Figure 14 shows a summary of the most notable works in the application of agricultural control.

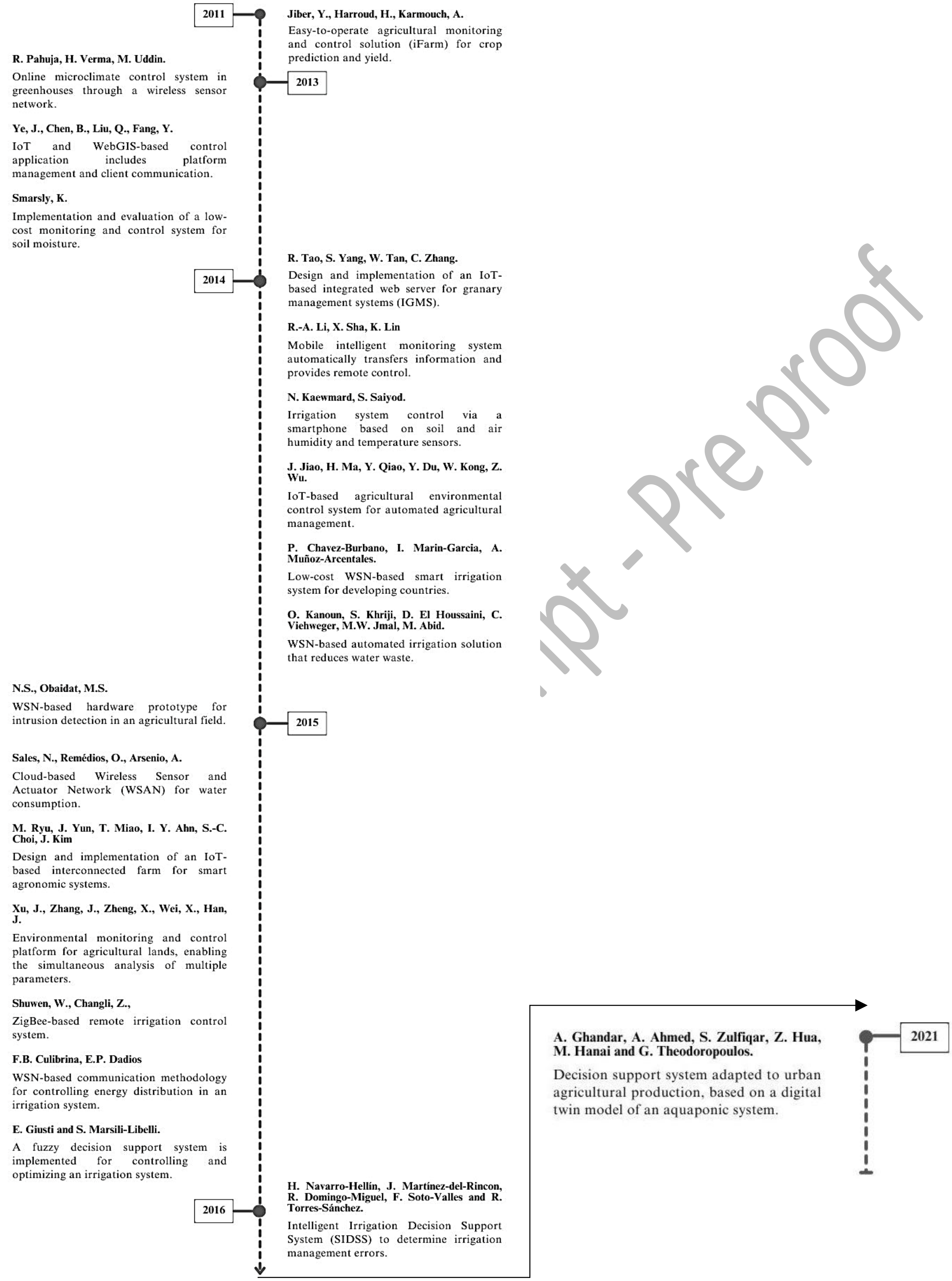

Figure 14. Summary of the most outstanding works that present results using agricultural control techniques.

Prediction

Prediction is a function that follows the monitoring and recording stages of tasks executed within a sector's processes. It requires real-time historical data to develop optimal analytical methods for predicting specific events (Villa-Henriksen et al. 2020). Today, the agricultural industry is equipped with machines and technologies capable of learning and producing prediction models. The application of real-time predictive prototypes complements the crop monitoring and control process by predicting the optimal harvest time, identifying potential pest or disease outbreaks, and estimating the exact quantity of agricultural inputs required for crops, thereby enabling the design of effective agricultural management strategies (Araújo et al. 2021, 2023). Figure 15 shows a summary of the most outstanding works in the application of agricultural prediction.

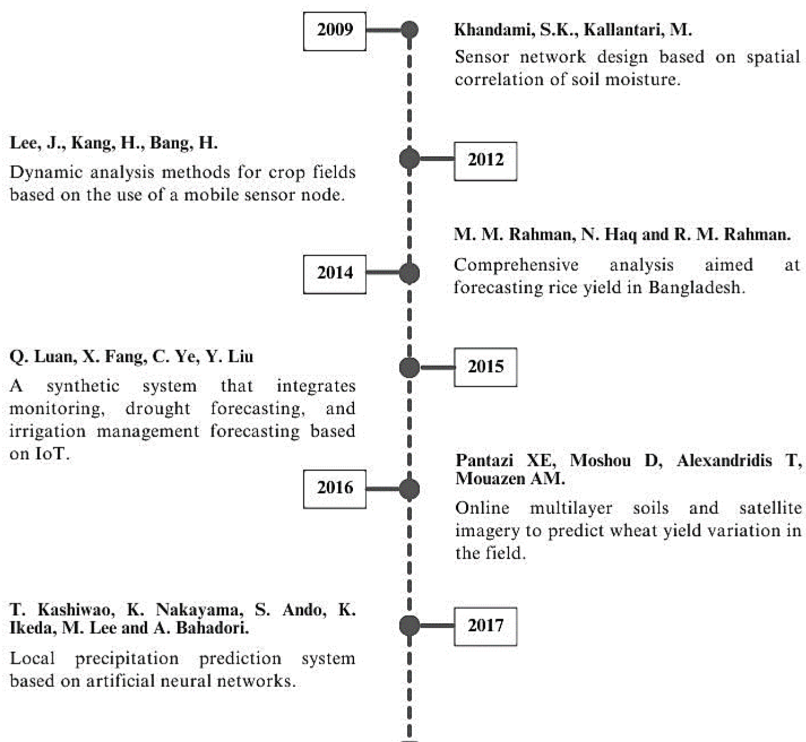

Figure 15. Summary of the most outstanding works in the application of agricultural prediction.

Logistics

Currently, there is a growing consumer trend toward understanding how purchased products are produced, handled, packaged, stored, and distributed. The agricultural sector is responding to these needs and also seeking information on the authenticity, origin, and traceability of these products. Therefore, mastering logistics is crucial in the agricultural context.

This concept refers to the physical flow of entities and information that seeks to satisfy consumer demand from producer to consumer (Talavera et al. 2017). The tools and technologies that support all stages of logistics face the challenge of maintaining product integrity and quality. In agriculture, these systems are considered vital mechanisms for preserving quality and ensuring the safety of agricultural products throughout the entire process, from farming to consumption (Prashar et al. 2020). Figure 16 shows a summary of the most notable works in the application of agricultural logistics.

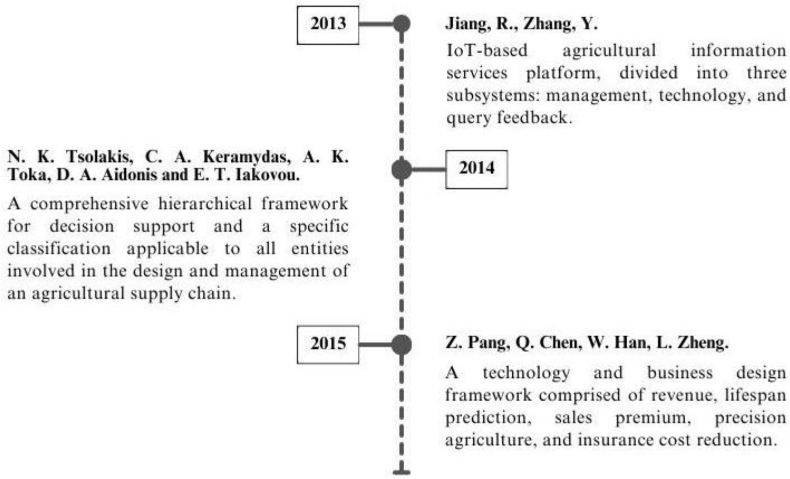

Figure 16. Summary of the most outstanding works in the application of agricultural logistics.

Opportunity areas and current trends in agriculture

Based on the literature review, it is possible to define opportunity areas and current trends in the application of innovative technologies in agriculture, categorized into the following areas: A) technological innovation, B) application scenarios, and C) business and commercialization.

Innovative tools will produce more solutions based on new and disruptive technologies in the agricultural sector. Tables 5, 6, and 7 describe some of the areas identified in the domains of technological innovation, application scenarios, and business and commercialization, respectively.

Table 5. Future works in the domain of technological innovation.

A. Technological Innovation	*Universal agricultural platform based on IoT* IoT adaptation is not limited to a specific crop, providing the opportunity to develop a universal platform that enables the use of smart and precision agriculture tools and devices to monitor and control the productivity of any crop. It can be modified to include agricultural activities in the field, including the management of administrative tasks involved throughout the agricultural supply chain. This architecture is free of geographical limitations and functions as a facilitator for the development of smart technology-based agriculture. This platform requires the design of digital libraries that enable agricultural users to efficiently access available documents, classes, codes, and other relevant data.
	Information quality The development and adaptation of an IoT platform in agriculture requires quality in data handling at every stage of the digital architecture. The ability of a smart device to send relevant information while ensuring its quality remains an area of ongoing research for academics and researchers. Therefore, further research is needed to develop mechanisms that ensure quality in data handling at all stages of the platform.
	Security and privacy preservation Device and information security are of interest to academics and researchers, necessitating research focused on designing devices that support reliable security schemes. Various privacy-preserving methods have been proposed that allow information extraction while preserving user privacy.

Adapted from Elijah et al. (2018), Shi et al. (2019), Farooq et al. (2019), Wang et al. (2024), and Toader et al. (2024).

Table 6. Future work in the domain of application scenarios.

B. Application Scenarios	*Large-scale architectures* Currently, IoT software platforms and devices are constantly evolving. Research is underway into innovative technologies that can offer low-cost solutions for large-scale prototype design, allowing for the inclusion of these tools in agriculture. In the future, the development of large-scale architectures throughout the agricultural supply chain and applications is anticipated, not only in developed countries but also in developing countries.
	Urban agriculture Urban agriculture involves applying agricultural perspectives and techniques to urban food production, thereby contributing to overall food security and sustainability. As the urban population grows, it is necessary to develop techniques that allow people to produce their food. Renewing the food production and distribution network so that consumers become producers who share the same urban environment provides the opportunity to design new business and market models. Food production could be developed individually by individuals within cities based on local demand and distributed, avoiding the need for long-term storage. It would allow for revolutionary changes in the operations of the food demand chain. By matching supply with demand, there is the potential to minimize waste significantly. Likewise, new agricultural methods such as aquaponics and aeroponics for urban agriculture have different concepts and elements compared to established agricultural techniques, where intelligent decision-making support is often applied.

Adapted from Thomaier et al. (2015), and Dorr et al. (2023).

Table 7. Future work in the business and marketing domain.

C. Business and commercialization	*Policies and regulations* It is necessary to determine and delimit the regulatory and legal frameworks regarding the control of ownership of agricultural data between farmers and the companies from which the information comes. Hence, a trend towards conducting more research focused on the application of policies and standardization of innovative technology adaptation in the agricultural sector is expected. It is essential to ensure the participation of various government levels and agricultural organizations and departments when developing policies and standards, as these regulations may differ significantly from one country to another or even within the same region. It will facilitate the adequate adoption of innovative technologies in agriculture and avoid various technical, competition, data privacy, and security challenges that may affect the performance of activities in the agricultural sector**.**
	Business model A business model or agricultural business approach based on innovative technologies remains undefined, as the set of essential elements and operational processes required for the organizational structure is still under development and transformation. The adoption of IoT-based smart devices is expected to optimize energy consumption and boost mass production, ultimately leading to cost reductions. In the future, it will be possible to develop research focused on integrating operational technologies with intelligent administrative tools that minimize installation and operating costs while also providing accessible platforms for business decision-making that do not compromise organizational performance or food safety for all stakeholders in agriculture. Business Intelligence (BI) can drive the agricultural sector to improve operational efficiency, reduce costs, increase revenue, and provide new opportunities for business development. Easy access to timely and accurate information enables the agricultural sector to make informed decisions, mitigate risks, and develop solutions that respond more efficiently to dynamic market conditions.
	Cost analysis In the agricultural sector, a balance between the implementation of innovative technologies and the economic profit margin is necessary. When adopting a BI system, there is a significant cost in acquiring the entire digital infrastructure and physical devices. In addition, there are maintenance costs that are essential for managing all the services and processes involved in the agricultural environment. One of the main factors hindering the proper adaptation of a system based on innovative technologies is the lack of knowledge about digital tools such as IoT and artificial intelligence, as well as their various applications. This results in training costs. It proves to be a significant challenge for agricultural development, given that, for the most part, farmers lack adequate academic preparation, which hinders the adoption of technology. Therefore, it is essential to establish training or education models based on innovative technologies for farmers.

Adapted from Mikalef et al. (2017), Elijah et al. (2018), Farooq et al. (2019), Passlick et al. (2023), Munazza et al. (2023), and Lamolinara et al. (2024).

CONCLUSION

This study provides an overview of the main smart technologies applied to agriculture, along with a conceptual characterization of precision and smart agriculture. The literature review reveals that most research focuses on applications for monitoring, controlling, and optimizing production processes, with an emphasis on energy savings, water efficiency, reducing crop stress, and increasing yield. However, a significant opportunity has been identified to expand research into the administrative areas of the agricultural sector, including organizational processes, marketing, and strategic decision-making, where the application of Artificial Intelligence algorithms can significantly contribute to the design of predictive strategies and intelligent management. Furthermore, although tools such as decision support systems (DSS) have contributed to the management of agricultural information, their limited autonomy and functional scope highlight the need to adopt more comprehensive approaches based on Business Intelligence (BI).

A business intelligence (BI) system is designed to mitigate risks and uncertainties in decision-making, providing efficient support at each stage and enabling management through structured data analysis. Furthermore, its evolution has allowed its application from the operational to the strategic level of organizations, fostering cross-functional information integration.

The integration of Business Intelligence systems in the agricultural sector represents a significant opportunity to improve operational efficiency, reduce costs, increase revenue, and drive new business development. In this regard, the convergence of agricultural practices and data-driven business decision-making is a priority research area for strengthening the sector's competitiveness and sustainability. Integrating BI with emerging technologies such as Artificial Intelligence and IoT could fully consolidate smart agricultural environments, especially in small- and medium-scale contexts.

Finally, the digital transformation of the agricultural sector depends not only on technological development but also on appropriate regulatory frameworks. It is essential to ensure coordinated participation by different levels of government, as well as by agricultural organizations and departments, in the formulation of policies and regulations. Since these can vary between countries and regions, their proper harmonization will facilitate the effective adoption of smart technologies and help mitigate technical, economic, and organizational challenges. Consequently, based on the literature review, it is necessary to design public policies aimed at agricultural digitization; this constitutes a strategic line of research and action to consolidate smart agriculture at a global level.

CONFLICT OF INTERESTS

The authors declare that they have no conflicts of interest.

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