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Integrating Artificial Intelligence in the Sustainable Development of Agriculture: Applications and Challenges in the Resource-Based Theory Approach

Monica Aureliana Petcu [1], Maria-Iulia Sobolevschi-David [1], Stefania Cristina Curea [1,*] and Dumitru Florin Moise [2]

[1] Department of Financial and Economic Analysis and Valuation, Bucharest University of Economic Studies, 010374 Bucharest, Romania; monica.petcu@cig.ase.ro (M.A.P.); maria.sobolevschi@cig.ase.ro (M.-I.S.-D.)
[2] Doctoral School of Accounting, Bucharest University of Economic Studies, 010374 Bucharest, Romania; moiseflorin21@stud.ase.ro
* Correspondence: stefania.curea@ase.ro

Abstract: In the electronics sector, artificial intelligence (AI) has grown into a disruptive force that is changing how humans engage with technology and creating new opportunities. AI is expanding the capabilities of electronic devices, granting them higher intelligence, increased intuitiveness, and the ability to comprehend and react to human behavior. The purpose of this approach is to highlight the knowledge structure in artificial intelligence application in agriculture and its challenges within the European Union. A bibliometric analysis was conducted, distinguishing the following items as the main research themes: agriculture 4.0; advanced monitoring and controlling strategies in intelligent agriculture; the automation of agriculture by including practices such as cloud computing, Internet of Things (IoT), big data, blockchain, robotics and AI, information security; new skills, and responsible leadership. The regression analysis revealed that the employers' assumption of responsibility, by ensuring opportunities for training and development of digital skills, determines the growth of added value (0.013) and its rate (0.0003). Enhancing labor productivity depends on Internet access for the integration of technologies based on artificial intelligence (1.343). An increasing employment rate of low-skilled people affects agricultural production (0.0127). The contributions of this two-dimensional approach consist in supporting the integration of digital technology in agriculture as a condition for achieving the goals of sustainable development.

Keywords: intelligent agriculture; production; added value; productivity; skills; Internet

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1. Introduction

Artificial intelligence represents the ability of a digital computer or computer-controlled robot to perform tasks commonly associated with intelligent beings [1]. Technological evolution and the widespread use of artificial intelligence are both opportunities, ensuring the optimization of actions for efficiency, and societal challenges, through the expected changes, the required resources, and the debates on ethics in artificial intelligence. Digitalization involves a complex process whose main objective is to create a culture of innovation and continuous improvement. Artificial intelligence is a subset of digitalization that provides the automation of processes through the use of algorithms and machine learning [2]. AI is becoming an integral component of modern electronics. This technology increases precision, efficiency, and performance, and reduces human intervention. The European Council adopted the Artificial Intelligence Act in December 2020, which aims to ensure that artificial intelligence systems placed on and used in the EU market are safe and comply with existing legislation on fundamental rights and Union values. Investments and innovations in artificial intelligence, a risk-based approach, and a uniform horizontal legal framework in the field are therefore promoted.

In the context of the existing population growth trend, climate change attempts to reduce the use of harmful pesticides in an intensive manner that affects soil fertility, the rise in costs of necessary resources, price volatility, and access to capital and its costs, along with the alarming wastage of food render agriculture a major global concern. The European Union's agriculture and rural development policies, in line with the UN 2030 Agenda for Sustainable Development, have as their main objectives the eradication of hunger and food security through increased agricultural productivity, while supporting other sustainable development goals (SDGs), with priority: SDG 1—poverty eradication, SDG 8—decent work and growth, SDG 12—responsible consumption and production, and SDG 13—climate action. The introduction of artificial intelligence in agriculture ensures an increase in the sector's resilience and innovation potential.

Using a variety of cutting-edge technologies that support disruptive solutions at every stage of the agricultural production chain, agriculture 4.0 transforms conventional production techniques and global agriculture strategies into an optimized value chain [3]. Agriculture 4.0 is approached from various perspectives: precision farming evolution, Industry 4.0 in agriculture, digital technologies, informed decision-making, and beyond-the-farm boundaries [4], the term being associated with concepts such as digital agriculture [5,6], smart farm/agriculture [7–9], and precision agriculture [10,11]. The inclusion of the topic of artificial intelligence in agriculture in the scientific mainstream has circumscribed a diverse set of issues: applications of artificial intelligence in agriculture, rules and moral principles guiding the development, implementation, and the use of artificial intelligence technologies. The application of AI in agriculture aims at intelligent personal assistants, integrated into various devices, using natural language processing, machine learning, and data analysis to understand and respond to commands and perform complex tasks [12,13]; autonomous devices that use computer vision and sensors technologies to make real-time decisions [13–15]; and smart farm systems that use AI algorithms to control production [16,17], ensure security [16–18], predict weather conditions [17,19,20], identify early signs of crop disease [21–23], map land, and crops [15,24] etc. Among the most frequently mentioned challenges in the application of artificial intelligence in agriculture are the high costs of the technologies, Internet connectivity and accessibility, the age of farm managers, and the need for digital literacy required for farmers to use these tools [15,16,25–27]. Regarding the data, an exhaustive examination reveals heterogeneity of data types and sources; selection and digitization of data that are viable for AI applications, ensuring sufficient linkage between biological materials and data used for AI applications; standardization and curation of data and related software to a level appropriate for AI applications; obtaining training and adequate ground truth data for model validation and development; access to and use of computing and modeling platforms and related expertise, improving responsible data access; and engagement across plant scientists, data scientists, and other stakeholders [28].

Emerging with the work of Edith Penrose in 1959 [29], which provided important insights into the process of acquiring, exploiting, and expanding resources to achieve a competitive advantage, the resource-based view (RBV) is a well-established stream of study in strategy research. The tangible and intangible resources of a company are considered the strengths and weaknesses, determining the corporate strategy and the organizational structure, which influence the economic performance [30]. The resource-based theory (RBT) emphasizes the relevance of resources and capabilities in achieving performance based on a competitive advantage [31]. The RBT entails first determining the possible critical resources and then formulating a plan for utilizing them to generate synergy. RBT develops resources that are rare, valuable, difficult to replicate, and exploitable to gain a prolonged competitive advantage. Based on the idea that resources and capabilities are not dispersed equally and that entities with valued resources and capabilities can achieve a competitive advantage, RBT is an approach to analyze and manage performance.

This study aims to identify the main issues addressed in the research in this field and the applications of AI in agriculture and to analyze the challenges in implementing artificial

intelligence in agriculture in the EU Member States. Given the topics analyzed, the contributions of this paper are found both at the theoretical and practical levels. The research questions focus on the following: what are the main research topics and the configuration of the knowledge structure in the field of artificial intelligence integration in agriculture (RQ1)? What are the determinisms between the indicators that characterize production in agriculture, in terms of size and efficiency, and the indicators that characterize the resources needed to implement specific technologies of agriculture 4.0, namely, labor force, as well as internet access and its quality (RQ2)? The performance–digital technology integration determinism, circumscribed by the implicit constraints from the RBT perspective, will be analyzed. The following section reviews the literature. The research methodology, empirical results, and their discussion, conclusions, and future research directions are then presented.

2. Problem Statement

2.1. Research on the Integration of AI in Agriculture

Digital innovation is actively manifested in the agricultural sector, with particular concepts and technologies being developed: precision agriculture, remote sensing, robots, information systems for farm management, and decision support systems. Within the scientific publications that address the issue of applying artificial intelligence in agriculture, there is a significant concern regarding the literature review. In the study of Ref. [32], five thematic clusters of the literature were identified: the adoption, use, and adaptation of digital technologies on the farm; the effects of digitalization on farmer identity, farmer skills, and farm work; power, ownership, privacy, and ethics in digitalizing agricultural production systems and value chains; digitalization and knowledge systems and innovation in agriculture, as well as the economics and management of agricultural production systems and digitalized value chains. New thematic areas are proposed: social system conceptualizations of digital agriculture, digital agricultural policy processes, digitally enabled agricultural transition pathways, and the global geography of digital agriculture development.

Agricultural automation involves the inclusion of various practices, such as cloud computing, Internet of Things, big data, blockchain, robotics, and artificial intelligence. The implementation of these techniques will ensure the analysis of farmers' data, the integration of new data repositories from external providers, and the transformation of data into the knowledge needed for decision support systems [33]. Studies on the applicability of artificial intelligence in agriculture investigate complex aspects, such as the areas of applicability and the particularities of the technologies. As a subset of artificial intelligence, machine learning offers opportunities for data-intensive science in the field of multidisciplinary agro-technologies, with the main applications being structured around topics such as crop management, including yield prediction, disease detection, weed detection, crop quality and species recognition applications; animal management, including animal welfare and animal production applications; water management; and soil management [34]. The review of papers studying the applicability of computer vision combined with artificial intelligence algorithms in precision agriculture for grain production, disease detection, grain quality, and phenotyping, identified opportunities for exploiting graphics processing units and advanced artificial intelligence techniques, such as deep belief networks [35]. Integrated artificial intelligence technology has become a focus of research in the development of new methods for detecting changes on the Earth's surface with applicability in agriculture [36].

Complementary to the benefits of using artificial intelligence in agriculture, the related difficulties are mentioned, which mainly consist in the difficulty of identifying a single standard solution, given the continuous change of conditions in the agricultural field, as well as the complexity of the factors; a machine learning algorithm that fulfills a task well in one domain, such as weather, soil quality, or pests, not being viable for the other domains and regions; the gap between farmers and researchers in the field of artificial intelligence; and data protection, given that artificial neural networks, fuzzy control systems, and other artificial intelligence engines involve a large amount of data [37].

2.2. Practical Aspects Regarding the Main Crops in the Context of AI Integration

The main crop category that involves a higher level of digitalization are big crops with sub-categories such as cereals, rape seeds, corn, sunflower, vegetables, fruit trees, and vineyards.

For big crops, the digitalization process is the most complex, as the return on investment should be significant considering the high level of risks that can be addressed using it or the high level of revenues that can be obtained by farms. The main areas of development for these crops are related to crop mapping, satellite tracking, management programs, automated irrigation systems, and the application of inputs with the help of drones. These technologies are common for all big crops, as farmers are obliged to rotate the crops every few years for at least two main reasons: the technological process requires this for better land conservation, and these conditions are imposed by authorities for granting the subsidies. On the other hand, farmers cultivate more types of crops in the same year for risk management purposes. If one or more crops are affected, the others should sustain partial losses.

Lot mapping is achieved directly with agriculture equipment when the crops are harvested. Therefore, farmers know the exact yield for each part of the surface, and they can act to make improvements for the following year by adjusting the fertilization scheme.

Compared with lot mapping, which involves corrective actions after harvest, satellite mapping is a preventive method. By using it, farmers have the ability to detect any disease or any lack of nutrients in a timely manner. Within the management programs, they collect all the available data from the equipment using GPS systems. This helps them to adjust the technologies accordingly with the specific changes in the process using drones to apply the inputs exactly in the place they are needed. Automated irrigation systems are based on data received from different sensors and weather stations.

Vegetables are easier to manage when they are grown in greenhouses, which are protected environments. The most developed technologies refer to sensors for humidity, temperature, and solar radiation. In this case, the control mechanism is just for the ambient environment. Depending on the data received from these sensors, a specific plan can be applied automatically. Overall, the process is semi-automated. The conditions are added to the system manually and after that, the process becomes automatic, and the fertilizers or pesticides are applied based on the orders from the system but in quantities defined by people.

For fruit trees and vineyards, the technologies are not so advanced. They consist of weather stations for monitoring favorable conditions for the development of certain diseases. Based on these analyses, the treatments are applied manually by people.

2.3. Resource-Based Theory

The creation of economic value is not due to the possession of resources but to effective and innovative management of resources [38]. RBT implies specific approaches to resources. A strategic resource presents four attributes: it is valuable, it is rare, it is difficult to imitate, and it is non-substitutable. A resource is valuable if its use improves efficiency and effectiveness. The scarcity of a valuable resource ensures a competitive advantage. Resources are difficult to imitate because they evolve and reflect specific aspects of a firm. The substitutability of resources takes into account the degree of involvement of different resources. A resource is non-substitutable when it is difficult to identify alternative ways of obtaining the benefits that a resource provides [39]. The use of AI in agriculture improves performance, contributes significantly to resource management and efficiency, capitalizes on opportunities, and neutralizes the multiple constraints specific to the sector. Additionally, the knowledge and skills of the agricultural personnel represent valuable elements in ensuring efficiency and profitability. Air, water, and soil are necessary for agriculture to function. AI may assist with labor management and input optimization. Smart agriculture, based on artificial intelligence, optimizes water use and the sustainable management of soil and crop yields, reducing environmental stress. For instance, farmers

can increase yields by using AI virtual agronomy advisers, which mine data sets like weather, soil conditions, and pest and disease pressure. Farmers can determine which regions require pesticide treatment, fertilizer, or irrigation by using real-time crop insights obtained with the application of AI in agriculture. In addition, farm management and skills among farmers constitute a rare resource, considering the shortage of human resources in this sector. The efficiency with which AI combines information from satellite and drone photos, in addition to meteorological data to forecast the weather, assess agricultural sustainability, and monitor farms for pests, illnesses, and malnourished plants, turns it into a resource difficult to substitute.

RBT entails the structuring of resources into tangible assets, such as physical assets, including property, plants, equipment, cash, and intangible assets, which include experience, information, know-how, management skills, relationships, corporate culture, and the ability to process information. A basic concept of RBT is represented by capabilities, which involve resource conversion, or what can be accomplished based on the possessed resources, and cognition [38]. Intangible assets are an important source of strong competitive advantage, being essential for value creation. Integrating AI in agriculture requires significant intangible assets. Being a combination of software (algorithms), hardware, and database use, AI can be utilized to account for both intangible assets and tangible assets. AI focuses on understanding and making decisions according to data. Access to real-time data ensures the viability of the decision. AI often relies on an Internet connection to function; this is also an intangible asset. Additionally, agricultural expertise and skills are considered intangible assets. Knowledge infrastructure is more necessary as assets become more intangible.

3. Materials and Methods

Specific research methods were used to answer the research questions. Thus, to identify the main issues of interest in the research on the integration of artificial intelligence in agriculture, a bibliometric study based on network analysis was carried out. The introspection of studies in the field involved the selection of scientific publications from the Web of Science platform, using the keywords "artificial intelligence" and "agriculture". The sample consisted of 1655 papers, involving a total of 6525 authors. The data were processed with the VOSviewer 1.6.18 software tool. To observe the structure of the content of scientific publications in terms of the nature of the topics addressed and to build a specific network of themes, an analysis of the co-occurrence of terms and keywords was performed. Ten was considered the minimum number of occurrences of a term in the titles and abstracts of the articles, respectively, of a keyword. A relevance score was determined for each of the terms, and keywords that reached the threshold and the most relevant ones were selected. In addition, a bibliographic analysis was carried out linking the documents, considering 10 as the minimum number of citations of a document, with those with the highest total strength of links being selected.

The analysis of the challenges of artificial intelligence integration in agriculture in the European Union was carried out based on the following variables considered relevant (Table 1).

Table 1. Model variables.

Dependent Variables	Abbreviation	Independent Variables	Abbreviation
production	PD	share of businesses that provided training to develop/improve the ICT skills of their staff	EDSK
added value	AV	employment rate of low-skilled people, age group 20–64 years	LSK
added value rate	RAV	Internet access	IA
labor productivity	W	Internet speed	IS

Aiming to quantify the size of the economic activity of entities active in agriculture, production and added value were included in the model. The correlation of the two indicators allows the determination of the added value rate, which characterizes the added value achieved in agricultural activities, depending on the efficiency of the allocation and use of resources, constituting a reference of the degree of vertical integration of the entities. The approach of this indicator to 1 reveals a high degree of capitalization of technical, human, and financial resources, with a significant contribution of the economic entity to the achievement of production. In general terms, a high-value crop yields more profits per unit of land area than grain or other basic staple crops. Instead of using biological yield per unit land area, which is the conventional indicator of agricultural productivity, the definition is in terms of economic yield. Avoiding post-harvest losses, industrialization, creating jobs, exporting, extending the supply of commodities, earning foreign exchange, diversifying products, and marketing involve adding value. Product transformation, distribution, storage, and additional service are the four main ways that value is added to crops along the value chain.

The increase in labor productivity as a result of technical and scientific progress ensures the sustainable development of agriculture. Labor productivity is determined by reporting production per 1000 annual work units. Labor represents an important factor in agricultural production, capitalizing on the operating resources. From an economic point of view, labor remuneration has a high share in the production costs of farms. As independent variables, indicators allowing the assessment of human resources and Internet access and quality were included in the analysis as basic requirements for the implementation of artificial intelligence in agriculture. In an increasingly digitalized world, where conducting business involves highly automated processes to ensure competitiveness, entrepreneurs should become aware of the importance of training and developing digital skills and provide learning opportunities for employees to acquire the necessary skills and knowledge. Due to climate change, crop production is very vulnerable, especially for big crops. To maintain a high level of efficiency, farmers should act very quickly against different diseases or factors that may slow down plant development. AI is able to provide complex data within the technological decision-making process. This requires specific skills of farmers and appropriate qualifications. In this context, the share of enterprises that provided training to develop/improve the ICT skills of their staff was included in the analysis models. The employment rate of low-skilled workers aged 20–64 is specific to agriculture, with frequent part-time work and seasonal jobs. Ensuring upskilling of workers in agriculture under the constraints of the integration of artificial intelligence involves a cumulative effort at the levels of the individual, entrepreneurs, and the state. Career development and a work environment that enhances competence generate significant effects on employee performance. Internet access and its quality are essential in delivering agriculture 4.0. Collecting data, monitoring crops and animals, and optimizing operations in real-time involves the use of the Internet. For these reasons, specific indicators have been included in the analysis models.

The sample studied includes EU member countries (27). Data were collected from the Eurostat Database for the period 2017–2022, with annual frequency. To obtain consistent results, the added value and production data were transformed into their logarithmic forms. The establishment of links between agricultural activity, assessed based on production and degree of integration, and progress in the digital domain was carried out by regression analysis. To verify the stationarity of the series, the unit root test (augmented Dickey–Fuller test) was performed. Obtaining stationary series required transforming the data by differencing. The redundancy test (redundant fixed effects) rejects the null hypothesis that fixed effects are redundant for both individual and time-specific effects and for the combination of individual fixed effects and time-specific effects, with associated probability values less than 5%. The Hausman test rejects the hypothesis of random individual and/or time effects, with associated probabilities less than 5%. The regression equation was

estimated using the ordinary least squares (OLS) method, with corrections for fixed effects in the panel data.

4. Results and Discussion

4.1. Main Aspects of the Inclusion of Artificial Intelligence in Agricultural Issues—Bibliometric Analysis

4.1.1. Co-Occurrence of Terms

Aiming to identify the main research themes in the field, a co-occurrence analysis of terms was carried out. Out of 36,698 terms, 1210 met the selection criteria. Based on the relevance score, the most relevant terms (726) were selected and structured in the co-occurrence network into four clusters:

(i) Research theme 1: Agriculture 4.0

The definition of this cluster was made based on the relevant terms: innovation, digitalization, big data, IoT, cloud computing, robots, artificial intelligence, sensors, blockchain, and smart farm.

Precision agriculture is conceptualized through a systems approach, which aims to move toward sustainable, low-input, high-efficiency agriculture [40]. This new approach capitalizes on the emergence and convergence of multiple technologies. The three techniques of artificial intelligence are expert systems, fuzzy systems, and artificial neural networks. Ref. [17] carried out an analysis of the current state of automation implementation in agriculture. Among the main developed models are the prediction model elaborated by [41], which uses meteorological data regarding humidity, temperature, precipitation, cloud cover, and wind direction; the Comax (COtton Management eXpert) model developed by [42], which considers three parameters: irrigation scheduling, field nitrogen maintenance, and cotton crop growth; the COTFLEX model developed by [43], which integrates a field and farm database with simulation models and an expert system to advise on key strategic and tactical decisions related to cotton production; the PRITHVI expert system, based on fuzzy logic developed by [44] for soybean cultivation; and the POMME expert system [45], used in insecticide spraying decisions on apple fruit. Artificial intelligence is also used for pest identification (TEAPEST model developed by [46]). With drone technology, crops can be monitored for pests, diseases, dead soil, or irregular crop degradation. Artificial-intelligence-based technologies and sensors are used to observe soil health to maximize the value per acre (CropIn, Bengaluru, India) and to analyze images (Intello Labs, Haryana, India), which uses Deep Learning) [47]. In terms of weed management, advanced artificial intelligence practices have been designed to reduce herbicide use [48,49]. The development of revolutionary technologies (artificial intelligence, satellite imagery, cloud-based machine learning, and advanced analytics) provides the prerequisites for sustainable, efficient, and smart agriculture, resulting in high yields and increased control over quantities to ensure profitability [47]. Ref. [50] proposed an artificial neural network model for estimating the yield of plant production depending on soil parameters.

The IoT represents a family of technologies that allows the intensive development of agriculture. Cloud computing and fog computing offer resources and solutions to support, store, and analyze large amounts of data generated by IoT devices, needed in forecasts and for making decisions to improve activities, even in real-time [51]. The particularities of wireless systems in agriculture have been debated in the specialized literature. Ref. [52] addressed the issue of IoT implementation in agriculture, presenting the IoT agricultural network platform, which refers to both the big data analysis model and the cloud model. Big data analysis takes into account the experience of farmers, in terms of crops (monoculture, different types of crops), as well as predictive analyses (vegetable production, weather, profit, diseases), monitoring (soil and air humidity, pH value, wind, pressure, temperature), communication protocol (Internet, code division multiple access, Wi-Fi, ZigBee), storage services, and physical implementation (sensors; different types of actuators and microcontrollers; and other network equipment, such as switches, routers, and gateways).

The potential of these technologies in the field of agriculture was structured by [51] in the following areas: agricultural monitoring and control, controlled environment agriculture, open-field agriculture (measurement of climatic conditions, soil monitoring), livestock applications, food supply chain tracking, interoperability, and commercial solutions. Ref. [9] developed a smart system to maintain humidity and temperature that requires a remote smart device or a computer connected to the Internet, interface sensors, Wi-Fi, or ZigBee modules. In the use of water sensors, the importance of site-specific calibration was highlighted to improve accuracy in data estimation [53].

(ii) Research topic 2: Main challenges in the agricultural sector

The definition of this cluster was made based on the relevant terms: disease, disease detection, disease management, crop disease, leaf disease, plant disease, damage, fruit quality, water stress, insect, insecticide, nutrient deficiency, pest infestation, weed detection, growth stage, and early detection.

(iii) Research topic 3: Research methodology

The definition of this cluster was based on the relevant terms: model, prediction, regression, coefficient, decision, period, algorithm, mean square deviation, support vector machines, artificial intelligence, and artificial neural network.

(iv) Research topic 4: Dissemination of information

The definition of this cluster was based on the relevant terms: experts, open access to articles, publishing services, and CC-BY-NC-ND.

4.1.2. Co-Occurrence of Keywords

Among the 6517 keywords from the scientific works that address the topic of artificial intelligence in agriculture, 419 met the criteria. In the related knowledge structure, the nodes with the strongest connection in research are artificial intelligence (2966), agriculture (1869), precision agriculture (1619), machine learning (1548), deep learning (1148), big data (958), IoT (763), management (785), Internet (735), and prediction (719). The connection between artificial intelligence and precision agriculture circumscribes the data-based strategy, which adapts agricultural operations to the particular requirements of certain plants or regions of agricultural land, to base decisions on the efficient use of resources and to increase productivity. As a subfield of artificial intelligence, automatic learning in agriculture aims to create algorithms based on structures identified in databases collected from sensors, satellites, and drones, giving precision in decisions specific to farms. As a subcategory of machine learning, deep learning uses artificial neural networks to process data for plant or crop classification, pest and crop yield prediction, disaster monitoring, nutrient and water management, planting and harvesting decision-making, etc. The role of tools based on artificial intelligence in the agricultural sector is thus revealed, presenting the ability to predict based on parallel reasoning as the main advantage. In addition, IoT optimizes agricultural operations, supporting precision agriculture and monitoring and effective management of crops, with effects in increasing production, reducing costs, and ensuring the sustainability of agricultural systems. The concurrence of artificial intelligence and IoT nodes is a reference to prospects in agriculture, AIoT being the combination of artificial intelligence technologies with the infrastructure of the IoT, making IoT operations more efficient and improving data management and analysis. Furthermore, AIoT is expected to integrate with emerging technologies, such as 5G, edge computing, and blockchain. Internet access is a significant challenge in agriculture, given the dispersion and location of the land.

4.1.3. Bibliographic Coupling

Of the 1655 documents, 504 met the threshold, the largest set of linked articles consisting of 481. Thirteen clusters were identified, corresponding to the issue of interest.

Cluster 1. The digital agricultural revolution: More productive and sustainable agriculture in a changing climate requires a digitalization process, a revolutionary process of integrating innovations to support farmers by increasing crop yields while reducing environmental impact and meeting the needs of the global population in the future, according to the objectives of sustainable development [54].

Cluster 2. Agriculture 4.0: The use of emerging Industry 4.0 technologies in agricultural production and agri-food supply chain management, including the IoT (agricultural applications include precision agriculture, livestock monitoring, smart greenhouse, fisheries management, and weather tracking), robotics and autonomous systems (RAS), artificial intelligence and big data (agricultural expert systems and agricultural predictive analytics are based on big data, which can provide farmers with intelligent recommendations in precision agriculture, accurate assessment, and agricultural risk management), and blockchain (smart contract and cyber security) [37].

Cluster 3. Advanced monitoring and controlling strategies in intelligent agriculture: The implementation of monitoring and controlling strategies through the automation of agriculture involves the identification of factors (soil erosion, pesticides, fertilizers, climate change, water use), the assessment of impact (environmental degradation; low soil quality; health damage; air, water, and soil pollution; reduction in productivity, yield, and quality), and the selection of specific technologies (IoT and artificial intelligence techniques) [55].

Cluster 4. Artificial intelligence: The feasibility of artificial intelligence approaches provides farmers with decisive management information [56].

Cluster 5. Machine learning in agriculture: Machine learning, a subset of artificial intelligence, has considerable potential to address the many challenges in establishing knowledge-based agricultural systems. The most effective machine learning algorithms are those belonging to artificial neural networks. Additionally, a variety of sensors, attached to satellites and unmanned ground and aerial vehicles, have been used in obtaining reliable data [57].

Cluster 6. Deep learning in agriculture: The use of deep neural networks is viable in agricultural operations, allowing real-time monitoring and decision-making [58].

Cluster 7. The application of IoT in agriculture: The main areas in which IoT is used in agriculture include automation and efficiency; risk control; and monitoring seeds, soil, water, fertilizers, pesticides, energy, animals, and business relationships [59]. IoT applications for precision agriculture can be classified into five groups: sensor networks, IoT computing (Cloud and Edge/Fog), forecasting and analysis, remote sensing (drones and robots), and security and privacy [60].

Cluster 8. Applications of remote sensing in precision agriculture include crop monitoring, irrigation management, nutrient application, disease and pest management, and yield prediction [61].

Cluster 9. Edge computing in agriculture: Applying edge computing in AIoT and investigating the combination of edge computing and artificial intelligence, blockchain, and virtual/augmented reality technology in agriculture create greater value in the network, business, application, and intelligence [62].

Cluster 10. Sustainable crop yield improvement: Various tools, such as machine learning, deep learning, image processing, artificial neural network, wireless sensor network (WSN) technology, wireless communication, robotics, the IoT, and different genetic algorithms, are used in precision agriculture, disease detection, and crop phenotyping, reducing the use of chemicals, ensuring a reduction in expenses, improving soil fertility, and increasing productivity [63].

Cluster 11. Information security: The use of the IoT and intelligent communication technologies creates exposure to cyber security threats and vulnerabilities in smart agricultural environments. Data security and privacy are important requirements and a primary objective for ensuring reliable operation in an intelligent agricultural system. The main aspects aim at data security, authorization, authentication, compliance, and regulations [64], using a generalized security architecture based on blockchain technology [65].

Cluster 12. New skills of workers: Smart agriculture requires new skills of workers to innovate, learn, and adapt to evolving digital technologies, as digital technologies change the codification of knowledge for productive and innovative activities [66]; digital transformation in agriculture expects a human-centered artificial intelligence approach that incorporates sociological, ethical, and legal issues. From this perspective, artificial intelligence constitutes an enhancer of natural intelligence, aiming to include human experience, prior knowledge, and the conceptual understanding of human experts to improve and strengthen human capabilities with artificial intelligence and not to replace humans [67].

Cluster 13. Smart agriculture through responsible leadership: Smart agriculture involves responsible leadership, which can support and improve the use of artificial intelligence and IoT technologies in sustainable agriculture [68].

4.2. Challenges in the Introduction of Artificial Intelligence in the Agriculture of the European Union Member States

At the level of the European Union countries, there are still significant discrepancies regarding the situation of agriculture, as well as the progress in ensuring the basic conditions for the integration of artificial intelligence in the field.

Agriculture contributes to different measures in the GDP of the member states of the European Union (Figure 1), with values between 0.2% (Luxembourg, 2019–2021) and 5.7% (Latvia, 2022). The low values correspond to the level of development of the considered societies, with specific structural configurations of the economy characterized by a high degree of industrialization and orientation towards services.

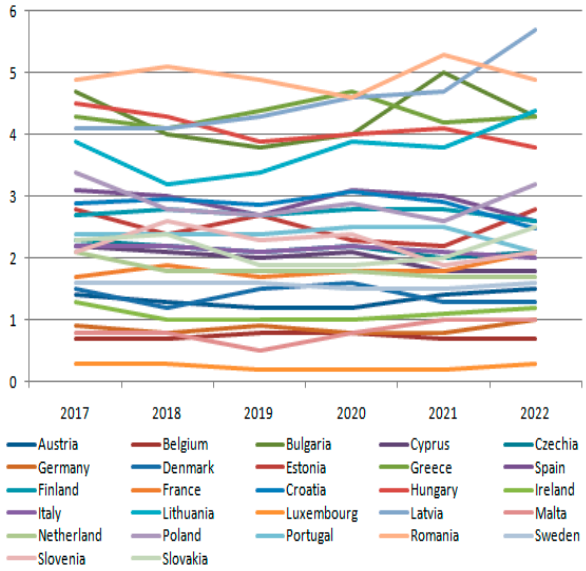


Figure 1. The evolution of the share of agriculture in GDP.

The rate of added value (Figure 2), as a share in agricultural production, shows values that fluctuate between a maximum of 0.58 (Italy, 2018) and a minimum of 0.23 (Slovakia, 2019). In the analyzed interval, both production and added value grew, with higher average increases in added value relative to production in Croatia, Bulgaria, France, Italy (with values higher than the sample median), Latvia, Luxembourg, Sweden, Slovakia, Finland, Germany, and the Czech Republic (with values lower than the median at the sample level). Conversely, there are countries with a volume of activity increasing at a rate higher than that of value-added, with the biggest gaps in Hungary, Malta (with values above the sample median), and the Netherlands (with values close to the sample median). These developments are mainly generated by a change in the share of products with a higher added value and a dependence on subsidy revenues, as well as the dynamics of

production. The acceleration of the growth rate of agricultural production at the level of the European Union Member States is generated by innovations and knowledge in technology and science.

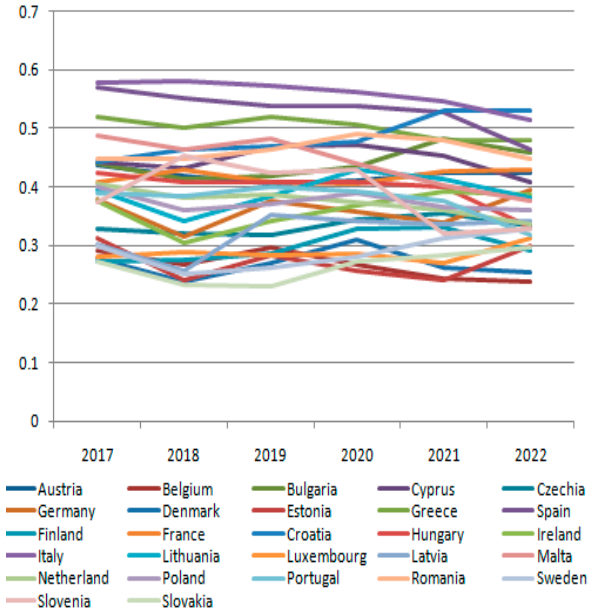


Figure 2. The evolution of the added value rate.

Complementarily, the evaluation of the efficiency of agricultural activities is carried out based on average labor productivity (Figure 3). The average labor productivity records values between a maximum of EUR 299.45 million per 1000 annual work units (Denmark, 2022) and a minimum of EUR 11.44 million per 1000 annual work units (Romania, 2017). Agriculture becomes more efficient, with a higher capital–labor ratio, implying knowledge and skills for a sector in which part-time and seasonal work is specific. The highest production per square kilometer is obtained by the Netherlands (EUR 1.69 million per square km), and the lowest by Romania (EUR 0.1 million per square km), which is in the top five countries in terms of agricultural land owned.

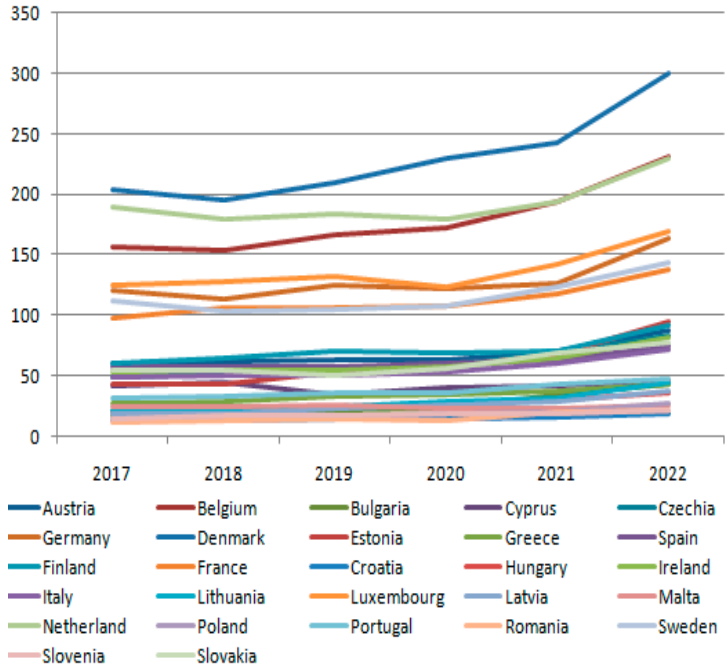


Figure 3. The evolution of average labor productivity.

The transition to agriculture 4.0 involves specific knowledge and new skills of personnel through training and development of digital skills, as well as access to high-speed Internet. The involvement of employers in the training and development of employees' ICT skills differs at the level of the European Union, between a minimum of 4.4% (Romania, 2017) and a maximum of 39.8% (Finland, 2022) (Figure 4).

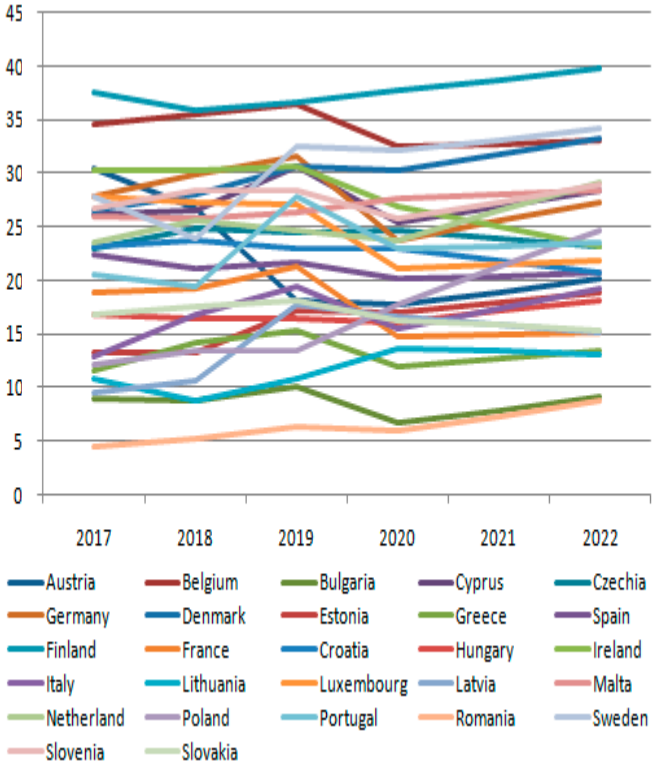


Figure 4. The evolution of EDSK.

The employment rate of low-skilled people aged 20–64 is between a maximum of 67.7% (Portugal, 2017) and a minimum of 34.70% (Croatia, 2017), with deterioration in all European countries, except Romania, Slovakia, and Sweden, which recorded decreasing values of this rate in the considered interval (Figure 5).

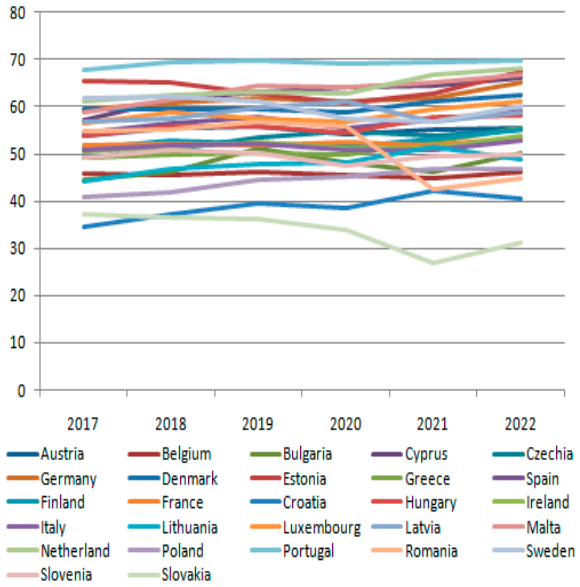


Figure 5. The evolution of LSK.

Regarding access to the Internet, the countries of the European Union show a tendency to reduce the differences, with a share of households with Internet access that evolves between a minimum of 67.33% (Bulgaria, 2017) and a maximum of 98.28% (Netherlands, 2020), with the mention of the inclusion of all the countries in a range between 87.31% and 98.28% in 2022. Significant differences at the level of the European Union are maintained in the degree of broadband Internet coverage according to speed (Figure 6). Greece is the country with the lowest share of households with Internet speeds greater than 100 megabits per second (2017–2018), while Malta has 100% high-speed Internet coverage. The differences between countries are decreasing, from a range between 0.4% and 94.20% in 2017 to a range between 63.90% and 100% in 2022.

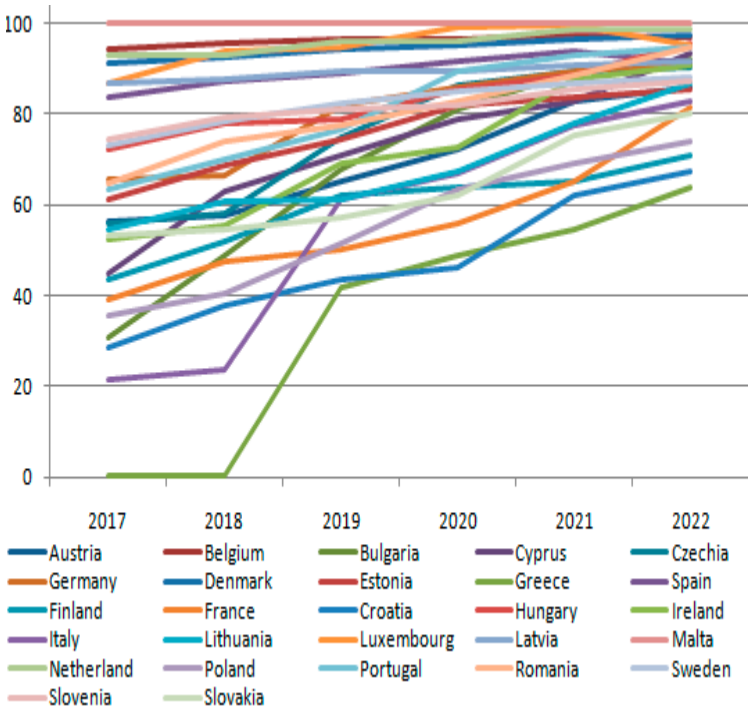


Figure 6. The evolution of IS.

To identify the limits and risks regarding the implementation of artificial intelligence in agriculture, a regression analysis was performed. The consideration of alternative dependent variables of added value, production, rate of added value, and productivity in agriculture, as well as the gradual inclusion in the analysis of constraints in the implementation of artificial intelligence generated particular estimated results, presented in Table 2.

The agricultural sector involves a growing concern of society, considering the estimated trend of the significant increase in food demand as a result of population growth and the implications in the relationship with climate change. Complementary to the approach as an objective of the investors, the performance in the agricultural sector is desired at the macroeconomic level. Ensuring the increase in production, added value, and efficiency of the sector positively determines performance. This implies efficient capitalization of the resources involved in agricultural activities using a competent human resource. At the same time, the training and development of digital skills is an important objective in agriculture, allowing the implementation of research results in the field of artificial intelligence. Between the added value, especially the rate of added value, and the share of enterprises that offered training to develop/improve the ICT skills of their staff, there is a significant statistical link to the interest in staff capable of using the results of the development in the field, materializing in an increase in the results obtained from agriculture. The active involvement of employers in ensuring digital skills is a factor in performance in agricultural activity. The requirements regarding access to and the quality of the Internet

do not represent statistically significant factors in determining the added value, regardless of the rate of added value, in European agriculture. The R-square values obtained in the case of the added value analysis models, especially those of the rate of added value, reveal the contribution of the Internet as a requirement of agriculture 4.0. A high value of the employment rate of low-skilled people aged 20–64 years adversely influences agricultural production, with a statistically significant negative link between the two variables being found at the sample level. Ensuring competitiveness and specialization in agriculture requires an appropriate level of technical, economic, and legal training, including expertise in new information technologies, to meet community requirements in the field and quality standards. Our results are consistent with those obtained by [69]; their studies highlighted the fact that the level of education is an important factor in the use of computers and the Internet in agriculture. Educational programs promoting the benefits of computer use on farms are effective on farms with lower incomes, less education, and older farmers [70]. In addition, in the case of the production analysis models, the R-square values reveal the contribution of the Internet as a requirement of agriculture 4.0.

Table 2. Estimation of analysis models.

Dependent Variable	**Added Value**		**Production**	
Independent Variable	**Coefficient**		**Coefficient**	
EDSK		0.0130 *		0.0042
LSK		−0.0008		−0.0127 *
IA	0.0107	0.0090	0.0018	0.0032
IS	0.0008	0.0012	−0.0003	−0.0006
R-square	0.320815	0.349753	0.314461	0.375566
Number of observations	135		108	
Dependent Variable	**Added Value Rate**		**Labor Productivity**	
Independent Variable	**Coefficient**		**Coefficient**	
EDSK		0.0003 *		0.4139
LSK		0.0013		−0.5243
IA	0.0019	0.0012	1.3104 *	1.3430 *
IS	0.00005	0.0006	0.0950	0.0834
R-square	0.2559	0.305039	0.4141	0.4360
Number of observations	135		108	

Note: * $p < 0.05$.

From the analysis carried out, it was found that there is a positive, statistically significant connection between the efficiency of the activity in agriculture and access to the Internet. Smart agriculture is a management concept aimed at increasing labor productivity and ensuring food security, under the constraints of environmental protection. Access to the Internet and the use of artificial intelligence for processing databases and transforming them into action factors are mandatory.

There is no statistically significant relationship between value-added/production/value-added rate/productivity in agriculture and Internet quality. At the level of European countries, the speed of the Internet does not constitute a potential barrier to the integration of artificial intelligence in agriculture. The European Commission adopted the work program for the digital component of the Connecting Europe Facility, which defines the scope and objectives of the actions needed to improve Europe's digital connectivity infrastructures. By benefiting to a greater extent from high-speed Internet, European countries will be able to more easily integrate new achievements in the field of artificial intelligence, ensuring a large-scale transition to agriculture 4.0. Superior performances are obtained in countries that have expanded fiber optic networks (FTTP) compared to those that use FTTC and ADSL solutions to a greater extent. There is also a strong correlation between the size of the geographical area covered and the speed of the Internet, with large locations being more difficult to service and upgrade, implying lower average speeds (Figure 7).

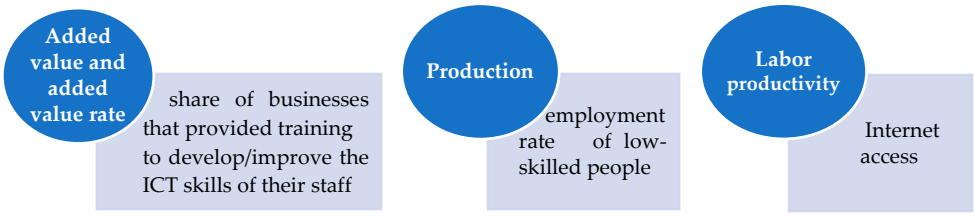


Figure 7. Challenges in the integration of AI in European agriculture.

Complementary to the analyzed factors, some aspects regarding the main challenges of the potential introduction of robots in agriculture are mentioned. A challenge, especially for big crops, is related to a very high dependency on human interventions. Even if digitalization helps farmers to identify different problems very quickly, in the end, people are confirming the agricultural treatment, as they need to do field tests to identify the need for fertilizers and pesticides. Given the short time to assess situations and the need to act quickly, experimental treatments cannot solve the problem, as they require precise solutions. Data availability represents another important challenge. In the case of greenhouses, the environment is a small one, and it is easier to define models that can be used later by AI. In the case of large crops, the unpredictability is high, and history is more difficult to create. For robots, it is more difficult to make the proper decision in a very short time from this point of view. Furthermore, a high level of initial investment and access to financing sources are constraints in the introduction of robots in agriculture [71]. A significant initial investment is required to implement AI technologies in agriculture. Small-scale farmers might encounter financial difficulties as it relates to the acquisition and integration of AI-driven systems, equipment, and infrastructure. Budgets may also be further strained by the expenses of acquiring and training qualified staff to operate these complex systems. Another challenge in implementing AI in agriculture is the drawn-out adoption process for new technologies. Farmers will need time to adjust to new technologies, understand how they work, and successfully integrate them into their current systems. Certain AI solutions may require a learning curve due to their complexity, which would further delay adoption. Data collection and analysis are key components of AI systems. The security and privacy of sensitive agricultural data are concerns for farmers in the context of potential cyber security risks, including malicious attacks and unauthorized access, necessary strong cyber security defenses, ethical data-processing procedures, and strict privacy laws. Furthermore, although AI maximizes the use of resources, the expansion of its application can have unforeseen effects on the environment by producing waste from obsolete systems, higher energy consumption, or even a failure to comply with conventional ecological measures.

Integrating robots into farms has proven to be challenging due to wide variations in shape, size, growth rate and type, product type, and environmental requirements for different types of crops [72]. Several challenges regarding the introduction of AI in different crops are identified in the literature. Thus, there are many challenges associated with the automatic identification of plant diseases using visible images. Capture conditions are difficult to manage and can degrade image quality and complicate disease identification. It is difficult to distinguish between healthy and diseased areas since most symptoms do not have distinct boundaries and gradually disappear into normal tissue. Depending on its stage of development and, occasionally, its location on the plant, a given disease can have a wide range of characteristics. It may be difficult to distinguish symptoms caused by many diseases occurring simultaneously. Different diseases can have identical visual symptoms, so the techniques for distinguishing between them must be based on extremely easy distinctions [73]. In the case of pests, the existence of previous management of species, the color similarity of some species and plants, and the variability of the size and shape of the insects due to their stage of development make it difficult to identify them through image segmentation and the accurate counting of them [35]. The image-based method that automatically detects the flowering of paddy rice has been applied, demonstrating that the varied lighting, the diversity of the appearance of the flowering parts of the

panicles, the shape deformation, the partial occlusion, and the complex background make the development of such a method difficult [74]. Some limitations were noted concerning the autonomous identification and robotic tracking of sugar pea pods. The major drawback of the robot design was related to the LED lighting rig, which could easily be blocked by the outer leaves of the plants, leading to overexposed areas in the output images where the leaves happened to block the LED sources, and the global threshold step is unable to discriminate overexposed leaves and/or stems from pods. Regarding the methodology used for bridge identification, the ellipses discrimination steps in the algorithm were not able to discriminate each bridge when they appeared close together in a cluster, only retrieving the general shape of the group, which can lead to the conclusion that several close pods in a cluster are likely to be classified as unsuitable for the picking process [75].

5. Conclusions

This research aims to improve the efficiency of agricultural activities from the perspective of sustainable development. The first contribution consists of revealing the knowledge structure in the field of artificial intelligence application in agriculture, with the detection of research themes, such as agriculture 4.0; advanced monitoring and controlling strategies in intelligent agriculture; the automation of agriculture by including different practices, such as cloud computing, IoT, big data, blockchain, and robotics and artificial intelligence; information security; new worker skills; and responsible leadership.

Identifying research topics contributes to defining the particular requirements of agriculture and enables the creation of tailored solutions to address contemporary issues, including production optimization, resource efficiency, and environmental protection. Cloud computing makes it feasible for farmers to remotely store and analyze huge amounts of data regarding market trends and weather forecasts, useful for monitoring and controlling temperature, lighting, and water flow, and, consequently, in decision-making. Real-time field conditions, such as weather patterns, soil parameters, and crop health, can be tracked by IoT sensors. Better yields arise from farmers employing these data to inform their decisions about controlling insects, fertilization, and irrigation. Additionally, large datasets can be analyzed in search of previously overlooked patterns and insights, useful in supply chain management, planting schedule optimization, rainfall patterns, water cycles, fertilizer requirements, and crop performance prediction. Blockchain is used in plant management, targeting aspects such as seed quality and crop growth, enhancing transparency, efficiency, and accountability in food, which reduces food waste throughout the supply chain, ensuring the identification of the origin of products and confirming their quality in accordance with the increase in consumer demands. It should be mentioned that this is a costly procedure. Robotics-based automation in planting, fertilization, harvesting, and weeding can make farm processes more efficient and reduce labor costs, allowing for more precise control while involving significant investment efforts. AI is able, based on data analysis, to provide predictions and recommendations, finding its usefulness in all the processes carried out on farms, including pest control, watering, and fertilization. The most developed technologies are related to big crops, as they involve the highest level of investment and the highest level of risk, as well. The control of equipment using GPS will continue to be a development priority, together with lot and satellite mapping. More sustainable farming methods, lower expenses, and more production result from the integration of these technologies. In addition, automation contributes to addressing issues such as climate change and workforce shortages, strengthening agriculture's resilience for the future. Furthermore, this research can foster cooperation between scientists, farmers, and the technology sector, resulting in an innovative ecosystem that is beneficial to all parties. Therefore, addressing these research themes improves farming methods and supports the long-term viability and sustainability of the agricultural industry.

Complementarily, to assess the main challenges of implementing artificial intelligence in agriculture, an empirical study at the level of the European Union countries was performed. Approaching the issue of AI integration in agriculture from the perspective of

the determining factors allows identifying them and establishing their impact to direct efforts toward the introduction and efficiency of the operationalization of advanced technologies, to increase efficiency and productivity and ensure sustainability in this field. The discussions herein aim to optimize agricultural processes, crop monitoring, and resource management, as well as challenges related to costs, accessibility, and staff training. By studying these aspects, solutions can be identified to support farmers and contribute to a smarter and greener agriculture. We found a statistically significant positive relationship between the added value, especially the added value rate, and the share of enterprises that provided training to develop/improve the ICT skills of their staff, as well as between labor productivity and access to the Internet. On the one hand, the creation of an environment to support the concerns regarding the development of the digital skills of agricultural workers is a decisive factor in the efficient use of all the resources involved, by capitalizing on their specific potentialities, particularly in agriculture. The appropriate qualification of the human resource in agriculture contributes to the development of its skills with direct incidents on the efficiency, innovation, and optimization of internal processes and customer satisfaction, which generate an increase in the long-term added value. On the other hand, increasing the efficiency of workers, evaluated based on labor productivity, involves access to the Internet to apply technologies based on artificial intelligence. Internet access is a basic condition in the use of AI, making many of the specific functionalities and services accessible and operating without significant limitations. Some AI-based productivity tools involve accessing online resources from external servers, and proper operation requires a constant connection to them. Most AI-based productivity solutions work in the cloud, which requires a constant Internet connection. Internet access is also necessary in view of continuous improvement through updates and optimizations of AI models that are carried out on external servers. There is a statistically significant negative relationship between agricultural production and the employment rate of low-skilled people aged 20–64, with measures being imposed accordingly. There is still a significant reliance on human interventions, especially for large crops. A higher level of training ensures efficiency and competence, and farms can produce more in certain resource configurations. The ability to adapt to new technologies, to identify innovative solutions, to manage resources and risks more efficiently, and to adopt good practices involves training agricultural workers and ensures superior production. Additionally, leadership and collaboration skills are developed, building a sustainable organizational culture. Companies that invest in the training of their staff are competitive, generating an adequate response to risks and rapid adaptability to changes.

The main future research directions aim to include in the analysis information on the aspects of the introduction of digital technologies in agricultural activity in the European Union countries and to identify the advantages of the specialized application of different technologies based on artificial intelligence on different branches of agriculture, as well as the impact of meeting the SDGs.

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References

1. Copeland, B.J. Artificial Intelligence. Encyclopedia Britannica. 2023. Available online: https://www.britannica.com/technology/artificial-intelligence (accessed on 7 November 2024).
2. Fahle, S.; Prinz, C.; Kuhlenkötter, B. Systematic Review on Machine Learning (ML) Methods for Manufacturing Processes—Identifying Artificial Intelligence (AI) Methods for Field Application. *Procedia CIRP* **2020**, *93*, 413–418. [CrossRef]

3. Da Silveira, F.; Lermen, F.H.; Amaral, F.G. An Overview of Agriculture 4.0 Development: Systematic Review of Descriptions, Technologies, Barriers, Advantages, and Disadvantages. *Comput. Electron. Agric.* **2021**, *189*, 106405. [CrossRef]
4. Sponchioni, G.; Vezzoni, M.; Bacchetti, A.; Pavesi, M.; Renga, F.M. The 4.0 Revolution in Agriculture: A Multi-Perspective Definition. In Proceedings of the Summer School "Francesco Turco" Industrial Systems Engineering—Proceedings of the XXIV Edition, Brescia, Italy, 11–13 September 2019; pp. 143–149.
5. Basso, B.; Antle, J. Digital Agriculture to Design Sustainable Agricultural Systems. *Nat. Sustain.* **2020**, *3*, 254–256. [CrossRef]
6. Lajoie-O'Malley, A.; Bronson, K.; van der Burg, S.; Klerkx, L. The Future(s) of Digital Agriculture and Sustainable Food Systems: An Analysis of High-Level Policy Documents. *Ecosyst. Serv.* **2020**, *45*, 101183. [CrossRef]
7. Wolfert, S.; Ge, L.; Verdouw, C.; Bogaardt, M.J. Big Data in Smart Farming—A Review. *Agric. Syst.* **2017**, *153*, 69–80. [CrossRef]
8. Prathibha, S.R.; Hongal, A.; Jyothi, M.P. IoT-Based Monitoring System in Smart Agriculture. In Proceedings of the 2017 International Conference on Recent Advances in Electronics and Communication Technology (ICRAECT), Bengaluru, India, 16–17 March 2017; IEEE: New York, NY, USA, 2017; pp. 81–84.
9. Gondchawar, N.; Kawitkar, R.S. IoT-Based Smart Agriculture. *Int. J. Adv. Res. Comput. Commun. Eng.* **2016**, *5*, 838–842.
10. Finger, R.; Swinton, S.M.; El Benni, N.; Walter, A. Precision Farming at the Nexus of Agricultural Production and the Environment. *Annu. Rev. Resour. Econ.* **2019**, *11*, 313–335. [CrossRef]
11. Blackmore, S. Precision Farming: An Introduction. *Outlook Agric.* **1994**, *23*, 275–280. [CrossRef]
12. Talaviya, T.; Shah, D.; Patel, N.; Yagnik, H.; Shah, M. Implementation of Artificial Intelligence in Agriculture for Optimization of Irrigation and Application of Pesticides and Herbicides. *Artif. Intell. Agric.* **2020**, *4*, 58–73.
13. Smith, M.J. Getting Value from Artificial Intelligence in Agriculture. *Anim. Prod. Sci.* **2018**, *60*, 46–54. [CrossRef]
14. Tien, J.M. Internet of Things, Real-Time Decision Making, and Artificial Intelligence. *Ann. Data Sci.* **2017**, *4*, 149–178. [CrossRef]
15. Javaid, M.; Haleem, A.; Khan, I.H.; Suman, R. Understanding the Potential Applications of Artificial Intelligence in the Agriculture Sector. *Adv. Agrochem* **2023**, *2*, 15–30. [CrossRef]
16. Ben Ayed, R.; Hanana, M. Artificial Intelligence to Improve the Food and Agriculture Sector. *J. Food Qual.* **2021**, *2021*, 5584754. [CrossRef]
17. Jha, K.; Doshi, A.; Patel, P.; Shah, M. A Comprehensive Review on Automation in Agriculture Using Artificial Intelligence. *Artif. Intell. Agric.* **2019**, *2*, 1–12. [CrossRef]
18. Tzachor, A.; Devare, M.; King, B.; Avin, S.; Ó hÉigeartaigh, S. Responsible Artificial Intelligence in Agriculture Requires Systemic Understanding of Risks and Externalities. *Nat. Mach. Intell.* **2022**, *4*, 104–109. [CrossRef]
19. Eli-Chukwu, N.C. Applications of Artificial Intelligence in Agriculture: A Review. *Eng. Technol. Appl. Sci. Res.* **2019**, *9*, 4377–4383. [CrossRef]
20. Ukhurebor, K.E.; Adetunji, C.O.; Olugbemi, O.T.; Nwankwo, W.; Olayinka, A.S.; Umezuruike, C.; Hefft, D.I. Precision Agriculture: Weather Forecasting for Future Farming. In *AI, Edge, and IoT-Based Smart Agriculture*; Academic Press: Cambridge, MA, USA, 2022; pp. 101–121.
21. Orchi, H.; Sadik, M.; Khaldoun, M. On Using Artificial Intelligence and the Internet of Things for Crop Disease Detection: A Contemporary Survey. *Agriculture* **2021**, *12*, 9. [CrossRef]
22. Liu, S.Y. Artificial Intelligence (AI) in Agriculture. *IT Prof.* **2020**, *22*, 14–15. [CrossRef]
23. Kothari, J.D. Plant Disease Identification Using Artificial Intelligence: Machine Learning Approach. *Int. J. Innov. Res. Comput. Commun. Eng.* **2018**, *7*, 11082–11085.
24. Akkem, Y.; Biswas, S.K.; Varanasi, A. Smart Farming Using Artificial Intelligence: A Review. *Eng. Appl. Artif. Intell.* **2023**, *120*, 105899. [CrossRef]
25. Oliveira, R.C.D.; Silva, R.D.D.S.E. Artificial Intelligence in Agriculture: Benefits, Challenges, and Trends. *Appl. Sci.* **2023**, *13*, 7405. [CrossRef]
26. Tang, Y.; Dananjayan, S.; Hou, C.; Guo, Q.; Luo, S.; He, Y. A Survey on the 5G Network and Its Impact on Agriculture: Challenges and Opportunities. *Comput. Electron. Agric.* **2021**, *180*, 105895. [CrossRef]
27. Mohr, S.; Kühl, R. Acceptance of Artificial Intelligence in German Agriculture: An Application of the Technology Acceptance Model and the Theory of Planned Behavior. *Precis. Agric.* **2021**, *22*, 1816–1844. [CrossRef]
28. Williamson, H.F.; Brettschneider, J.; Caccamo, M.; Davey, R.P.; Goble, C.; Kersey, P.J.; Leonelli, S. Data Management Challenges for Artificial Intelligence in Plant and Agricultural Research. *F1000Research* **2021**, *10*, 324. [CrossRef]
29. Penrose, E.G. *The Theory of the Growth of the Firm*; Wiley: New York, NY, USA, 1959.
30. Caves, R.E. Industrial Organization, Corporate Strategy and Structure. In *Readings in Accounting for Management Control*; Springer: Boston, MA, USA, 1980; pp. 335–370.
31. Barney, J.B. Resource-Based Theories of Competitive Advantage: A Ten-Year Retrospective on the Resource-Based View. *J. Manag.* **2001**, *27*, 643–650. [CrossRef]
32. Klerks, M.; Bernal, M.J.; Roman, S.; Bodenstab, S.; Gil, A.; Sanchez-Siles, L.M. Infant cereals: Current status, challenges, and future opportunities for whole grains. *Nutrients* **2019**, *11*, 473. [CrossRef] [PubMed]
33. Lezoche, M.; Hernandez, J.E.; Díaz, M.D.M.E.A.; Panetto, H.; Kacprzyk, J. Agri-food 4.0: A survey of the supply chains and technologies for the future agriculture. *Comput. Ind.* **2020**, *117*, 103187. [CrossRef]
34. Liakos, K.G.; Busato, P.; Moshou, D.; Pearson, S.; Bochtis, D. Machine learning in agriculture: A review. *Sensors* **2018**, *18*, 2674. [CrossRef]

35. Patrício, D.I.; Rieder, R. Computer vision and artificial intelligence in precision agriculture for grain crops: A systematic review. *Comput. Electron. Agric.* **2018**, *153*, 69–81. [CrossRef]
36. Shi, W.; Zhang, M.; Zhang, R.; Chen, S.; Zhan, Z. Change detection based on artificial intelligence: State-of-the-art and challenges. *Remote Sens.* **2020**, *12*, 1688. [CrossRef]
37. Liu, Y.; Ma, X.; Shu, L.; Hancke, G.P.; Abu-Mahfouz, A.M. From Industry 4.0 to Agriculture 4.0: Current status, enabling technologies, and research challenges. *IEEE Trans. Ind. Inform.* **2020**, *17*, 4322–4334. [CrossRef]
38. Mahoney, J.T. The management of resources and the resource of management. *J. Bus. Res.* **1995**, *33*, 91–101. [CrossRef]
39. Barney, J. Firm resources and sustained competitive advantage. *J. Manag.* **1991**, *17*, 99–120. [CrossRef]
40. Shibusawa, S. Precision farming and terramechanics. In Proceedings of the 5th Asia-Pacific Regional Conference ISTVS, Seoul, Republic of Korea, 20–22 October 1998; pp. 251–261.
41. Robinson, C.; Mort, N. A neural network system for the protection of citrus crops from frost damage. *Comput. Electron. Agric.* **1997**, *16*, 177–187. [CrossRef]
42. Lemmon, H. COMAX: An expert system for cotton crop management. *Science* **1986**, *233*, 29–33. [CrossRef]
43. Stone, N.D.; Toman, T.W. A dynamically linked expert database system for decision support in Texas cotton production. *Comput. Electron. Agric.* **1989**, *4*, 139–148. [CrossRef]
44. Prakash, C.; Rathor, A.S.; Thakur, G.S.M. Fuzzy-based Agriculture expert system for Soyabean. In Proceedings of the International Conference on Computing Sciences WILKES100-ICCS2013, Jalandhar, Punjab, India, 14–15 November 2013; Volume 113.
45. Roach, J.; Virkar, R.; Drake, C.; Weaver, M. An expert system for helping apple growers. *Comput. Electron. Agric.* **1987**, *2*, 97–108. [CrossRef]
46. Ghosh, I.; Samanta, R.K. TEAPEST: An expert system for insect pest management in tea. *Appl. Eng. Agric.* **2003**, *19*, 619. [CrossRef]
47. Sharma, R. Artificial intelligence in agriculture: A review. In Proceedings of the 2021 5th International Conference on Intelligent Computing and Control Systems (ICICCS), Madurai, India, 6–8 May 2021; pp. 937–942.
48. Pasqual, G. Development of an expert system for the identification and control of weeds in wheat triticale barley and oat crops. *Comput. Electron. Agric.* **1994**, *10*, 117–134. [CrossRef]
49. Burks, T.F.; Shearer, S.A.; Heath, J.R.; Donohue, K.D. Evaluation of neural-network classifiers for weed species discrimination. *Biosyst. Eng.* **2005**, *91*, 293–304. [CrossRef]
50. Liu, G.; Yang, X.; Li, M. An artificial neural network model for crop yield responding to soil parameters. In Proceedings of the Advances in Neural Networks–ISNN 2005: Second International Symposium on Neural Networks, Chongqing, China, 30 May–1 June 2005; Springer: Berlin/Heidelberg, Germany, 2005; Proceedings, Part III 2; pp. 1017–1021.
51. Tzounis, A.; Katsoulas, N.; Bartzanas, T.; Kittas, C. Internet of Things in agriculture, recent advances and future challenges. *Biosyst. Eng.* **2017**, *164*, 31–48. [CrossRef]
52. Farooq, M.S.; Riaz, S.; Abid, A.; Abid, K.; Naeem, M.A. A Survey on the Role of IoT in Agriculture for the Implementation of Smart Farming. *IEEE Access* **2019**, *7*, 156237–156271. [CrossRef]
53. Ganjegunte, G.K.; Sheng, Z.; Clark, J.A. Evaluating the accuracy of soil water sensors for irrigation scheduling to conserve freshwater. *Appl. Water Sci.* **2012**, *2*, 119–125. [CrossRef]
54. Bertoglio, R.; Corbo, C.; Renga, F.M.; Matteucci, M. The digital agricultural revolution: A bibliometric analysis literature review. *IEEE Access* **2021**, *9*, 134762–134782. [CrossRef]
55. Hassan, S.I.; Alam, M.M.; Illahi, U.; Al Ghamdi, M.A.; Almotiri, S.H.; Su'ud, M.M. A systematic review on monitoring and advanced control strategies in smart agriculture. *IEEE Access* **2021**, *9*, 32517–32548. [CrossRef]
56. Chang, C.L.; Chung, S.C.; Fu, W.L.; Huang, C.C. Artificial intelligence approaches to predict growth, harvest day, and quality of lettuce (*Lactuca sativa* L.) in an IoT-enabled greenhouse system. *Biosyst. Eng.* **2021**, *212*, 77–105. [CrossRef]
57. Benos, L.; Tagarakis, A.C.; Dolias, G.; Berruto, R.; Kateris, D.; Bochtis, D. Machine learning in agriculture: A comprehensive updated review. *Sensors* **2021**, *21*, 3758. [CrossRef]
58. Rakhmatulin, I.; Kamilaris, A.; Andreasen, C. Deep neural networks to detect weeds from crops in agricultural environments in real-time: A review. *Remote Sens.* **2021**, *13*, 4486. [CrossRef]
59. Rejeb, A.; Rejeb, K.; Abdollahi, A.; Al-Turjman, F.; Treiblmaier, H. The Interplay between the Internet of Things and agriculture: A bibliometric analysis and research agenda. *Internet Things* **2022**, *19*, 100580. [CrossRef]
60. Singh, R.K.; Berkvens, R.; Weyn, M. AgriFusion: An architecture for IoT and emerging technologies based on a precision agriculture survey. *IEEE Access* **2021**, *9*, 136253–136283. [CrossRef]
61. Sishodia, R.P.; Ray, R.L.; Singh, S.K. Applications of remote sensing in precision agriculture: A review. *Remote Sens.* **2020**, *12*, 3136. [CrossRef]
62. Zhang, X.; Cao, Z.; Dong, W. Overview of edge computing in the agricultural internet of things: Key technologies, applications, challenges. *IEEE Access* **2020**, *8*, 141748–141761. [CrossRef]
63. Pathan, M.; Patel, N.; Yagnik, H.; Shah, M. Artificial cognition for applications in smart agriculture: A comprehensive review. *Artif. Intell. Agric.* **2020**, *4*, 81–95. [CrossRef]
64. Gupta, M.; Abdelsalam, M.; Khorsandroo, S.; Mittal, S. Security and privacy in smart farming: Challenges and opportunities. *IEEE Access* **2020**, *8*, 34564–34584. [CrossRef]
65. Vangala, A.; Das, A.K.; Kumar, N.; Alazab, M. Smart secure sensing for IoT-based agriculture: Blockchain perspective. *IEEE Sens. J.* **2020**, *21*, 17591–17607. [CrossRef]

66. Ciarli, T.; Kenney, M.; Massini, S.; Piscitello, L. Digital technologies, innovation, and skills: Emerging trajectories and challenges. *Res. Policy* **2021**, *50*, 104289. [CrossRef]
67. Holzinger, A.; Saranti, A.; Angerschmid, A.; Retzlaff, C.O.; Gronauer, A.; Pejakovic, V.; Medel-Jimenez, F.; Krexner, T.; Gollob, C.; Stampfer, K. Digital transformation in smart farm and forest operations needs human-centered AI: Challenges and future directions. *Sensors* **2022**, *22*, 3043. [CrossRef] [PubMed]
68. Haque, A.; Islam, N.; Samrat, N.H.; Dey, S.; Ray, B. Smart farming through responsible leadership in Bangladesh: Possibilities, opportunities, and beyond. *Sustainability* **2021**, *13*, 4511. [CrossRef]
69. Carrer, M.J.; de Souza Filho, H.M.; Batalha, M.O. Factors influencing the adoption of Farm Management Information Systems (FMIS) by Brazilian citrus farmers. *Comput. Electron. Agric.* **2017**, *138*, 11–19. [CrossRef]
70. Briggeman, B.C.; Whitacre, B.E. Farming and the Internet: Reasons for non-use. *Agric. Resour. Econ. Rev.* **2010**, *39*, 571–584. [CrossRef]
71. Aravind, K.R.; Raja, P.; Pérez-Ruiz, M. Task-Based Agricultural Mobile Robots in Arable Farming: A Review. *Span. J. Agric. Res.* **2017**, *15*, e02R01. [CrossRef]
72. Birner, R.; Daum, T.; Pray, C. Who Drives the Digital Revolution in Agriculture? A Review of Supply-Side Trends, Players and Challenges. *Appl. Econ. Perspect. Policy* **2021**, *43*, 1260–1285. [CrossRef]
73. Barbedo, J.G.A. A Review on the Main Challenges in Automatic Plant Disease Identification Based on Visible Range Images. *Biosyst. Eng.* **2016**, *144*, 52–60. [CrossRef]
74. Guo, W.; Fukatsu, T.; Ninomiya, S. Automated Characterization of Flowering Dynamics in Rice Using Field-Acquired Time-Series RGB Images. *Plant Methods* **2015**, *11*, 7. [CrossRef]
75. Tejada, V.F.; Stoelen, M.F.; Kusnierek, K.; Heiberg, N.; Korsaeth, A. Proof-of-Concept Robot Platform for Exploring Automated Harvesting of Sugar Snap Peas. *Precis. Agric.* **2017**, *18*, 952–972. [CrossRef]

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