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Research article

The readiness to adopt green intelligent and sustainable manufacturing for agriculture in industry 4.0

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Abstract: The desire to balance environmental sustainability and food security is causing a significant upheaval in the agricultural sector. This study investigated how prepared stakeholders are to embrace agriculture in Industry 4.0, which integrates green, intelligent, and sustainable technologies like blockchain, IoT, and AI. Although these advances promise increased resilience and efficiency, they present significant obstacles to implementation, such as inadequate infrastructure, socioeconomic inequality, and a lack of technology awareness. This study highlights these technologies' theoretical and managerial implications and finds critical gaps using bibliometric and thematic analysis. To overcome adoption obstacles, it emphasizes the significance of inclusive policies, strategic alliances, and capacity-building programs. The study concludes that these impediments must be addressed to secure food systems for future generations and align agriculture with global sustainability goals. Longitudinal studies, stakeholder-centric methodologies, and investigating emergent technology synergies are among the suggestions for future research.

Keywords: artificial intelligence; machine learning; industry 4.0; smart manufacturing; green intelligence; sustainable manufacturing; agriculture; bibliometric analysis

1. Introduction

With the help of Artificial Intelligence (AI), Machine Learning (ML), and Internet of Things (IoT) technologies, the agriculture sector is developing, increasing productivity while maintaining environmental sustainability. These innovations enhance food security and resource efficiency and make accurate decision-making possible [1]. Agriculture 4.0 plays a crucial role in transforming conventional farming into more sustainable and environmentally friendly systems. By leveraging advanced technologies such as AI, IoT, and big data analytics, Agriculture 4.0 enhances precision in resource management, reducing water usage, minimizing chemical inputs, and lowering greenhouse gas emissions. These improvements contribute directly to global sustainability goals and help mitigate the environmental impact of agriculture, which is one of the largest contributors to land degradation and climate change [2,3]. As they tackle important issues like resource optimization and climate change mitigation, green, intelligent, and sustainable manufacturing systems have grown in popularity [4]. By incorporating digital tools and promoting a circular economy, implementing these technologies in agriculture, often referred to as Agriculture 4.0, is anticipated to completely transform the sector [5]. Machine learning has been effectively utilized for pesticide residue detection through advanced spectral and chemometric methods, enabling accurate and rapid food safety assessments [6,7]. Additionally, AI-driven models have shown strong performance in the classification and quality evaluation of agricultural products, contributing to improved efficiency in agricultural processing and monitoring [8]. The willingness of stakeholders to embrace such systems is still a major worry despite these developments. The rate of adoption can be affected by variables like infrastructure constraints, economic viability, and technology literacy [9]. For example, policy gaps and resource limitations frequently make it difficult for low- and middle-income nations to acquire these advances [10]. Furthermore, maintaining the broad adoption of sustainable agriculture practices requires tackling socioeconomic gaps and promoting inclusivity [11].

Assessing farmers, policymakers, and industry leaders' readiness to adopt and integrate green technologies into current agricultural frameworks is crucial in meeting the demands of a growing population and achieving global sustainability goals [12]. To identify best practices and remove obstacles, stakeholders must collaborate and conduct thorough research, which will pave the way for a resilient and technology-driven agricultural sector [13].

This study is driven by the pressing need to address the economic, social, and environmental issues that the agriculture industry is currently confronting. The growing global population has increased food needs, putting agricultural systems under previously unheard-of strain. Sustainable practices must be implemented simultaneously with environmental issues like resource depletion and climate change. To create solutions that support these two imperatives, it is essential to comprehend stakeholder preparedness to adapt agriculture to Industry 4.0. Additionally, a significant challenge lies in the misalignment between existing environmental regulations and current technological capabilities. For instance, while electric agricultural vehicles are seen as a clean energy solution, they remain constrained by limited range and inadequate charging infrastructure, particularly in rural areas [14]. These gaps highlight the urgent need for closer collaboration among policymakers, researchers, and industry to align technology development with regulatory frameworks.

The following are the study's main goals:

- To determine whether farmers, legislators, and business executives are prepared to embrace intelligent, sustainable, and green manufacturing technology.
- To determine the main obstacles to the adoption of agriculture 4.0 technology, with an emphasis on policy gaps and infrastructural and socioeconomic concerns.
- To offer practical suggestions for improving the uptake of sustainable practices, with a focus on strategic partnerships, inclusivity, and capacity building.

2. Methodology

2.1. Bibliometric approach

In contrast to meta-analysis, which synthesizes findings from various studies, and systematic literature reviews, which offer thorough summaries of existing knowledge, bibliometric analysis emphasizes quantitative assessments of thematic and relational aspects within the literature [15]. Bibliometric analysis is a well-known and rigorous method for methodically investigating large collections of scientific literature. This approach enables researchers to explore the development of specific research domains, identify emerging trends, and assess the relationships between studies [16]. For bibliometric mapping and visualization, VOSviewer was utilized due to its proven effectiveness in illustrating author collaborations, keyword co-occurrences, and citation relationships, as supported by recent research [17]. This study will apply two analyses, as shown below.

2.1.1. Bibliographic coupling

Bibliographic coupling illuminates the conceptual similarities between investigations by revealing shared references among research papers. By enabling the examination of recent papers, including those with fewer citations, this method offers a more comprehensive perspective of emerging research trends [18]. Bibliographic coupling captures more distinctive information than co-citation or direct citation [19].

2.1.2. Co-word analysis

Co-word network analysis is a bibliometric method that uses article keywords to objectively find research themes [20]. Co-word analysis has shown that academic interest in AI was gradually moving from problem domain–specific AI to organization-specific AI. Citation data determines the most significant (cited) authors, (cited) publications, journals, organizations, and nations [21]. The visualizations formed by VOSviewer in this study are mainly those from co-word analysis and bibliographic coupling performance as suggestion graphs by representative nodes such as keywords or publications, and edges representing the strength of their associations. While some studies use machine learning algorithms like clustering or neural networks to calculate the weight of such links, these approaches often involve complex training data and may decrease interpretability. Instead, this study uses association graphs for their clarity, transparency, and compatibility with expert-guided analysis, aligning with former bibliometric research [22,23]. Nonetheless, future work would benefit from incorporating machine learning techniques to improve automation and uncover latent patterns in bibliographic networks [24].

2.2. Research design and data collection procedure

We used the search string below to find papers containing pertinent keywords (Table 1). The literature, synonyms, and thesaurus are used to determine the search query related to green intelligence and sustainable manufacturing in agriculture. The topic search option was used to search the Scopus database. This option searches publications for keywords in the abstract, title, and authors' names. Furthermore, this analysis only includes journal articles; it excludes conference proceedings, books, book chapters, and editorials. Limiting the study to journal articles exclusively ensures the caliber of peer-reviewed studies that are part of the science mapping analysis [25].

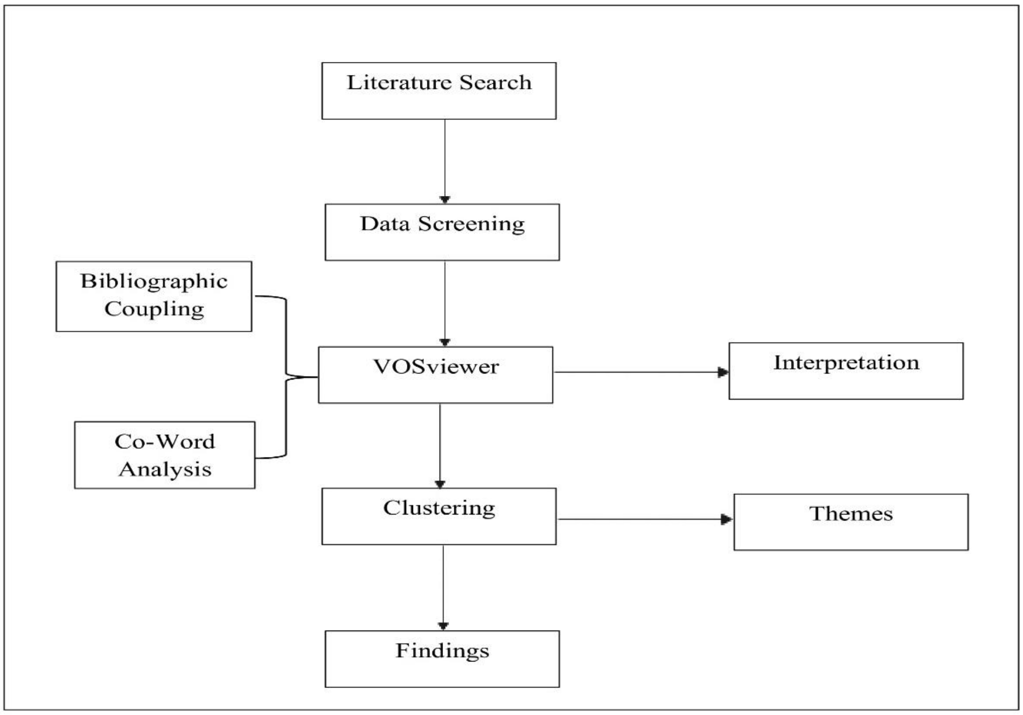

Figure 1. Flowchart of the research.

The flowchart in Figure 1 describes the systematic methodology applied for research analysis. It starts with an inclusive literature search, where relevant existing studies are identified and aggregated. Following this, data screening is executed to determine the quality and importance of the literature. The analysis employs VOSviewer, a specialized software tool designed for visualizing bibliometric networks, enabling the formation of visual representations that explain the relationships among research papers. Two critical techniques are utilized: bibliographic coupling, which classifies interconnectedness between papers based on shared references, and co-word analysis, which investigates the occurrence of keywords to disclose current trends within the research domain. The outcomes of these analyses conclude in clustering, where related papers or themes are grouped according to identified similarities. This methodological process eventually leads to the extraction of themes, representing the principal ideas that develop from the clustered data. Finally, these themes are subjected to interpretation, leading to resilient, meaningful conclusions based on the entire findings of the research.

Table 1. Search string used throughout the study.

No	Keywords	Justification
1	(“Artificial intelligence” OR “AI” OR “Machine learning” OR “ML” OR “Robotics” OR “Industry 4.0” OR “smart industry” OR “innovative renewable energy technologies” OR “green intelligence” OR “sustainable manufacturing” OR “machine learning” OR “advanced robotics” OR “automation smart manufacturing”)	To identify literature related to green, intelligent, and sustainable manufacturing
2	(“smart agriculture”)	To identify literature related to smart agriculture
3	(“readiness” OR “preparedness”)	To identify literature related to the readiness of organizations for green intelligence and sustainable manufacturing

Source: Authors’ own creation/own work

3. Findings and discussion

The search focused on adaptive human-centered production systems using green intelligence and agriculture alongside AI and IoT. ML algorithms analyze vast IoT data in real time, enabling predictive maintenance and efficient resource allocation. This supports sustainable manufacturing in the agriculture sector.

3.1. Bibliographic coupling

48 documents out of 504 achieved the 42-citation criterion in the bibliographic coupling. These 48 papers resulted in five clusters. Through a series of studies, the threshold was determined until the network visualization generated the most dependable and appropriate number of clusters for further reading. Several tests were applied before the most stable map was produced on the threshold. Because bibliographic coupling considers the link of the citing publication, the publication's total liking strength (TLS) is the value of interest. According to total link strength (TLS), the top three documents were Allioui & Mourdi (72 TLS) [26], Samizadeh Nikoui et al. (2021) (67 TLS) [27], and Rejeb et al. (2022) (64 TLS) [5]. The top 10 bibliographic coupling documents emphasize the connections between documents, as shown in Table 2. The importance of these papers in the network is indicated by their TLS, where higher TLS values denote more central or significant articles.

Table 2. Top 10 documents in bibliographic coupling analysis.

Rank	Publication	Scope	Citation	Total link strength
1.	[26]	A thorough analysis of the Internet of Things full potential for improved financial stability and growth.	167	72
2.	[27]	A comprehensive analysis of the issues associated with Internet of Things architecture.	50	67
3.	[5]	A bibliometric analysis and research plan on the relationship between agriculture and the Internet of Things.	59	64
4.	[28]	Defining the Emerging Trends, Difficulties, and Opportunities of the Agriculture 4.0 Landscape.	154	63
5.	[29]	Arable farming and the Internet of Things: Implementation, uses, difficulties, and possibilities.	50	67
6.	[30]	An In-Depth Review of IoT Architecture: Core Technologies, Middleware Frameworks, and Fog/Edge Computing Integration	60	18
7.	[31]	A comprehensive survey of the literature on agriculture 4.0 and the digitization of the agricultural sector.	154	63
8.	[32]	Smart farming technological revolutions: current developments, obstacles, and prospects.	254	45
9.	[33]	An outline of agricultural 4.0 development: a methodical examination of the technologies, descriptions, obstacles, benefits, and drawbacks	216	36
10.	[34]	A Review of Agriculture 4.0: Digital Transformation for a Sustainable Future	123	35

Source: Authors' own creation/own work.

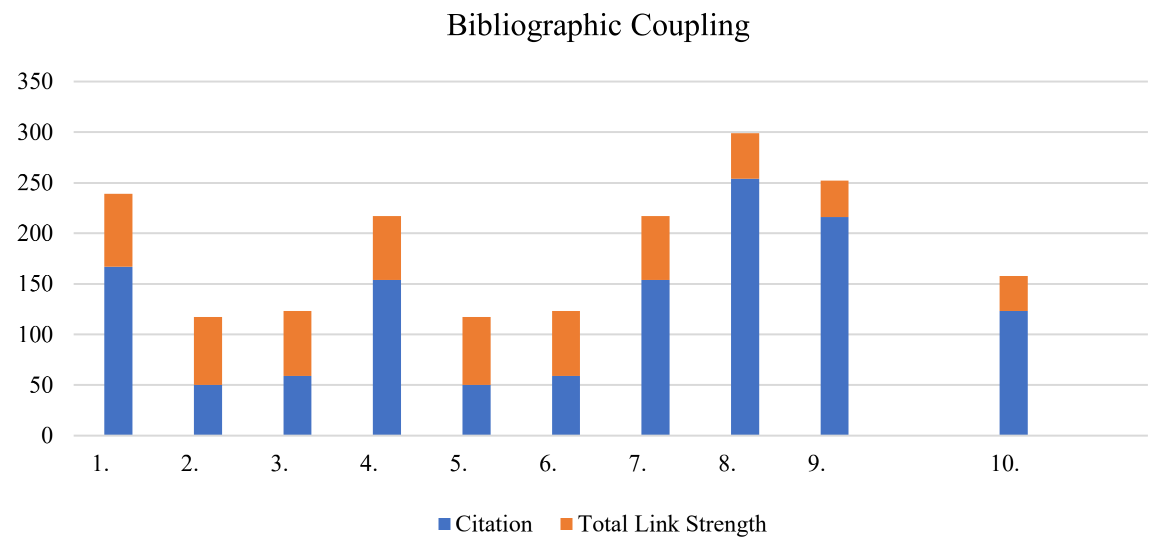

Figure 2. Bibliographic coupling. Source: Authors' own creation/own work.

Figure 2 illustrates the bibliographic coupling metrics, specifically showing the number of citations and total link strength for the top ten items analyzed. The network visualization of bibliographic coupling is shown in Figure 3, showing that the five groups are unrelated to one another. Reexamining representative articles within the clusters and synthesizing them based on shared themes and research streams is how the clusters are identified using inductive interpretation.

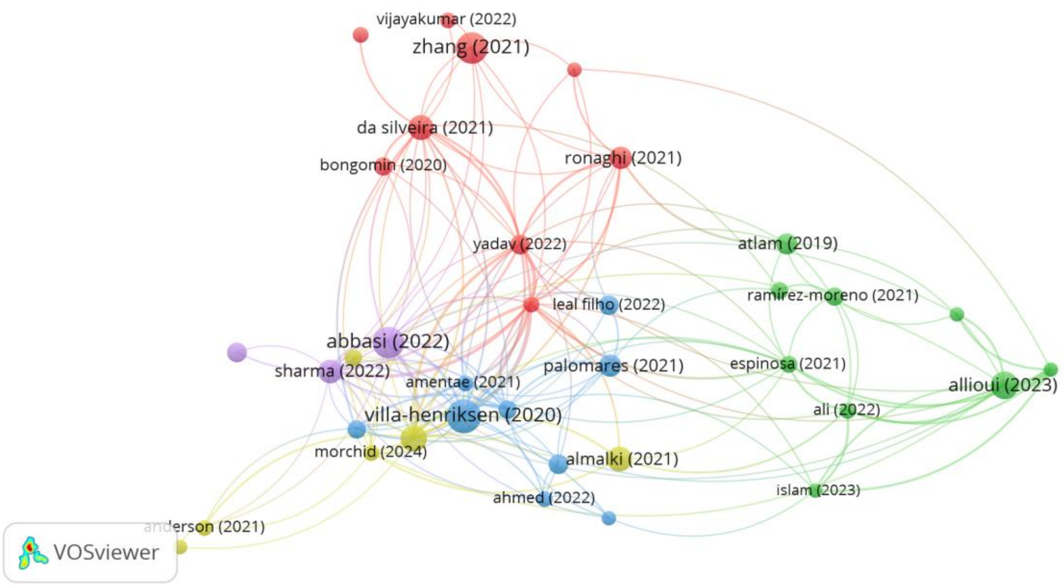

Figure 3. Bibliographic coupling. Source: Authors' own creation/own work.

Cluster 1 (Red): Technological innovations and challenges in agriculture and Industry 4.0

The growth of IoT technology has significantly impacted agriculture, but a complete grasp of its benefits is still emerging, pointing out how it affects important resources like water, soil, and technology infrastructures while laying the groundwork for further studies [5]. Agriculture 4.0

technologies, advantages, disadvantages, and barriers across technological, economic, political, social, and environmental dimensions have been systematically reviewed [33]. AI, IoT, blockchain, and robotics are disruptive technologies transforming industries as part of Industry 4.0. Important industries are undergoing major changes, including logistics, healthcare, agriculture, and education [35]. Blockchain technology enhances agricultural supply chains by enabling efficient information exchange and product tracking through tools like smart contracts and IoT [36]. Nanotechnology can potentially revolutionize the food and agriculture sectors by providing exact molecular control. It can be used to improve biosensors, improve nutrition, preserve food, and replace conventional fertilizers and pesticides [37]. Production systems are changing because Industry 4.0 forces businesses to innovate their procedures and business plans. However, neglecting change management elements is the reason many digital transformation projects fail. According to an analysis of current models, successful transitions require a greater emphasis on implementation and consolidation while integrating change management concepts [38].

Cluster 2 (Green): Smart systems integration and IoT challenges

All technologies and standards related to the Internet of Things have their own set of problems. The development of IoT applications heavily relies on middleware platforms, and the incorporation of fog/edge networks is essential. The IoT stack must be optimized to create future-proof apps [30]. Public health, energy efficiency, and sustainable development are all aided by IoT integration in social health systems. A mixed approach assesses how well it works in practical settings. The examination focuses on how IoT affects sustainable development goals, the environment, and health [39]. IoT architecture, which consists of sensors, protocols, actuators, and cloud services, is essential to deliver required services across several domains. Scalability, security, and interoperability issues remain, despite the abundance of IoT systems [26,27]. The shift to smart cities is crucial for effective resource management as urban populations increase. Sensors are essential for tracking trash, water, security, mobility, health, and energy. Cybersecurity and privacy issues must be resolved to guarantee a better quality of life through inclusive community engagement [13].

Cluster 3 (Blue): Digitalization and climate-responsive agriculture

AI can greatly aid in adapting to climate change, particularly in fields like agriculture and water management. It improves global climate efforts by fortifying governance and policy consistency. AI applications are becoming more widely acknowledged for their capacity to tackle various climate-related issues [40]. AI and IoT are two examples of agriculture 4.0 technologies that are becoming increasingly popular worldwide but have not received enough attention in sub-Saharan Africa (SSA). Adoption is hampered by knowledge, talent, and financial and infrastructure barriers, notwithstanding its potential. A robust plan is required to close these gaps and assist smallholder farmers [10]. Arable farming is changing because of IoT's increased productivity and decreased environmental effects. Interoperability, affordability, and data security are major obstacles. To overcome these obstacles, solutions like intelligent data management and machine learning are crucial [29]. Digital technologies present both opportunities and challenges in rural and agricultural settings. The advantages and hazards are examined by stakeholders, including practitioners and political institutions [41]. The food system must be digitalized using technologies like blockchain, IoT, and AI to improve sustainability and resilience. The main advantages are better crisis response, decreased food waste, and enhanced traceability. For broader adoption, issues like infrastructure, expenses, and laws must be resolved [42].

Cluster 4 (Yellow): Innovations driving the smart agriculture revolution

A low-cost platform for real-time agricultural environmental monitoring, provided by the combination of IoT and UAVs, has been tested on a Tunisian farm. The system gathers and sends data from airborne and ground sensors for processing. Precision agriculture's crop productivity and resource management are improved by this creative method [43]. With the help of IoT, AI, and big data, agriculture 4.0 promises to develop sustainably. An analysis of new trends reveals both obstacles and chances for creativity. To facilitate the digital transformation of agriculture, an IoT architecture based on the cloud is suggested [28].

Technologies are enhancing fruit management by improving yield estimation. Key methods include machine vision, aerial imagery, and historical data models. These technologies, particularly machine vision, offer scalability and accuracy in estimating fruit load and harvest timing [44]. AI technologies can greatly aid in reducing food waste and advancing a circular economy. Artificial intelligence improves sustainability and resource efficiency by streamlining food production, supply chains, and surplus food distribution. These initiatives help to build a food system that is more ecologically friendly and egalitarian [11]. The goal of future IoT devices is autonomy through accurate sensing and wireless power. Energy harvesting and data transfer via electromagnetic waves are made possible by metamaterial perfect absorbers (MPAs). Their uses include optical switching, frequency absorption, and sensing, and their industrial significance is only increasing [45].

Cluster 5 (Purple): Sustainable AgriTech and emerging technologies

By utilizing digital technologies like IoT, robotics, and machine learning, agriculture 4.0 seeks to improve food security. According to research, open-air farms are being explored more often, and many technologies are still in the prototype stage. The main obstacles to full adoption are socioeconomic and technical [31]. Digital transformation frameworks integrating AI, IoT, cloud computing, blockchain, and renewable energy for sustainable Agriculture 4.0 have been reviewed [34]. With the rising global population, the demand for agricultural productivity has led to the integration of modern technologies in farming. Smart farming utilizes technologies like big data, machine learning, IoT, robotics, and blockchain, enhancing efficiency and sustainability [32]. By using smartphone photos to identify pests early, a YOLOv5-based system for agricultural insect pest detection helps cut down on the use of pesticides. The YOLOv5x model promotes sustainable farming practices by detecting 23 pest species with excellent accuracy (98.3% precision) [46].

The bibliographic coupling analysis is summarized in Table 3, which includes important metrics and conclusions regarding the degree of relationships between works. This contains metrics that show how important or central certain papers are inside a specific research network, such as the number of linked documents or the TLS.

Table 3. Summary of bibliographic coupling analysis.

Cluster number and color	Cluster label	Number of publications	Representative publications
1 (red)	Technological innovations and challenges in agriculture and Industry 4.0	9	[5], [33], [35], [36], [37], [38]
2 (green)	Smart systems integration and IoT challenges	9	[30], [39], [26], [27], [13]
3 (blue)	Digitalization and climate-responsive agriculture	9	[40], [10], [29], [41], [42]
4 (yellow)	Innovations driving the smart agriculture revolution	6	[43], [28], [44], [11], [45]
5 (purple)	Sustainable AgriTech and emerging technologies	3	[31], [34], [32], [46]

Source: Authors' own creation/own work

3.2. Co-word analysis

By applying the same database, 59 out of 3256 keywords presented through co-occurrence analysis met 9 thresholds, resulting in 5 clusters. The highest co-occurrence keywords are "Internet of things" (82 occurrences), "agriculture" (63), and "artificial intelligence" (60 occurrences). The top 15 keywords from the keyword co-occurrence analysis are shown in Table 4.

Table 4. Top 15 keywords ranked by occurrence and TLS in the co-occurrence analysis.

Rank	Keyword	Occurrences	Total link strength
1	Internet of Things	82	114
2	Agriculture	63	108
3	Artificial intelligence	60	82
4	Climate change	49	87
5	Sustainable development	49	100
6	Machine learning	37	59
7	Sustainability	37	61
8	Industry 4.0	35	41
9	Agricultural technology	30	62
10	Decision making	30	51
11	Precision agriculture	26	49
12	Smart agriculture	26	52
13	Farms	25	67
14	Food supply	23	69
15	Food security	22	56

Source: Authors' own creation/own work

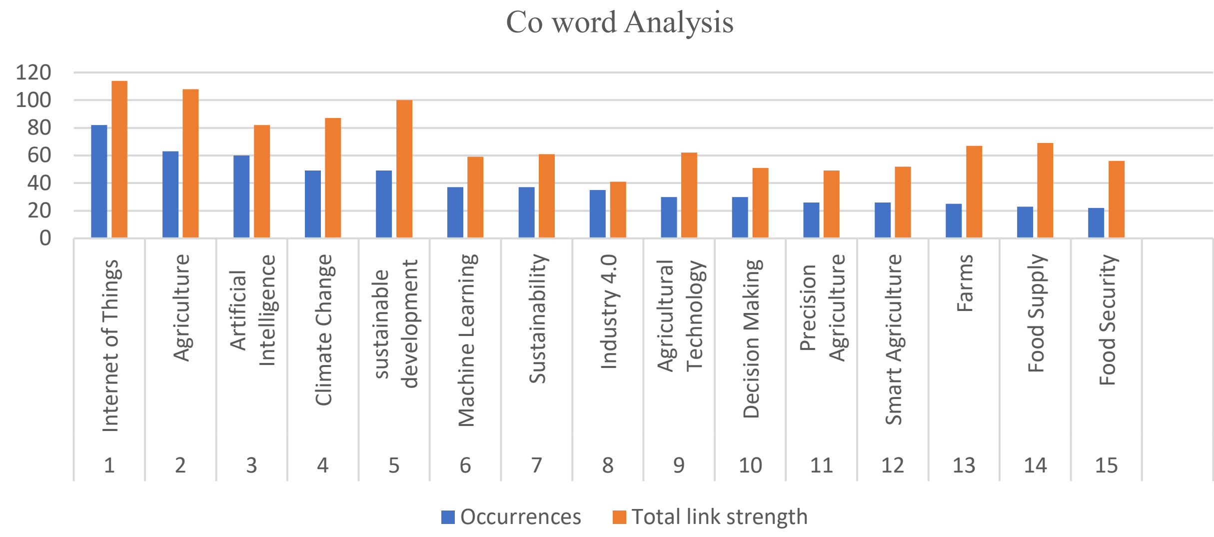

Figure 4. Bibliographic coupling. Source: Authors' own creation/own work.

Figure 4 shows the results of a keyword co-occurrence analysis, which describes the occurrences in blue and total link strength in orange of various key terms related to agriculture and technology, with "Internet of Things" and "Agriculture" exhibiting the highest frequencies and link strengths. Figure 5 presents the keyword analysis's network structure, which exhibits 5 clusters that represent 5 different themes. Following the author's inductive interpretation, the 5 clusters are assigned the proper labels.

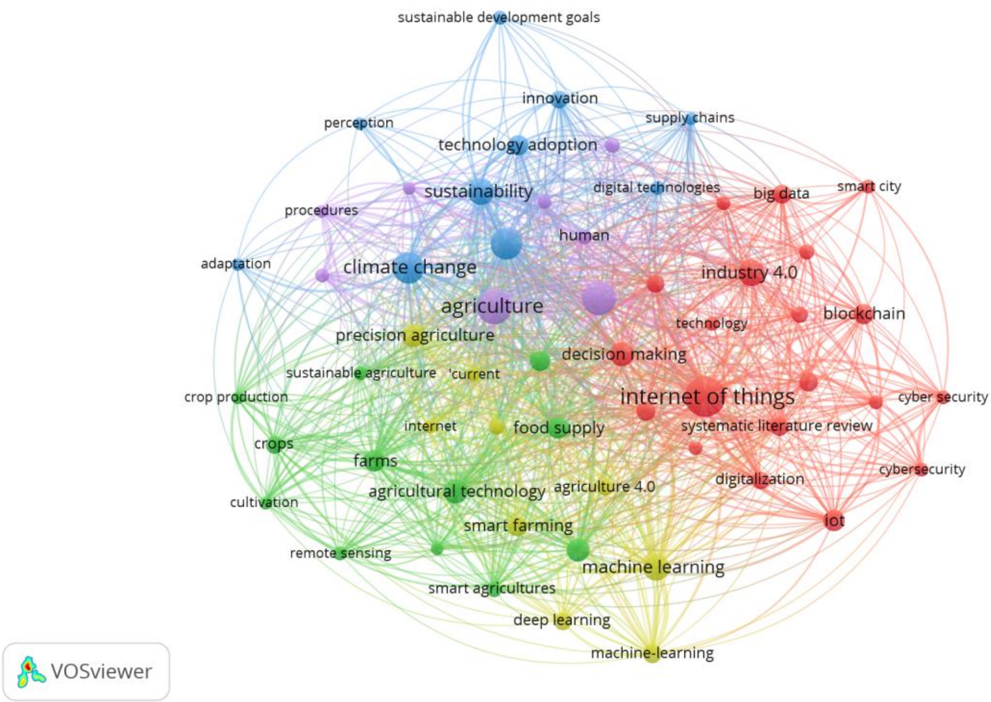

Figure 5. Co-word analysis map. Source: Authors' own creation/own work.

Cluster 1 (Red): Advancing smart solutions: integrating technology in agriculture and urban development

The idea of a smart city is an urban region that enhances infrastructure, governance, and quality of life by utilizing data, technology, and sustainable techniques. While it is frequently thought of as being solely associated with technology, smart cities require an integrated, multidisciplinary, and comprehensive approach to create a more efficient and livable urban space [31]. Digital technologies such as robotics, IoT, and machine learning are being adopted in agricultural 4.0. It primarily focuses on open-air farms. However, most applications are in the prototype stage [31]. To solve food security issues for a growing global population, IoT-enabled precision farming can improve smallholder farming. The state of IoT applications on farms today emphasizes successful examples in low- and middle-income nations [47]. With an emphasis on risks and assessment criteria unique to agricultural technologies, intrusion detection systems (IDS) are relevant to cybersecurity in Industry 4.0. It uses machine-learning approaches to evaluate IDS performance across cutting-edge agricultural technology, including smart grids, autonomous tractors, and the Internet of Things [48]. Meeting the dual objectives of providing environmental services and producing food technology might lead agriculture toward sustainability. It asks for policies to assist research, adoption, and effective allocation of environmental assets and identifies market failures, such as the lack of sustainable technologies [49].

Cluster 2 (Green): Emerging innovations in smart agriculture

The development of agricultural robots for field operations emphasizes combining subsystems to carry out activities in unstructured situations, achieving safe, cost-effective, and intelligent systems, and resulting in adaptable sensors and algorithms to changing agricultural conditions. To improve robot performance in agriculture, further research is needed in the areas of sensor fusion, path planning, and human operator integration [50]. Creating new technologies to speed up plant breeding and improve genetic diversity, genotyping, and phenotyping to boost crop yields is crucial. It strongly emphasizes providing these technologies in an accessible and cost-effective manner to developing nations to increase food security [4]. To modernize conventional farming methods and meet the challenges of growing global food demands, agriculture 4.0 incorporates digital technologies. The status of smart agriculture and its possible prospects are highlighted by examining the developments of the last ten years. These observations highlight how crucial new technologies are to overcome challenges [51].

Agricultural industry is embracing IoT and cutting-edge technologies to update old methods. Processes are optimized by innovations like sensors and UAVs, increasing yields and efficiency. While tackling integration issues, these developments have the potential for sustainable farming [52]. Remote sensing (RS) technologies allow for early agricultural intervention, maximizing sustainability and productivity. Although there are still knowledge and practicality gaps, their use has increased, especially with UASs. Although there is potential for wider applications, RS applications primarily concentrate on crop health and soil moisture [53].

Cluster 3 (Blue): Sustainable agricultural innovations and adaptation strategies

Nano-fertilizers (NFs) are a sustainable substitute for synthetic fertilizers that improve plant growth, soil quality, and stress tolerance. They enhance plant defense systems and control the availability of nutrients. NFs are becoming vital for global food security and sustainable agriculture [54]. Although agricultural innovation systems (AIS) are essential to transforming food systems, their relationship to transformational ideas is frequently disregarded. Understanding the forces behind and obstacles to this change can be aided by a mission-oriented agricultural innovation system (MAIS) approach [12]. Climate change is anticipated to aggravate food insecurity in Southern Africa by lowering rainfall and agricultural production. To sustain agricultural productivity, water and energy resources must be managed effectively. Sustainable adaptation solutions are required to achieve sustainable growth and guarantee long-term development [55].

Economic, technological, and sociocultural constraints impede the adoption of advanced agricultural technologies in emerging nations. Enhancing irrigation, financial availability, and research-extension-farmer ties should be the main priorities of policymakers. Adoption rates can be raised by including farmers in the development of new technologies [56]. Crop production must be sustainable to counteract environmental harm and climate change. The phyto-microbiome, particularly PGPR, can enhance crop efficiency and growth. However, obstacles, including regulatory barriers and microbiological competition, prevent it from being widely used [57].

Cluster 4 (Yellow): Digital agriculture revolution: machine learning and IoT integration

The primary advantage of using digital technology in agriculture, as reported by 84% of Brazilian farmers, is higher productivity. However, high machinery, equipment, and communication prices continue to be major obstacles. Despite this, 95% of farmers are still keen to learn more about new technologies for agricultural development [58]. Agriculture is undergoing a revolution thanks to machine learning, especially in the areas of crop, water, soil, and livestock management. The most effective algorithms are artificial neural networks, which are used to improve agricultural practices focusing on maize, wheat, cattle, and sheep. Satellite and unmanned aerial vehicle sensors provide accurate data [59]. Agricultural data processing, including crop categorization and pest identification, has been enhanced by deep learning, especially using convolutional neural networks. Coulibaly et al. [60] stated that dealing with user perception, doing statistical tests, and validating models are among the difficulties in improving deep learning's use in agriculture. Machine learning (ML) and the Internet of Things (IoT) are revolutionizing agriculture by enhancing forecasts for crop yields, soil quality, and pest control. These devices also help with livestock monitoring and effective watering by lowering labor and resource consumption. Improving sustainable agricultural productivity requires their combination [61].

Cluster 5 (Purple): Sustainable AgriTech advancements: policies, automation, and nanotechnology

Sustainable agriculture techniques are more likely to be adopted via incentive-based initiatives that are connected to immediate financial gains. Perceived environmental and agricultural benefits are what propel long-term acceptance. Technical support and alignment with the target population's characteristics are necessary for effective policies to provide improved results [9]. Powered by IoT, AI, and machine learning, automation in agriculture tackles issues including disease control, irrigation, and excessive pesticide use. These developments contribute to increased crop yields and better soil fertility. These technologies must be used to sustainably fulfil the rising demand for food [62]. In agriculture, nanotechnology has the potential to increase output, rebuild ecosystems, and lessen dependency on dangerous chemicals. It answers problems like soil management, pest control, and nutrient efficiency. Notwithstanding obstacles, its potential uses in the future could greatly improve sustainable agricultural methods [1]. Although pesticides are essential for raising agricultural yields, they can also pollute the environment and damage organisms that are not their intended target. They contribute significantly to the world's food output. However, the use of pesticides is rising due to climate change, which emphasizes the need for improved management techniques [63].

The co-word analysis summary in Table 5 sheds light on the connections between keywords or terms commonly occurring in a collection of texts. Finding patterns in the terminology used throughout a corpus of writing using co-word analysis reveals the connections between ideas or subjects.

Table 5. Summary of co-word analysis.

Cluster number and color	Cluster label	Number of keywords	Representative keywords
1 (red)	Advancing smart solutions: integrating technology in agriculture and urban development	20	Smart City, Agriculture 4.0, Internet of Things, Cybersecurity
2 (green)	Emerging innovations in smart agriculture	12	Agricultural technology, smart agriculture, remote sensing, cultivation
3 (blue)	Sustainable agricultural innovations and adaptation strategies	10	Sustainability, technology adoption, sustainable development goal, climate change
4 (yellow)	Digital agriculture revolution: machine learning and IoT integration	9	Smart farming, machine learning, deep learning, precision agriculture
5 (purple)	Sustainable AgriTech advancements: policies, automation, and nanotechnology	8	Adoption, artificial intelligence, nanotechnology, environmental impact

Source: Authors' own creation/own work

4. Future research avenues

Future studies ought to concentrate on administrative measures that promote the uptake of green technologies, especially in underserved areas. It will be crucial to investigate how public-private partnerships, regulatory frameworks, and financial incentives might promote sustainability. Moreover, there are chances for increased readiness in agriculture through the combination of AI, IoT, and nanotechnology; however, further research is required to examine their viability, affordability, and implementation difficulties. Given that farmers' leaning to switch to sustainable methods is greatly influenced by behavioral and economic variables, it is also critical to understand how they see and use these technologies.

The socioeconomic effects of smart farming are a vital topic for study because new technologies may potentially and unintentionally increase inequality. Future research should look at ways to guarantee that these improvements benefit all farmers, regardless of their financial situation. To create robust solutions, regional differences in sustainable agriculture readiness must also be investigated. Future policy will benefit greatly from longitudinal studies on the effects of sustainable practices on the environment and food security. Eventually, issues with data security and privacy need to be addressed as digital technologies are increasingly incorporated into agriculture. Research is required to determine whether current regulatory frameworks are sufficient to protect farmers' information.

5. Implications

The study's conclusions offer insightful information about theoretical developments and real-world applications in sustainable agriculture. By looking at how new technologies are influencing coexisting farming methods, the study identifies important areas that require more research. These implications provide a comprehensive knowledge of the study's influence and are divided into theoretical and managerial dimensions.

5.1. Theoretical implications

By considering how cutting-edge technologies impact sustainable agriculture, this study adds to the theoretical framework. The study establishes the groundwork for further research on blockchain's wider applicability in agriculture by emphasizing how it might improve supply chain efficiency and transparency. Furthermore, it is emphasized that genetic advancements in crop production are crucial for enhancing climate change resilience, creating new opportunities for study on climate-smart farming methods [64]. The incorporation of renewable energy sources into smart agricultural systems is an important topic for additional theoretical research since it has the potential to greatly lessen reliance on fossil fuels and enhance sustainability.

Additionally, the study identifies the value of agroecological methods and how they advocate sustainable farming methods. Future studies could examine novel frameworks that combine cutting-edge technical solutions with customary ecological understanding. The identification of socioeconomic elements in the adoption of technology is another important theoretical contribution [65]. Even while technology is essential, there is still a lack of research in the literature on the behavioral, economic, and policy-driven factors that influence farmers' decisions. Closing these gaps may result in agricultural transformation models that are more successful and inclusive.

5.2. Managerial implications

The study focuses on the necessity of strategic planning and teamwork in the implementation of sustainable agriculture technologies from a managerial standpoint. One important discovery is that using accessible IoT solutions designed for small-scale farmers can upgrade resource management [66]. To make sure that green technologies are integrated into agricultural value chains, policymakers should focus on creating financial support systems that make them easier to acquire. Furthermore, motivating cross-sector partnerships between corporations, governments, and academic institutions can promote invention and the practical application of sustainable practices [67].

For smart farming technology to be embraced responsibly, regulatory frameworks are crucial. Scaling these solutions while maintaining user rights would require ensuring data privacy, cybersecurity, and interoperability inside IoT-driven agricultural systems [68]. Furthermore, the long-term sustainability of these technologies can be enhanced by engaging nearby farming communities through participatory methods. Offering financial incentives, knowledge-sharing platforms, and training courses can expand adoption rates and make agriculture more comprehensive [69]. In the end, creating resilient and sustainable food production systems will need to integrate technology with carefully thought-out regulations and stakeholder participation.

6. Limitations and future research

Some constraints may impact the overall comprehensiveness of this study. First, new trends that are not included in the reviewed literature may be overlooked due to the dependence on secondary data sources, such as bibliometric analyses [60]. Furthermore, the study's findings may not be as broadly applicable due to its regional focus, particularly when it comes to comprehending technology uptake in underrepresented areas [28]. Third, the potential for in-depth analysis is limited by the absence of primary data on stakeholder perceptions and ground-level adoption patterns [47]. Furthermore, sociocultural elements are frequently ignored by technical readiness indicators, though they are crucial to the success of sustainable practices [50]. Lastly, it can be difficult to keep findings relevant over time due to the dynamic nature of agricultural technologies [41].

Future studies should take a more inclusive and multidisciplinary approach to overcome these constraints. The dynamic character of technology adoption and its long-term effects on agricultural sustainability can be better understood by conducting longitudinal research [45]. A more comprehensive picture of global readiness may be obtained by broadening the geographic scope to encompass various socioeconomic circumstances [37]. Additionally, combining field research and stakeholder surveys can provide detailed insights into the factors that facilitate and hinder the adoption of new technologies. Another crucial topic for research is highlighting how policy interventions might promote the adoption of green technologies at various scales. Finally, investigating how cutting-edge technologies like AI and nanotechnology may work together in agriculture could lead to creative answers for sustainable food systems.

7. Conclusion

This study emphasizes how green, intelligent, and sustainable technology has the power to change the agriculture industry completely. Innovations like blockchain, IoT, and AI can be integrated to improve farming techniques' sustainability, resilience, and efficiency. Widespread adoption is nevertheless hampered by important obstacles, such as inadequate infrastructure, socioeconomic inequality, and low knowledge. Policymakers, business executives, and researchers must work together to create equitable policies, promote technical literacy, and set up strong financial structures to overcome these obstacles. These issues must be addressed to secure food systems for future generations, align the industry with global sustainability goals, and ensure a smooth transition to sustainable agriculture techniques. Through strategic alliances and ongoing research, the agricultural sector can use these technologies to create a more resilient and sustainable future.

Use of AI tools declaration

We have not used artificial intelligence (AI) tools to create this article.

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Conflict of interest

The authors hereby declare that there are no conflicts of interest in this research.

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