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Article

Smart Farming and the SDGs: Emerging Research Patterns and Sustainability Implications

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Abstract

Smart farming has established itself as a strategic field in the digital and sustainable transformation of the agri-food sector. The rise of technologies such as the Internet of Things (IoT), artificial intelligence (AI), machine learning, big data, and blockchain has revolutionized production systems, improving efficiency, sustainability, and adaptability to climate change. In this context, scientific research on smart farming has grown exponentially, becoming a key axis for the fulfillment of the Sustainable Development Goals (SDGs). The objective of this study was to analyze the evolution, structure, and impact of scientific production in smart farming, identifying its main trends, authors, journals, and contributions to the SDGs. To this end, a bibliometric analysis was applied to 1,580 articles indexed in the Web of Science (WoS) database, using productivity, citation, and impact indicators based on Price's, Lotka's, Bradford's, and Zipf's laws, as well as the Hirsch index. The results reveal important growth in scientific production between 2014 and 2024, with a strong concentration in high-impact journals and international collaboration networks. In conclusion, smart farming represents an engine of innovation and sustainability, integrating science, technology, and digital management to address the global challenges of food security, climate change, and sustainable development.

Keywords: precision agriculture; digitalization; big data; internet; technology adoption in agriculture; innovation

1. 1. Introduction

1.1. Smart Farming and Its Contribution to the Sustainable Development Goals (SDGs)

Smart farming has consolidated itself as an essential strategy to transform agri-food systems toward greater productivity, sustainability, and resilience, contributing directly to the Sustainable Development Goals (SDGs). Particularly SDG 1 (No Poverty), SDG 2 (Zero Hunger), SDG 3 (Good Health and Well-being), SDG 13 (Climate Action), and SDG 15 (Life on Land) [1,2]. This approach integrates emerging technologies such as Unmanned Aerial Vehicles (UAVs), Digital Twins, the Internet of Things (IoT), Artificial Intelligence (AI), and Cloud Computing to optimize agricultural management and reduce environmental impacts [3–6].

These technological innovations have enabled the monitoring of critical variables, such as humidity, temperature, water use, and pest detection, with unprecedented precision. However, their adoption remains uneven due to economic constraints, technological gaps, and limited digital training in rural regions [7–9]. Although automatic disease detection using computer vision reduces agrochemical use and enhances environmental sustainability [10,11], a systematic analysis linking these contributions to the SDGs is still lacking in determining which technologies generate the greatest impact on global sustainable development.

Considering this gap, it becomes necessary to conduct a bibliometric analysis exploring trends, collaboration networks, and research approaches in Smart Farming, to better understand its actual contribution to global sustainability [12].

1.2. Digital Transformation in Agriculture: From Management to Intelligent Systems.

Digital transformation has redefined modern agriculture, turning it into a data-driven, automated, and sustainability-oriented process [13]. Smart Farming represents the evolution of the traditional paradigm by integrating technologies such as IoT, AI, Big Data, and Robotics to optimize production processes and reduce environmental impacts [14,15]. These tools allow real-time monitoring and control of agricultural variables, such as soil moisture and water use, facilitating evidence-based decision-making [16]. Examples such as the Cross Layer – IoT protocol, which enables remote decisions and reduces energy consumption, demonstrate the transformative potential of agricultural digitalization [16].

Agricultural management has thus become a strategic axis that articulates the planning, organization, and control of resources through digital systems. In the era of Agriculture 4.0, data-driven management enables a shift from reactive to predictive models, strengthening the resilience of agri-food chains and fostering more sustainable decision-making [17,18]. Technologies such as Farm Management Information Systems (FMIS) and Precision Agriculture illustrate how information can transform agricultural productivity and sustainability [19,20].

Smart farming systems therefore constitute interconnected networks of devices, sensors, and digital platforms that enable integrated resource management in real time. Empirical evidence shows their impact for instance, in Brazil, agricultural digitalization has increased productivity in more than 84% of producers adopting digital technologies [21]. Similarly, In Italy, the use of UAVs and open-source software for the sustainable mapping of weeds on small and medium-sized agricultural lands [22].

Consequently, agricultural sustainability has become a key pillar in the digital transformation of the sector, driven by intelligent technologies that seek to balance productivity, sustainability, and climate resilience. Various studies emphasize how agricultural digitalization based on IoT, AI, and robotics optimizes resource use and reduces environmental impacts [19,23–25]. Initiatives such as Climate-Smart Agriculture promote resilient systems in the face of climate change [26,27], while innovative approaches such as Predator Smart Farming reinforce the coexistence between sustainability, animal welfare, and productivity [28]. Altogether, these strategies delineate an intelligent agroecological model oriented toward sustainable development.

1.3. The Internet of Things (IoT) and Cyber-Physical Integration in Smart Farming

The Internet of Things (IoT) constitutes the technological backbone of smart farming, enabling the interconnection of sensors, devices, and platforms that monitor agro-environmental conditions in real time [29–31]. Its purpose is to transform traditional agricultural systems into intelligent ecosystems where data collected through sensors and wireless networks are processed in the cloud or in distributed architectures to improve efficiency and sustainability [32–34].

Notable examples include low-cost IoT systems integrated with drones (UAVs) that enable automated irrigation and monitoring [35], or intelligent frost-control systems based on neural networks that autonomously activate anti-freeze irrigation mechanisms [36]. Furthermore, agricultural security solutions combining LoRa, blockchain, and cloud monitoring ensure data

integrity and transparency in production processes [37–39]. These applications confirm that IoT drives a more resilient, transparent, and SDG-aligned agriculture, consistent with the principles of Agriculture 5.0.

1.4. *Smart Farming and Machine Learning in Agricultural Decision-Making*

Smart farming integrates Artificial Intelligence (AI) and Machine Learning (ML) as foundational tools for data-driven decision-making. These technologies analyze large volumes of information from sensors, satellite imagery, and IoT systems, optimizing crop and resource management [40,41]. Their main goal is to create interconnected technological ecosystems capable of responding in real time to environmental conditions [42].

The use of blockchain and smart contracts enhances the traceability and security of agricultural data [43], while energy-autonomous sensors and plant-wearable devices facilitate sustainable data collection [44]. Moreover, LoRaWAN networks have shown that digitalization can adapt to rural contexts through low-cost solutions [45].

Machine learning is applied to crop yield prediction through neural networks [46], weed detection [47], and animal health monitoring [48]. These techniques, complemented by deep learning and big data analytics, strengthen precision decision-making [49,50]. Beyond automation, ML fosters hybrid agricultural intelligence, where collaboration between algorithms and human knowledge enables more robust and sustainable decisions [51–53].

Accordingly, this study seeks to investigate: What are the emerging trends in smart farming research? How do these most relevant studies contribute to the advancement of the Sustainable Development Goals? And who are the key actors driving this knowledge production?

2. Methods

2.1. *General Approach*

This research adopted a bibliometric approach aimed at analyzing key actors, collaboration networks, and emerging trends in scientific production on Smart Farming, emphasizing how these contributions support the achievement of the Sustainable Development Goals (SDGs). Widely recognized methods and recommendations in bibliometric studies were applied to ensure rigor and reproducibility [54,55].

2.2. *Data Collection*

The primary data source was the Web of Science Core Collection (WoSCC), one of the most recognized and widely used international databases for analyzing scientific output [56]. The search was conducted on October 17, 2025, using the search vector: {TS=(Smart NEAR/O Farming)}, restricted to records containing the term in the title, abstract, keywords authors or keywords plus.

Inclusion criteria:

- Document type: articles.
- Language: unrestricted (predominantly English).
- Time: unrestricted.
- Thematic coverage: all categories available on the Web of Science Core Collection (WoSCC).

2.3. *Analytical Techniques Applied*

The analytical process was structured into four main dimensions: scientific productivity, academic impact, scientific networks, and relation to the SDGs.

2.3.1. Scientific Growth

The Price's Law was applied to analyze the exponential (J) or logistic (S) growth of science by evaluating the annual increase in the number of publications as an indicator of a consolidated critical

mass of knowledge in the field. These laws also explain scientific obsolescence by dividing the bibliographic corpus into two semi-periods based on the chronological median, distinguishing between contemporary and obsolete literature, and identifying classic works recognized for their lasting influence and high citation rates [57–59].

2.3.2. Scientific Productivity

Bradford's law, his study concentrates on the journals, mainly in what is known as Bradford's core, the smallest subset of journals that manages to concentrate one third of the total number of documents studied. The subsets that manage to concentrate the other thirds of documents according to their increasing order in number of journals are known as zones 1 and 2. Although all the attention is focused on the Bradford core for being the production environment that tends to congregate the most specialized authors, reviewers, and editors in a specific topic of study [60,61].

In the other hand, Authors with the highest number of publications in Smart Farming were identified which prolific authors. To estimate the concentration of production, Lotka's Law [62] was applied, which posits that a small proportion of authors produce most published works.

2.3.3. Academic Impact

The Hirsch index (h-index) was used to measure researcher impact, allowing for the simultaneous evaluation of productivity and scientific influence [63,64]. This method helped identify the most influential authors and research groups in the field by citations of published documents. Additionally, the SDG classification from the Web of Science was used to determine the extent to which Smart Farming studies contribute to global sustainability goals, offering insights into their social, environmental, and policy relevance.

2.3.4. Relationships and Scientific Networks

Network analysis was used to explore the relational structure of the scientific community through keyword co-occurrence networks: to characterize thematic organization and its temporal evolution [65].

2.3.5. Relationship between Academic Impact and Sustainable Development Goals

The selection of the 30 most cited articles on the topic of *Smart Farming* is grounded in the principles of classical bibliometrics, which recognize that the most frequently cited works represent the primary centers of influence and the consolidation of scientific knowledge. This approach enables the identification of the conceptual and methodological cores that have guided the evolution of the smart farming field, in accordance with [54], who note that the most cited articles form the foundation of the central intellectual structures of a scientific discipline. Considering the effects of Smart Farming, it is assumed that the most frequently linked SDGs are SDG 9 (Industry, Innovation, and Infrastructure), SDG 2 (Zero Hunger), and SDG 13 (Climate Action), although this relationship must be analyzed rigorously.

2.4. Analytical Procedure

Classical bibliometric laws were applied: Price's Law describing exponential or logistic growth and obsolescence [57–59]; Lotka's Law explaining unequal productivity distribution among authors [62]. Zipf's Law analyzing the frequency of keyword usage [65]. Hirsch's h-index evaluating the relationship between productivity and impact [63,64]. and Bradford's Law [60,66,67] assessing journal dispersion. Together, these models contextualized the results, supporting the identification of epistemic communities and strategic actors in Smart Farming research.

Software tools used:

- VOSviewer (v.1.6.19): for network analyses (co-authorship, keyword co-occurrence) and visualization of thematic clusters.

- Microsoft Excel 365: for applying Price’s, Bradford’s, and Lotka’s laws and graphically representing annual publication trends.
 - SPSS (v.23): for generating adjusted models for applying Price’s, exponential fit and S fit.
- Data visualization was conducted using VOSviewer [68], a tool specialized in mapping bibliometric networks, generating visual representations of authors, institutions, keywords, and emerging topics. This facilitated the identification of thematic clusters, high-knowledge density zones, and patterns of international collaboration.

2.5. Study limitations

This analysis was limited to documents indexed in the Web of Science Core Collection (WoSCC). Although a high degree of overlap exists between WoS, Scopus, and Google Scholar, differences in regional coverage may affect the results. Integrating multiple sources presents methodological challenges such as duplication, inconsistent coverage, and citation discrepancies [69–71]. Additionally, the bibliometric approach, being quantitative and descriptive, does not address the qualitative or interpretative dimensions of content, which are typically examined through systematic reviews [72].

Table 1 analyzed corpus comprises 1,580 articles published between 1983 and 2025, distributed across 582 scientific sources and authored by 6,244 researchers. The bibliometric analysis applied Price’s, Bradford’s, Lotka’s, and Zipf’s Laws, as well as Hirsch’s h-index, revealing classical patterns of growth, dispersion, and scientific productivity.

Table 1. Description of the analyzed bibliographic corpus.

Variable	Value / Sample (n)	Unit of Analysis	Subsampling criterion
Time period	1983 – 2025	Years	Price’s Law
Sources analyzed	582	Journals / Sources	Bradford’s Law
Authors identified	6244	Researchers	Lotka’s Law
Documents total	1580	Scientific articles	Hirsch’s index (h-index)
Keywords Plus	6337	Terms	Zipf’s Law

3. Results

3.1. Scientific Growth

The bibliometric search identified a total of 1,580 articles on smart farming published between 1983 and 2025. During the first period (1983–2013), scientific output remained limited, with only nine articles published at an irregular rate of zero to two per year. However, starting in 2014, there was a significant change, with no more years with blank results, and 1,571 publications produced up to 2025, evidence of a strong boom in research in the field of smart farming. (See Figure 1)

Consequently, scientific production exhibits exponential growth, fitting Price’s Law with an adjustment coefficient (R^2) of 92.7%, confirming the rapid expansion of knowledge in *Smart Farming* within the broader digital transformation of agri-food systems. The contemporaneous semi period is dated between 2023 and 2025, 55% of the total studies were published, driven by post-pandemic digitalization and the widespread use of IoT, Artificial Intelligence (AI), and cyber-physical systems. Thus, knowledge about smart farming is renewed every three years.

Although publications increased from 9 in 2017 to 300 in 2024, representing growth of more than 3200%, this reflects an acceleration in the study of this topic and the renewal of current theoretical and methodological frameworks. The slowdown in the curve over the last three full years has led us to analyze the growth of the S curve, for which there is also an excellent degree of fit ($R^2 = 92.8\%$), reflecting the proximity to reaching maturity in the field and the presumed consolidation of scientific networks (See Table 2) [57–59].

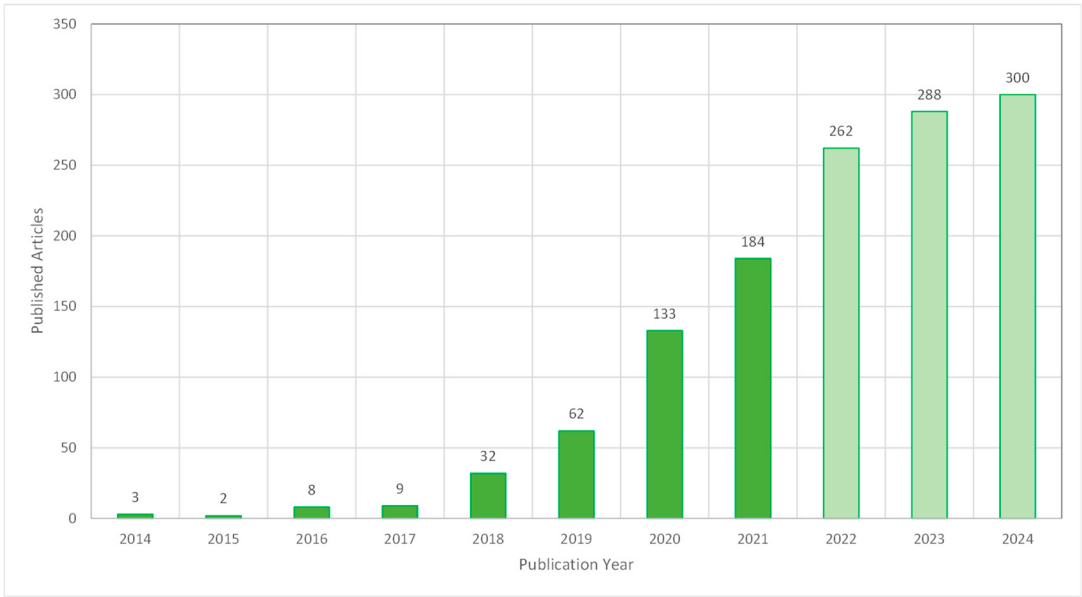


Figure 1. Published articles in WoSCC on Smart Farming (1983–2025).

The bars represent the total number of articles published on Smart Farming each year, with the lighter colored bars corresponding to the contemporary half-period.

Both models presented in Table 2 show excellent fit ($R^2 \approx 0.93$), with very high correlations and robust statistical significance ($p < 0.001$). The exponential model indicates continuous growth in published articles based on the year of publication, describing a dynamic of accelerated expansion with no upper limit. In contrast, the S model introduces a saturation behavior: although initial growth is rapid, it tends to stabilize around a maximum value (reflected in the constant of 1120.495). The difference in coefficients reflects this logic: the exponential depends directly on PY, while the S depends on the inverse transformation ($1/PY$), capturing the slowdown in growth. In practical terms, both models fit almost equally well, but the S model offers a more realistic interpretation in contexts where there is a natural or institutional limit to academic production.

Table 2. Description of the analyzed bibliographic corpus.

Statistic	Exponential Model	Logistic (S) Model
R	0.967	0.967
R ²	0.934	0.935
Adjusted R ²	0.927	0.928
Std. Error of Estimate	0.512	0.510
F (ANOVA)	128.279	129.186
Sig. (ANOVA)	0.000	0.000
Predictor Coefficient	B = 0.553 (PY)	B = -2,254,803 (1/PY)
Constant	0.000	1120.495
Dependent Variable	ln(ART)*	ln(ART)*

* ln is natural logarithm.

3.2. Scientific Productivity

These articles were published in 582 journals (See Table 3), though in low concentration. The publications are grouped primarily within nine core journals, as detailed in the Bradford Zone below.

Table 3. Bradford’s Zones.

Zone	Number of articles	%	Journals	%	Bradford multipliers	Journals
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			(Empirical series)		(Theoretical series)	
Nucleus	512	32%	13	2%		$9 \times (n^0) = 9$
Zone 1	523	33%	98	17%	$7.54 = 98/13$	$9 \times (n^1) = 68$
Zone 2	545	34%	471	81%	$4.81 = 471/98$	$9 \times (n^2) = 516$
Total	$\Sigma = 1.580$	100%	$\Sigma = 582$	100%	$n = 6.17$	$\Sigma = 588$

% error (e_p) = -1.85%
The percentage error between empirical and theoretical series is expressed by Equation 1 (ec. 1).
$$e_p = \left(\frac{\text{Empirical} - \text{Theoretical}}{\text{Empirical}} \right) * 100 = \left(\frac{582 - 588}{582} \right) * 100 = -1.03\% \quad [\text{ec. 1}].$$

Table 4. Journals in the Bradford nucleus.

Journals	Articles	Citations , WoS Core	JIF 2024 (WoS)	Quartile of impact (Qx)
Sensors	75	1.836	3.5	Q1
Computers and Electronics in Agriculture	69	2.947	15.1	Q1
IEEE Access	60	1,968	3.6	Q1
Smart Agricultural Technology	50	475	5.7	Q1
Sustainability	48	688	3.3	Q1
Agriculture-Basel	45	734	3.6	Q1
Agronomy-Basel	37	743	3.4	Q1
Applied Sciences-Basel	34	433	2.5	Q1
IEEE Internet of Things Journal	24	1312	8.9	Q1
Animals	20	208	2.7	Q1
Scientific Reports	18	84	3.9	Q1
Multimedia Tools and Applications	17	336	3.7	Q1
Frontiers in Plant Science	15	278	4.8	Q1

* JIF: Journal Impact Factor.

The 1,580 articles analyzed were produced by 6,244 authors. According to Lotka’s Law, authorship distribution follows an exponential pattern with a coefficient of determination (R^2) exceeding 99%, confirming a prolific concentration of contributors. Applying Lotka’s model [62] and complementing it with the Hirsch index (h-index) [63], an approximate calculation of prolific authors ($\sqrt{6,244} = 80$) revealed that 75 authors had published four or more articles, as shown in Figure 2.

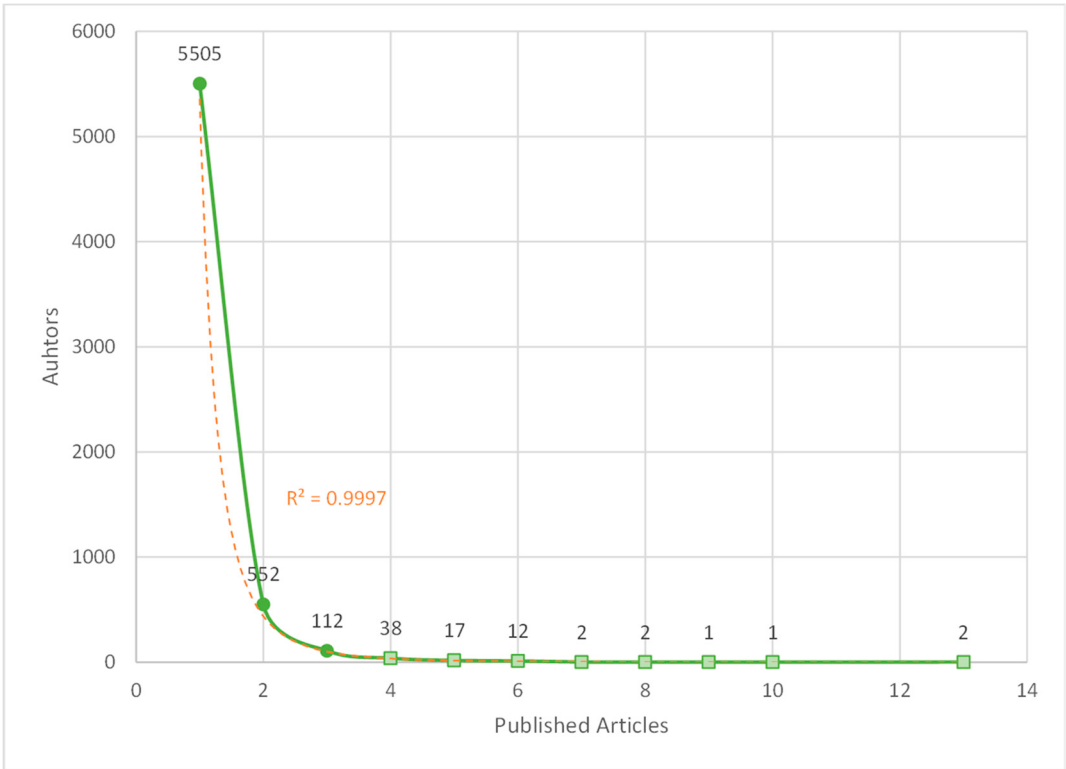


Figure 2. Prolific authors in Smart Farming research.

The green line represents the number of authors per number of published articles, while the light green squares above the green line show authors with four or more articles (75 authors). The segmented orange line is the fit to the potential decay curve with an R^2 of 99.97%.

3.3. Academic Impact

The Hirsch index ($h = 79$) indicates that 79 articles have received at least 79 citations each, demonstrating a high concentration of scientific impact within a relatively small corpus of publications. The total 31,205 citations recorded in Smart Farming research confirm the existence of seminal works that have driven theoretical and methodological development in the field. The cumulative citation growth curve (blue) and the scientific production curve (orange) show an ascending, divergent trend, suggesting the field's maturation and the consolidation of highly influential research clusters [63]. (See figure3.)

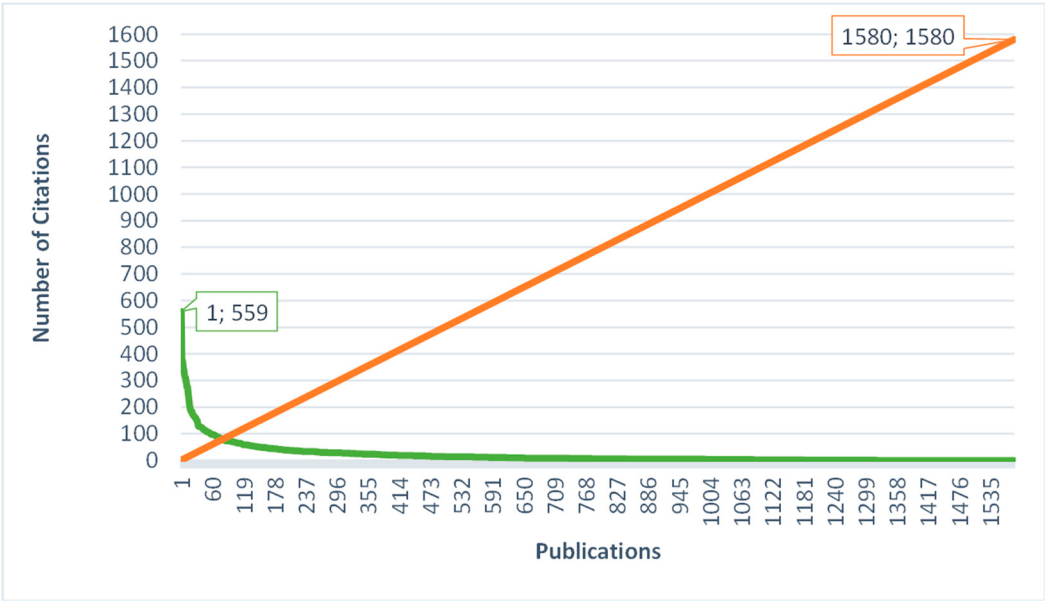


Figure 3. Prolific concentration of contributors.

The green line represents the number of citations per number of published articles (from 559 to 0). The orange line is the sum of the count of articles from 1 to 1580.

In addition to the traditional citation-based impact resulting from recognition by the international scientific community, publications on Smart Farming are catalogued by WoS according to their impact in contributing new knowledge to the advancement of the SDGs. Thus, 1,217 articles (77% of 1,580) are associated by WoS (Clarivate) with between one and six SDGs. These contributions, without discounting duplicate contributions in Figure 4.

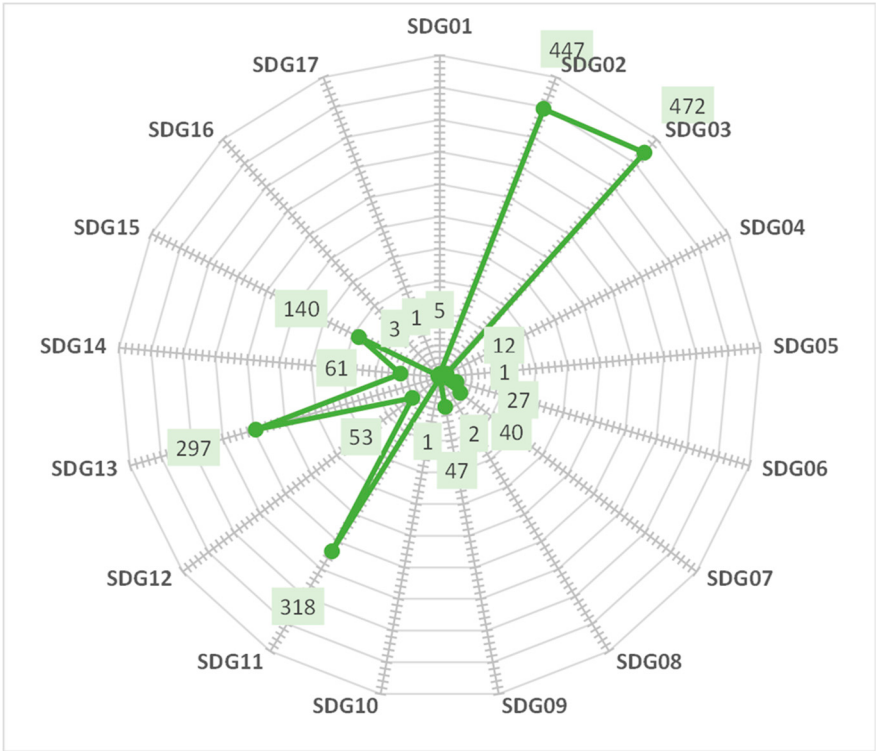


Figure 4. Prolific concentration of contributors.

3.4. Relationships and Scientific Networks

In the Keyword Co-occurrence Analysis conducted across 1,580 articles, a total of 4,822 Authors Keywords (AKW) were identified. Applying the square root method ($\sqrt{4.822}$), 76 AKW with a minimum of 10 occurrences were selected for analysis. Thus, the graph in Figure 5 illustrates an interdisciplinary map showing how contemporary agriculture is being transformed through the integration of emerging technologies. Each cluster represents a complementary dimension of the agro-technological ecosystem, from physical infrastructure to digital governance and sustainability in Smart Farming research.

Five well-defined sectoral clusters emerged:

a. The red cluster (Technological Transformation of Agriculture), which articulates the central concepts that define the paradigm of smart agriculture, with key terms such as smart farming, precision agriculture, digital agriculture, agriculture 4.0, technology adoption, artificial intelligence. This cluster represents the conceptual core of technological change in agriculture, highlighting the evolution towards automated systems based on data and algorithms. In terms of relationships, it connects with all other clusters, functioning as a coordinating hub.

b. The blue cluster (Sensory Infrastructure and Connectivity), a group that focuses on devices and systems that enable real-time data collection, with key terms such as: Internet of Things (IoT), smart agriculture, sensors, monitoring, real-time systems. This cluster provides the operational basis for the implementation of smart agriculture, facilitating continuous observation of the agricultural environment. In terms of its relationships, it is closely linked to the green cluster (analysis) and the red cluster (transformation).

c. The green cluster (Visual and Analytical Processing), a group that highlights the tools of analysis and computational perception applied to agriculture, with key terms such as computer vision, remote sensing, data analytics, smart farm, agriculture. This cluster allows images, satellite data, and metrics to be interpreted to make accurate agronomic decisions. Thematically, it acts as a bridge between infrastructure (blue) and strategic decision-making (yellow).

d. The yellow cluster (Sustainability and optimization), a group that introduces the environmental and energy efficiency dimension into the agricultural system, with key terms such as sustainability, climate change, energy efficiency, feature selection, data analysis. This cluster incorporates sustainability and algorithmic optimization criteria into agricultural management. Its terms are connected to data processing (green) and the strategic core (red).

e. The purple cluster (Digital Infrastructure and Cybersecurity), a group that addresses the technical aspects of data management and system protection, with key terms such as security, authentication, privacy, edge computing, and cloud computing. This cluster focuses on ensuring the integrity, privacy, and efficiency of data processing in distributed environments. It is a cluster that is linked to all clusters, especially the blue (sensors) and green (analysis) clusters.

This distribution evidence the interdisciplinary nature of Smart Farming research, integrating management, technology, and sustainability perspectives.

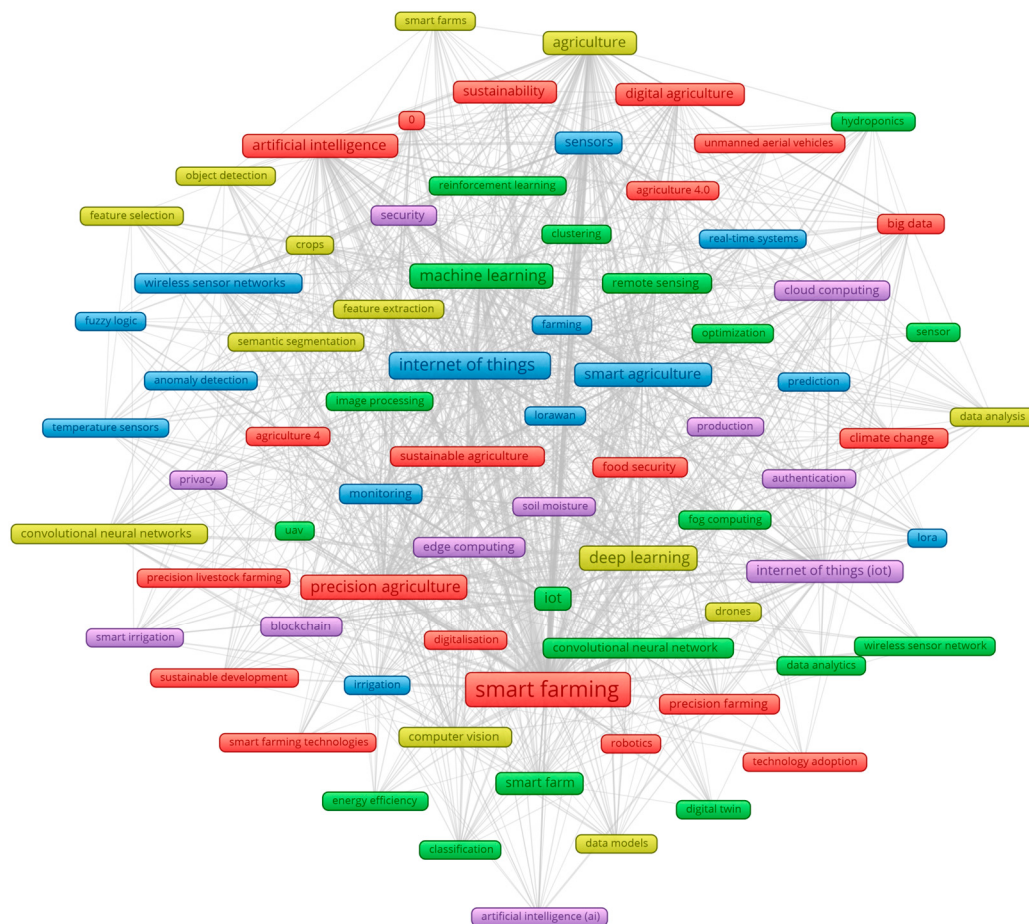


Figure 5. Keyword co-occurrence network in Smart Farming research.

3.5. Relationship between Academic Impact and Sustainable Development Goals

Finally, the connection between Smart Farming research and the Sustainable Development Goals (SDGs) was evaluated (See Table 5). The results show that the most strongly impacted SDGs are:

- a. SDG 2: Zero Hunger (447 articles), demonstrating Smart Farming's contribution to productivity, food security, and agricultural sustainability.
- b. SDG 3: Good Health (472 articles) is strongly represented, driven by research reducing chemical inputs, improving food quality and traceability, and enhancing safety through automation.
- c. SDG 11: Sustainable cities and communities (318) where Smart Farming technologies such as vertical farming, urban agriculture systems, and controlled environment agriculture support sustainable urban development and resilient food systems.
- d. SDG 13: Climate Action (297 articles), reflecting the growing interest in mitigating climate change through resilient, low-emission agricultural practices.
- e. SDG 15: Life on Land (140 articles), highlighting the field's strong orientation toward digitalization, automation, and technological innovation in agriculture.

Table 5. Distribution of Smart Farming research according to the Sustainable Development Goals (SDGs).

SDG	Published Articles *	SDG	Published Articles *
SDG 1	5	SDG 10	1
SDG 2	447	SDG 11	318

SDG 3	472	SDG 12	53
SDG 4	12	SDG 13	297
SDG 5	1	SDG 14	61
SDG 6	27	SDG 15	140
SDG 7	40	SDG 16	3
SDG 8	2	SDG 17	1
SDG 9	47		

* Included duplicate counting.

The data presented in Table 5 illustrate the comprehensive contribution of Smart Farming to the SDGs, confirming its interdisciplinary and cross-sectoral nature in promoting global sustainability and digital innovation in agriculture.

The analysis of the thirty most cited papers (See Table 6) shows a pattern that is consistent with the overall distribution of the 1,580 articles analyzed. These highly influential publications reveal a strong alignment with the most impacted SDGs. A substantial portion of the studies highlight Smart Farming’s contribution to SDG 2 (Zero Hunger, 447 articles) through advances in yield prediction, detection of pests and diseases, precision irrigation, and resource-efficient production systems.

These innovations strengthen food security, enhance productivity, and support sustainable agroecosystems particularly for smallholder farmers. Likewise, SDG 3 (Good Health 472 articles) emerges strongly due to research focused on reducing chemical inputs, improving food traceability, and enhancing occupational safety through automation, sensing technologies, and early warning systems. A significant contribution is also observed in SDG 11 (Sustainable Cities and Communities, 318 articles), where technologies such as urban agriculture, vertical farming, and controlled environment agriculture support resilient food systems and sustainable urban development. Although less frequent, SDG 13 (Climate Action, 297 articles) reflects growing scientific interest in climate-smart agriculture, emissions reduction, and adaptive technologies designed to strengthen resilience to climate variability.

Finally, SDG 15 (Life on Land, 140 articles) captures research linked to biodiversity protection, soil conservation, and sustainable land-use practices supported by sensor networks, monitoring systems, and precision management tools. Overall, these findings demonstrate that Smart Farming research not only accelerates agricultural digitalization but also positions sustainability, food security, public health, and climate resilience as interconnected pillars of global agricultural development.

Discussion

The bibliometric analysis of 1,580 articles demonstrates that *Smart Farming* has become a strategic scientific field within the digital transformation of the agri-food sector. Scientific production shows sustained exponential growth, with more than 90% of studies published between 2017 and 2025, in accordance with Price’s Law [57], confirming the rapid expansion of knowledge and the maturation of the field [73,74]. This growth has been driven by the technological convergence of the Internet of Things (IoT), Artificial Intelligence (AI), machine learning, and big data analytics, which have redefined efficiency, sustainability, and resilience in agricultural systems [24,75].

The distribution of authors, consistent with Lotka’s Law, reveals a consolidated scientific structure characterized by international collaboration and a concentration of knowledge within highly productive research core [76]. As noted by Armenta-Medina et al. [73], this pattern reflects the existence of an active and expanding academic community, supported by global networks focused on applied research and technological innovation, which fosters knowledge transfer between developed and emerging regions. Moreover, the concentration of publications in high-impact Q1 journals such as Sensors, Computers and Electronics in Agriculture, and IEEE Access confirms the scientific maturity, international relevance, and growing visibility of the *Smart Farming* field [24].

Citation patterns, as measured by the h-index (79), reveal a highly influential scientific community. The existence of articles with over 30,000 citations indicates the presence of seminal works that have shaped the theoretical and methodological foundations of the field [74,75]. This high citation rate suggests that Smart Farming has evolved from an emerging trend into a consolidated discipline that integrates science, technology, and innovation with a clear orientation toward sustainability.

Smart Farming research shows a strong alignment with the Sustainable Development Goals (SDGs). SDG 3 (Good Health) is the most represented, with 472 articles addressing reductions in chemical inputs, improved food quality, and safer agricultural environments through automation and sensing technologies [77,78]. SDG 2 (Zero Hunger) follows, with 447 studies focused on precision agriculture, predictive models, and automated irrigation, all contributing to food security and resource optimization [79,80]. SDG 13 (Climate Action) is supported by 297 publications examining climate-smart agriculture, energy efficiency, and emission-reducing technologies [81–83]. Collectively, these findings confirm that Smart Farming acts as a multidimensional driver of sustainable development, simultaneously advancing food security, public health, and climate resilience.

Table 6. Characterization of Smart Agriculture and its relationship with the Sustainable Development Goals.

Authors	Journals	Article Title	DOI	Times Cited	SDGs	Brief conclusions studies
Hartman et al., 2018 [84]	Microbiome	Cropping practices manipulate abundance patterns of root and soil microbiome members paving the way to smart farming	10.1186/s40168-017-0389-9	559	2, 13, 14, 15	Evidence suggests microbiome-targeted cropping can enhance soil health and sustainable yields; targeted practices may enable resilient, low-input production through strategic microbial management.
Cabreira et al., 2019 [85]	Drones-Basel	Survey on Coverage Path Planning with Unmanned Aerial Vehicles	10.3390/drones3010004	384	11	UAV coverage-path planning improves monitoring efficiency and resource-use, enabling precise interventions that reduce inputs and environmental footprint.
Farooq et al., 2019 [86]	IEEE Access	A Survey on the Role of IoT in Agriculture	10.1109/ACCESS	376	3, 11	IoT architecture facilitates

		for the Implementation of Smart Farming	S.2019.2 949703			continuous farm monitoring, supporting water and input efficiency while requiring security measures to protect data integrity.
Muangprathub et al., 2019 [87]	Comput. Electron. Agric.	IoT and agriculture data analysis for smart farm	10.1016/ j.compa g.2018.1 2.011	36	3, 11	Low-cost WSN- based irrigation control optimizes water use, reduces costs, and increases productivity, promoting sustainable vegetable production via automated decision- making.
Maddikunta et al., 2021 [3]	IEEE Sens. J.	Unmanned Aerial Vehicles in Smart Agriculture: Applications, Requirements, and Challenges	10.1109/ JSEN.20 21.3049 471	348	11	Affordable Bluetooth-enabled UAVs and sensors could democratize precision monitoring, lowering barriers and enabling sustainable smallholder uptake.
Rose & Chilvers 2018 [88]	Front. Sustain. Food Syst.	Agriculture 4.0: Broadening Responsible Innovation in an Era of Smart Farming	10.3389/ fsufs.20 18.0008 7	340	2	Responsible innovation frameworks are essential to ensure smart technologies advance sustainability without marginalizing farming communities.
Nevavuori et al., 2019 [46]	Comput. Electron. Agric.	Crop yield prediction with deep convolutional neural networks	10.1016/ j.compa g.2019.1 04859	318	13, 15	CNN-based UAV yield prediction supports precise input allocation and improved forecasting, enhancing resource efficiency and sustainable decision-making.
Wan & Goudos, 2020	Comput. Netw.	Faster R-CNN for multi-class fruit	10.1016/ j.comne	313	3	Deep-learning fruit detection enables

[89]		detection using a robotic vision system	t.2019.1 07036			autonomous harvesting and accurate yield mapping, reducing labor needs and postharvest losses for sustainable production.
Ahmed et al., 2018 [90]	IEEE Internet Things J.	Internet of Things (IoT) for Smart Precision Agriculture and Farming in Rural Areas	10.1109/JIOT.2018.2879579	311	3, 11	Fog-empowered IoT reduces latency and improves rural connectivity, enabling reliable, energy-efficient monitoring for sustainable farm management.
Verdouw et al., 2021 [4]	Agric. Syst.	Digital twins in smart farming	10.1016/j.agry.2020.103046	300	9,12	Digital Twins enable scenario testing and remote control, improving resource optimization and sustainability across diverse farming systems.
Wazid et al., 2018 [91]	IEEE Internet Things J.	Design of Secure User Authenticated Key Management Protocol for Generic IoT Networks	10.1109/JIOT.2017.2780232	287	3,11	Secure hierarchical IoT authentication strengthens data trustworthiness, a prerequisite for sustainable, data-driven agricultural decisions.
Finger et al., 2019 [92]	Annu. Rev. Resour. Econ.	Precision Farming at the Nexus of Agricultural Production and the Environment	10.1146/annurev-resour-e-100518-093929	275	2	Multi-layered cybersecurity strategies are critical to maintain resilient, trustworthy IoT ecosystems that underpin sustainable precision agriculture.
Gupta et al., 2020 [5]	IEEE Access	Security and Privacy in Smart Farming: Challenges and Opportunities	10.1109/ACCESS.2020.2975142	275	3, 11	Precision farming reduces input waste and environmental externalities, justifying policy support to democratize benefits for smallholders.

Zamora-Izquierdo et al., 2019 [93]	Biosyst. Eng.	Smart farming IoT platform based on edge and cloud computing	10.1016/j.biosystemseng.2018.10.014	248	3, 11	Open-source, low-cost platform for soilless greenhouses enables sustainable, resilient hydroponic production using edge-cloud orchestration and adaptive control.
Sa et al., 2018 [94]	IEEE Robot. Autom. Lett.	weedNet: Dense Semantic Weed Classification Using Multispectral Images and MAV for Smart Farming	10.1109/LRA.2017.2774979	241	3	Dense semantic weed classification with MAVs enables selective herbicide application, greatly reducing chemical use and environmental impact.
Jakku et al., 2019 [95]	NJAS-Wagen. J. Life Sci.	If they don't tell us what they do with it, why would we trust them? Trust, transparency and benefit-sharing in Smart Farming	10.1016/j.njas.2018.11.002	218	2	Socio-technical analyses reveal trust and data governance as central to equitable, sustainable big-data agriculture adoption.
Caffaro et al., 2020 [7]	J. Rural Stud.	Drivers of farmers intention to adopt technological innovations in Italy: The role of information sources, perceived usefulness, and perceived ease of use	10.1016/j.jrurstud.2020.04.028	206	2	Farmers' technology acceptance depends on perceived usefulness; tailored extension and credible information sources accelerate sustainable SFT uptake.
Jayaraman et al., 2016 [96]	Sensors	Internet of Things Platform for Smart Farming: Experiences and Lessons Learnt	10.3390/s16111884	193	3, 11	IoT-enabled crop performance platforms automate data collection and personalized recommendations, improving resource efficiency and adaptive management.
Wiseman et al., 2019 [97]	NJAS-Wagen. J. Life Sci.	Farmers and their data: An examination of farmers' reluctance to share their data through the lens of the laws impacting smart farming	10.1016/j.njas.2019.04.007	185	2	Deep-learning vineyard disease detection drastically reduces chemical usage by enabling targeted treatments, supporting

							sustainable viticulture.
Kerkech et al., 2020 [10]	Comput. Electron. Agric.	Vine disease detection in UAV multispectral images using optimized image registration and deep learning segmentation approach	10.1016/j.compag.2020.105446	185	13, 15		Lack of transparent data governance undermines farmer trust; robust policies and governance frameworks are essential for sustainable digital agriculture.
Jiang et al., 2020 [98]	Comput. Electron. Agric.	CNN feature based graph convolutional network for weed and crop recognition in smart farming	10.1016/j.compag.2020.105450	184	3		GCN-based weed recognition with limited labels supports affordable, accurate field automation, decreasing herbicide use and environmental harm.
Saggi & Jain 2019 [99]	Comput. Electron. Agric.	Reference evapotranspiration estimation and modeling of the Punjab Northern India using deep learning	10.1016/j.compag.2018.11.031	175	6,13,14		H2O ensemble models accurately estimate evapotranspiration, enabling water – efficient irrigation scheduling and sustainable water management.
Kernecker et al., 2020 [8]	Precis. Agric.	Experience versus expectation: farmers' perceptions of smart farming technologies for cropping systems across Europe	10.1007/s11119-019-09651-z	173	2		SFT adoption varies by farm context; inclusive co-design and impartial advice improve relevance and sustainability across diverse farms
Alonso et al., 2020 [6]	AD HOC NETW	An intelligent Edge-IoT platform for monitoring livestock and crops in a dairy farming scenario	10.1016/j.adhoc.2019.102047	169	3,11		IoT, edge, and blockchain integration enhance traceability and resource optimization, improving dairy farm sustainability and food-chain transparency.
Sanchez-Iborra et al., 2018 [100]	Sensors	Performance Evaluation of LoRa Considering Scenario Conditions	10.3390/s18030772	168	3,11		LoRa WAN performance studies guide low-power network deployment,

						enabling scalable, energy-efficient monitoring for sustainable rural IoT applications
Sozzi et al., 2022 [101]	Agronomy-Basel	Automatic Bunch Detection in White Grape Varieties Using YOLOv3, YOLOv4, and YOLOv5 Deep Learning Algorithms	10.3390/agronomy12020319	163	3	YOLO object detection for grapes supports real-time yield estimation, enabling efficient resource planning and reduced waste.
Bhat et al., 2021 [49]	IEEE Access	Big Data and AI Revolution in Precision Agriculture: Survey and Challenges	10.1109/ACCESS.2021.3102227	162	2	Big Data and ML applications can improve decision-making and sustainability, but social, economic, and policy barriers must be addressed.
Subeesh et al., 2021 [102]	Artif. Intell. Agric.	Automation and digitization of agriculture using artificial intelligence and internet of things	10.1016/j.aiia.2021.11.004	160	3,11	Integrated IoT–AI farm machinery accelerates automation, boosting productivity while demanding responsible governance to ensure sustainability and equity.
Carolan, 2020 [103]	J. Peasant Stud.	Automated agrifood futures: robotics, labor and the distributive politics of digital agriculture	10.1080/03066150.2019.1584189	156	2	Wind-energy–harvesting nanogenerators enable self-powered sensors, supporting autonomous, low-footprint monitoring and sustainable farm electrification.
Eastwood et al., 2019 [104]	J. Agric. Environ. Ethics	Managing Socio-Ethical Challenges in the Development of Smart Farming: From a Fragmented to a Comprehensive Approach for Responsible Research and Innovation	10.1007/s10806-017-9704-5	151	2	Responsible Research and Innovation (RRI) adoption in smart dairying promotes socially inclusive, ethically grounded technological development for sustainable livestock systems.

5. Conclusions

This bibliometric study provides a comprehensive overview of the evolution, productivity, and scientific impact of Smart Farming within the framework of the Sustainable Development Goals (SDGs). The findings demonstrate an exponential growth of knowledge, validated by Price's Law, accompanied by a solid collaboration structure consistent with Lotka's Law.

Empirical evidence shows that Smart Farming research has moved from a descriptive phase to a transformative one, where digitalization, automation, and data analytics define a new model of agricultural sustainability. The strong presence of SDG 3 underlines the relevance of technological innovation for safer and healthier food systems, while the links with SDGs 2, 11, and 13 highlight Smart Farming's contribution to food security, sustainable urban development, and climate resilience.

Furthermore, the high concentration of Q1 journal publications and the strong citation performance confirm the maturity and global relevance of the field. This study suggests that public policies, technical training, and international cooperation should focus on promoting the equitable adoption of smart technologies, particularly in developing countries.

In summary, Smart Farming emerges as a bridge between data science, technological innovation, and sustainability, playing a vital role in the transition toward resilient, inclusive, and sustainable agri-food systems.

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