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Review Article

Data-Driven Agriculture: Unveiling the Power of Internet of Things and Data Analytics For Transformative Farming Practices

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As the global population is projected to reach 10 billion by 2050, the urgent need for advanced agricultural technologies becomes increasingly apparent. The Internet of Things (IoT) and data analytics stand at the forefront of this technological revolution, offering unprecedented enhancements in real-time monitoring and decision-making to optimize farm productivity. However, there is a significant gap in the literature regarding the extensive application of IoT and data analytics in agriculture. Using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology, this review carefully examines the current landscape, highlighting the benefits and challenges of integrating IoT and data analytics into agriculture. From an initial pool of 1166 studies identified in Scopus and Web of Science (WoS), 28 pivotal studies were selected. Collectively, these studies provided deep insights into eight major research trends, underscored nine essential benefits, and articulated 14 significant challenges. This review not only proposes five methodologies to evaluate the effectiveness of these technologies but also introduces a robust conceptual model and framework, based on the analyzed literature, designed to guide future research and support the development of innovative and integrated agricultural solutions. As agriculture transitions to a digital and data-driven future, understanding the full spectrum of IoT and data analytics applications becomes crucial. This review addresses the current knowledge gap and provides a foundation for data-informed decision-making to enhance the sustainability and efficiency of agricultural practices.

Keywords: agriculture; big data; data analytics; Internet of Things; systematic review

1. Introduction

As the global population trajectory steers towards an estimated 10 billion by 2050, the agricultural sector faces unprecedented challenges in sustaining a reliable and abundant food supply [1]. This challenge is compounded by environmental degradation, climate change, and the diminishing availability of arable land. These factors threaten global food security, which involves ensuring access to sufficient and nutritious food for all [2, 3]. Projections suggest that food demand could increase by as much as 98%, while agricultural productivity may struggle to keep pace, necessitating a transformation in how food is produced, managed, and distributed.

In this context, smart farming has emerged as a transformative solution, redefining conventional agricultural practices to enhance productivity and efficiency while promoting sustainable development [4]. This evolution in agriculture has increased its complexity, demanding the integration of advanced technologies and sophisticated and data-driven decision-making processes [5]. Central to this is the Internet of Things (IoT), which has revolutionized on-farm operations through real-time monitoring and control of agricultural

Table 1: Comparison of existing works.

Factors	Gómez-Chabla et al. [14]	Farooq et al. [13]	Navarro et al. [15]	Terence and Purushothaman [16]	Present study
Range of years for articles reviewed	2011–2018	2006–2019	2011–2020	2011–2019	2019–2021
Number of search database	4	5	4	10	2
Final set of articles	60	67	159	64	28
Discusses both IoT and data analytics	No	No	No	No	Yes

parameters, facilitating a shift towards a more digital and data-centric approach to farm management [6, 7]. IoT's impact extends beyond individual farms, influencing interconnected sectors within the agriculture–livestock–forestry nexus and contributing to broader ecological and economic sustainability [8].

Furthermore, the current technological landscape in agriculture underscores the growing importance of data analytics [9]. Advanced analytical tools are now indispensable for extracting valuable information from vast data pools, including those generated by IoT systems, enabling evidence-based decision-making that can significantly enhance agricultural productivity and resilience [10]. This shift underscores the need to explore not only the optimization of data analytics within agricultural contexts but also the ethical implications of its use [11]. The authors' prior research supports the view that integrating IoT and data analytics holds immense potential for advancing agricultural practices [12].

Despite these advancements, a notable gap remains in our understanding of the interplay and collective impact of IoT and data analytics in agriculture. While some systematic reviews have explored IoT's applications in agriculture, they often lack a comprehensive examination of how data analytics can be integrated to maximize outcomes. Moreover, existing reviews predominantly focus on literature published before 2020, overlooking recent technological developments that have reshaped the field [13–16]. This gap highlights the need for a comprehensive and current analysis to capture the latest trends and innovations in this rapidly evolving domain. Table 1 presents a comparison between several existing reviews and the current systematic literature review (SLR).

To address this gap, the objective of this systematic review is to provide an in-depth analysis of the current state of IoT and data analytics in agriculture. This review identifies key research trends, benefits, challenges, and evaluation methodologies, offering a road map for future research and policymaking in this field. The findings from this study contribute to developing a conceptual framework that guides the design and implementation of IoT and data analytics systems tailored for agriculture. They aims to foster innovation and enhance user acceptance within the sector.

The research questions in this study are grounded in its purpose and are addressed through the selected studies. The research questions and the rationale behind them are presented in Table 2.

The structure of this study is organized as follows: Section 2 describes the methodology employed in this SLR. Section 3 examines the fundamental concepts underpinning this study. Section 4 presents the findings derived from the SLR. Section 5 discusses these findings. Finally, Section 6 concludes the study and summarizes the key insights and contributions of this research.

2. Research Methodology

This study presents a comprehensive examination of the existing literature on IoT and data analytics in agriculture by conducting a SLR. The review follows the guidelines of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) [17]. This approach was selected because Page et al. [18] reported that evidence from observational studies has demonstrated its effectiveness in producing high-quality systematic reviews. The PRISMA flow diagram in Figure 1 summarizes the systematic review process.

A review protocol, based on the methodology proposed by Krisnawijaya et al. [19], was established before conducting the systematic review. The first step of this protocol involves defining the research questions. Subsequently, the search protocol is defined, which entails the selection of electronic databases and the creation and utilization of search strings to identify relevant academic studies. Once the appropriate studies are identified, they undergo screening and evaluation using a set of selection and exclusion criteria, followed by quality assessments to determine their eligibility. The next step is data extraction, followed by data synthesis and the presentation of the results.

2.1. Search Protocol. Articles with the potential to address the research questions were identified using a systematic search method. This stage, known as the identification phase, is illustrated in the PRISMA diagram in Figure 1. Automated searches were performed on the Scopus and Web of Science (WoS) digital databases. The selection of these two databases was based on their relevance and comprehensive content, which align with the study's objectives. The general syntax or keywords used for the search string in both databases are provided in the query below:

("data analytics" OR "big data") AND ("IoT" OR "Internet of things") AND ("agriculture" OR "farming")

A total of 1166 studies were obtained through the search query, combining the results from Scopus and WoS. Most studies were retrieved from Scopus, totaling 718, compared

Table 2: List of research questions.

Number	Questions	Rationale
RQ1	What are the current trends of research regarding IoT and data analytics in agriculture?	To identify key focus areas and emerging trends, offering valuable insights into the evolving research landscape
RQ2	What are the advantages of utilizing IoT and data analytics in agriculture?	To highlight the benefits of IoT and data analytics in agriculture, deepening understanding of their transformative impact
RQ3	What barriers are present in implementing IoT and data analytics in agriculture?	To outline the obstacles to adopting IoT and data analytics in agriculture, enabling the development of strategies to overcome them
RQ4	How are the effectiveness of IoT and data analytics systems in agriculture evaluated?	To learn how to evaluate the effect these technologies have on agriculture
RQ5	What are future research directions for IoT and data analytics systems in agriculture?	To identify future research and development paths, advancing IoT and data analytics in agriculture

to 448 studies from WoS. The total number of collected studies is shown in Table 3.

2.2. Selection and Exclusion Criteria. The automated search yielded a substantial number of research studies. To identify relevant studies, a set of selection and exclusion criteria was applied, corresponding to the screening and eligibility phase depicted in the PRISMA diagram in Figure 1. The selection criteria define the requirements for including studies, while the exclusion criteria specify the conditions for removing them. The selection criteria are listed in Table 4, and the exclusion criteria are listed in Table 5.

2.3. Screening Process. Initially, duplicate studies in both Scopus and WoS were removed by searching for studies with similar titles. Out of the initial 1166 studies, 883 were identified as unique. The selection and exclusion criteria were then applied using the filters in the digital databases. A publication date filter was applied, selecting only studies from 2019, 2020, and 2021. This time frame was chosen because studies published during these years were expected to contain cutting-edge insights, while those published before 2020 were considered outdated. Due to limited availability as of the time of writing, studies published beyond 2022 were excluded from the review. As a result, only 87 studies remained eligible after applying the filters.

A detailed screening process was then applied to the remaining studies to ensure that only the most relevant and high-quality studies were included in the final review. The process involved initial screening, where the titles and abstracts of the eligible studies were reviewed to assess their relevance to the research questions. Studies that directly discussed IoT and data analytics in agricultural settings were retained, while irrelevant ones were excluded. Full-text screening followed, during which the remaining studies were thoroughly reviewed and evaluated against the selection and exclusion criteria. This stage involved a deeper examination of each study's objectives, methodology, and findings to ensure alignment with the research questions. Studies that lacked clear relevance, methodological rigor, or did not meet the quality standards were excluded.

After applying the selection and exclusion criteria and completing the screening process, 28 studies were chosen, while 55 studies were excluded for various reasons. Ten studies were inaccessible in full text, 19 were unrelated to IoT or data analytics in agriculture, 24 were review studies that did not meet the required document type of a journal article, five were retracted studies, and one was not in English. The selection process is presented in Table 3 and depicted in Figure 1.

2.4. Quality Assessment. The quality of the 28 studies was assessed before the data synthesis phase. The evaluation of the articles was based on a defined set of quality criteria, as cited in [19]. The studies were ranked using a 3-point scale, where a score of one is assigned for meeting the criteria, a score of zero indicates noncompliance, and a score of 0.5 represents partial compliance. Studies scoring below four out of eight were excluded from the analysis. All selected studies achieved a score higher than four, eliminating the need for further exclusion. The quality assessment criteria are presented in Table 6, and the scores assigned to the included studies are displayed in Table 7 and Figure 2.

2.5. Data Extraction. The 28 relevant articles were thoroughly reviewed and analyzed to address the research questions. Summaries of each article were obtained, and data relevant to the research questions were collected for analysis. Key information systematically extracted from each selected study included the study objectives, benefits of IoT and data analytics, challenges in adopting these technologies, methods for evaluating the effectiveness of IoT and data analytics systems, and proposed future research directions.

2.6. Data Synthesis. The data synthesis in this study utilizes umbrella concepts to categorize the diverse data related to IoT and data analytics in agriculture obtained from the data extraction phase, as cited in [19]. After extracting the relevant

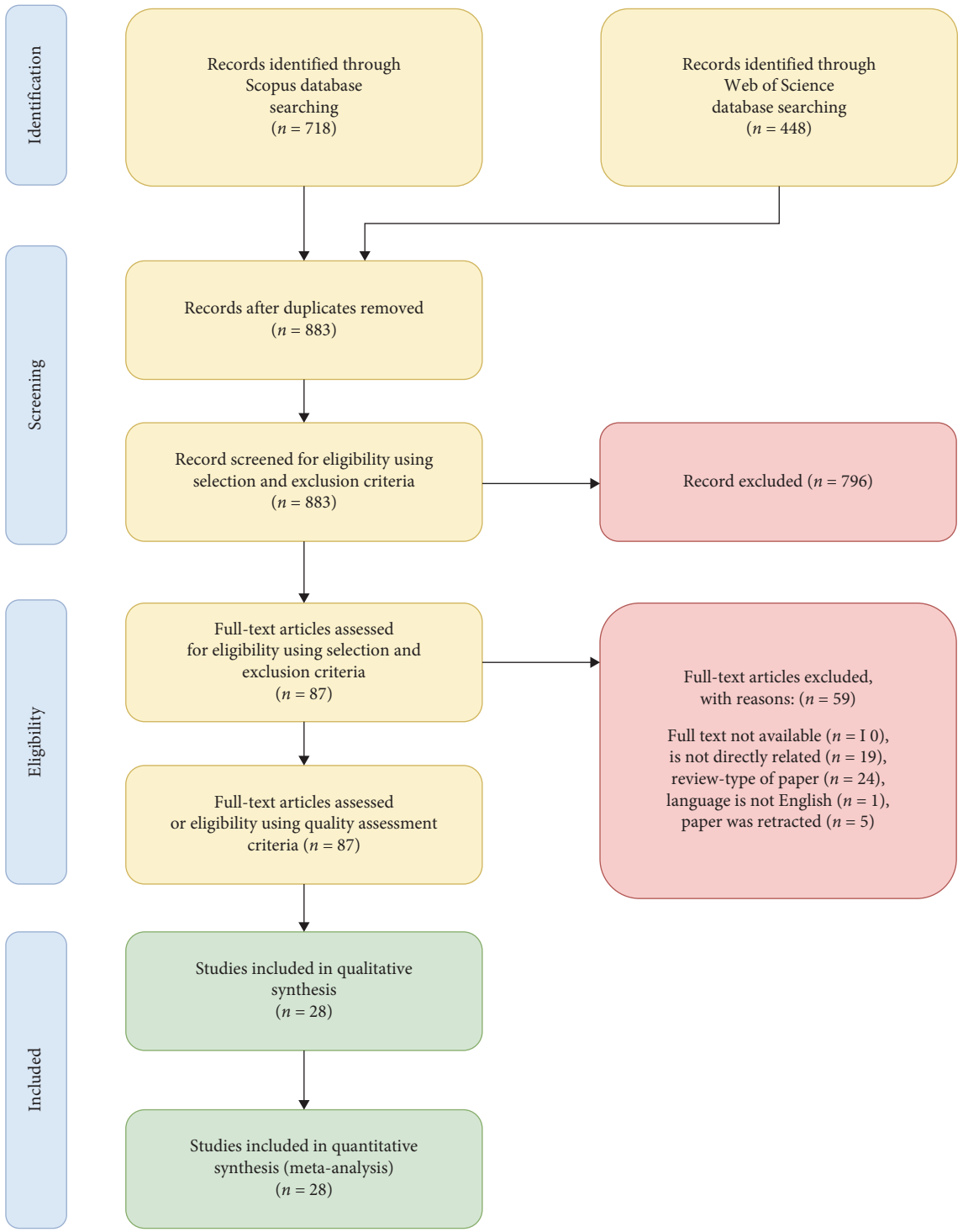

Figure 1: PRISMA flow diagram.

Table 3: Overview of search query result and selection process.

Sources	After automated search	After applying selection criteria
Scopus	718	25
Web of Science (WoS)	448	3
Total	1166	28

Table 4: List of selection criteria.

Number	Criteria
SC1	Studies that are related to IoT or data analytics in agriculture
SC2	Studies with full text available
SC3	Studies written in English
SC4	Studies that are journal articles
SC5	Studies that are in the field of computer science
SC6	Studies that are not retracted
SC7	Studies published in 2019, 2020, or 2021

Table 5: List of exclusion criteria.

Number	Criteria
EC1	Duplicate studies found in both sources
EC2	Studies that are not related to IoT or data analytics in agriculture
EC3	Studies missing full text
EC4	Studies not written in English
EC5	Studies that are not journal articles
EC6	Studies that are not in the field of computer science
EC7	Studies that have been retracted
EC8	Studies published before 2019 or after 2021

Table 6: Quality assessment criteria.

Number	Question	No (0)	Partial (0.5)	Yes (1)
Q1	Aims clearly stated	—	—	—
Q2	Scope and context clearly defined	—	—	—
Q3	Variable valid and reliable	—	—	—
Q4	The research process documented adequately	—	—	—
Q5	All study questions answered	—	—	—
Q6	Negative findings presented	—	—	—
Q7	The main findings clearly stated	—	—	—
Q8	Conclusions relate to the aim of the purpose of the study	—	—	—

information, the studies were grouped under the following umbrella concepts:

- Current trends: The study objectives extracted from each selected study were grouped by similarity and classified as research trends.
- Advantages: Studies reporting similar benefits of using IoT and data analytics systems in agriculture were grouped together under the advantages umbrella.
- Barriers: Studies identifying similar obstacles or challenges in adopting IoT and data analytics in agriculture were grouped under the barriers umbrella.
- Effectiveness evaluation method: Similar methods used by the selected studies to evaluate the effectiveness of IoT and data analytics systems in agriculture were grouped under the effectiveness evaluation umbrella.
- Future research directions: Similar recommendations from the selected studies on how to enhance or expand their current research in IoT and data analytics in agriculture were grouped under the future research directions umbrella.

Each umbrella concept was systematically applied across the selected studies to ensure consistency and clarity in the synthesis process. This structured approach not only provided a clear answer to the research questions but also facilitated the identification of patterns, trends, and gaps in the literature. The resulting synthesis offered a comprehensive overview of the state of IoT and data analytics in agriculture, providing valuable insights for researchers and practitioners alike.

2.7. Publication Statistics. The analysis of publications is instrumental in identifying emerging patterns, geographic disparities, reputable journals, and influential research findings, thereby enhancing the credibility, context, and understanding of the reviewed literature. Table 8 presents the publication details of the studies, including the year of publication, the country of the authors, the journal in which the study was

Table 7: Scores for each studies.

Studies	Criteria score								
	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Total
P1	0.5	1	1	1	1	0	1	1	6.5
P2	0.5	1	0.5	1	1	0.5	1	1	6.5
P3	0.5	1	1	0.5	1	0	0.5	1	5.5
P4	0.5	1	1	1	1	0	1	1	6.5
P5	1	1	1	1	1	0	1	1	7
P6	1	1	1	1	1	0.5	1	1	7.5
P7	1	1	1	0.5	1	0	1	1	6.5
P8	1	1	1	1	1	0	1	1	7
P9	0.5	0.5	1	1	1	0	1	1	6
P10	0.5	1	1	1	0.5	1	1	0.5	6.5
P11	0.5	1	1	1	1	0	1	1	6.5
P12	0.5	1	1	0.5	0.5	0	1	0.5	5
P13	0.5	1	1	1	1	0	1	1	6.5
P14	0.5	1	1	0.5	0.5	0	0.5	1	5
P15	1	1	1	1	0.5	0	0.5	1	6
P16	0.5	1	1	0.5	0.5	0	0.5	1	5
P17	0.5	1	1	0.5	1	0	1	1	6
P18	0.5	1	1	1	1	0	1	1	6.5
P19	0.5	0.5	1	1	1	0	0.5	1	5.5
P20	0.5	1	1	1	1	0	1	1	6.5
P21	1	1	1	1	1	0	1	0.5	6.5
P22	0.5	1	1	1	1	0	1	1	6.5
P23	0.5	1	1	1	1	0	1	1	6.5
P24	1	1	1	1	1	0	1	1	7
P25	0.5	1	1	1	1	0	1	0.5	6
P26	0.5	1	1	0.5	1	0	1	1	6
P27	0.5	1	1	1	1	0	0.5	1	6
P28	1	1	1	1	1	0	1	1	7

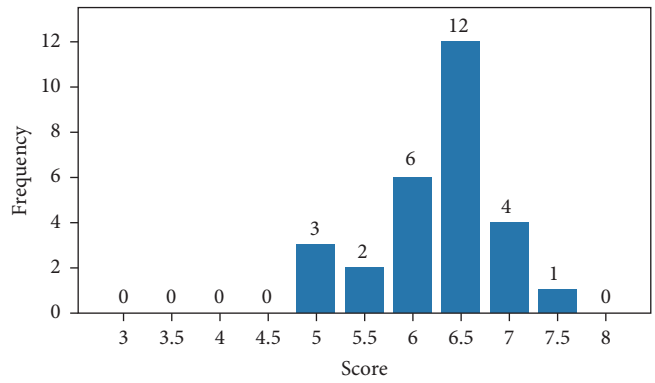

Figure 2: Quality score distribution of chosen literature.

published, and the Scopus cite score. Table 9 provides detailed information on the *h*-index of the authors.

2.7.1. Frequency of Studies Published Year-Wise. The study focused on 28 studies selected from the years 2019, 2020, and 2021. Eleven studies were from 2019, 12 from 2020, and five from 2021. The number of publications increased slightly from 2019 to 2020, but then declined in 2021. This prompts consideration of whether research in this area has declined overtime. Figure 3 depicts the distribution by year of the selected studies from 2019 to 2021.

2.7.2. Frequency of Studies Published Country-Wise. The selected studies were authored by individuals affiliated with

Table 8: Publication details of the studies.

Study	Year published	Country published	Journal published	Scopus cite score
P1	2019	Greece	Information	5.8
P2	2021	China	Journal of Supercomputing	5.4
P3	2020	Mexico	Computers and Electronics in Agriculture	13.6
P4	2021	Morocco	Indonesian Journal of Electrical Engineering and Computer Science	2.9
P5	2021	Bulgaria	Computers	4.7
P6	2021	United States	ACM Transactions on Sensor Networks	6.2
P7	2020	South Korea	Indonesian Journal of Electrical Engineering and Computer Science	2.9
P8	2020	France, Italy, Romania, Switzerland	Sensors	6.8
P9	2020	China	International Journal of Distributed Sensor Networks	6.0
P10	2020	Ireland	Computers and Electronics in Agriculture	13.6
P11	2020	China, India, United States	Symmetry	4.9
P12	2020	Spain	Ad Hoc Networks	12.1
P13	2020	India	International Journal of Cognitive Informatics and Natural Intelligence	1.7
P14	2020	China	Wireless Communications and Mobile Computing	2.3
P15	2019	India	International Journal of Innovative Technology and Exploring Engineering	0.6
P16	2019	India	International Journal of Innovative Technology and Exploring Engineering	0.6
P17	2020	Italy	International Journal of Grid and Utility Computing	1.8
P18	2020	Algeria, Saudi Arabia	IEEE Access	9.0
P19	2020	Brazil, India	Enterprise Information Systems	10.4
P20	2020	Pakistan, Qatar, Saudi Arabia	IEEE Access	9.0
P21	2019	China, Hong Kong, Japan	IEEE Transactions on Industrial Informatics	22.4
P22	2019	South Korea	Multimedia Tools and Applications	6.1
P23	2019	India	International Journal of Innovative Technology and Exploring Engineering	0.6
P24	2019	Ireland	Software: Practice and Experience	6.7
P25	2019	Malaysia	International Journal of Advanced Trends in Computer Science and Engineering	1.2
P26	2019	Taiwan	IEEE Access	9.0
P27	2019	China, United Arab Emirates	IEEE Access	9.0
P28	2019	India	International Journal of Innovative Technology and Exploring Engineering	0.6

Table 9: *H*-index information on the authors of the studies.

Study	Author name	H-index
P1	Anna Triantafyllou	7
	Panagiotis Sarigiannidis	32
	Stamatia Bibi	14
P2	Zhigang Gao	1
	Duchun Wang	3
	Hua Zhou	1
P3	Alejandro Castañeda-Miranda	8
	Victor M. Castaño-Meneses	43
P4	Loubna Rabhi	4
	Noureddine Falih	8
	Lekbir Afraites	10
	Belaid Bouikhalene	14
P5	Galina Ilieva	9
	Tania Yankova	8
	Irina Radeva	8
	Ivan Popchev	14
P6	Qiben Yan	23
	Jianzhi Lou	3
	Mehmet C. Vuran	36
	Suat Irmak	45
P7	Am Suk Oh	5
P8	Titus Balan	7
	Catalin Dumitru	1
	Gabriela Dudnik	7
	Enrico Alessi	10
	Suzanne Lesecq	15
	Marc Correvon	7
	Fabio Passaniti	2
	Antonella Licciardello	2
P9	Chunling Li	1
	Ben Niu	1
P10	Mohit Taneja	9
	John Byabazaire	7
	Nikita Jalodia	5
	Alan Davy	18
	Cristian Olariu	5
	Paul Malone	6
P11	Tai-hoon Kim	32
	Virendra Singh Solanki	1
	Hardik J. Baraiya	1
	Anirban Mitra	6
	Hirav Shah	3
	Sudipta Roy	29
P12	Ricardo S. Alonso	16
	Inés Sittón-Candanedo	12
	Óscar García	7
	Javier Prieto	27
	Sara Rodríguez-González	29
P13	Sowmya B.J.	7
	Krishna Chaitanya S.	2
	Seema S.	5
	K.G. Srinivasa	14
P14	Feng Zhang	10
	Yongheng Zhang	4
P15	Ashok Tatapudi	1
	P. Suresh Varma	5
P16	N. Revathi	2
	P. Sengottuvelan	7
P17	Silvia Angeloni	7
P18	Ahmad F. Subahi	9
	Kheir Eddine Bouazza	6
P19	Bright Keswani	6
	Ambarish G. Mohapatra	12
	Poonam Keswani	3
	Ashish Khanna	49
	Deepak Gupta	45
	Joel J. P. C. Rodrigues	89
P20	Rana M. Amir Latif	7
	Samir Brahim Belhaouari	20
	Saqib Saeed	15
	Laiqa Binte Imran	3
	Mazhar Sadiq	5
	Muhammad Farhan	18
P21	Junhu Ruan	21
	Hua Jiang	8
	Xiaoyu Li	3
	Yan Shi	27
	Felix T. S. Chan	73
	Weizhen Rao	8
P22	Yuha Park	2
	Myung Hwan Na	7
	Wanhyun Cho	7
P23	Ketan Joshi	1
	Swapnil Jain	1
	Ashish Patwari	2
P24	Mohit Taneja	9
	Nikita Jalodia	5
	John Byabazaire	7
	Alan Davy	18
	Cristian Olariu	5
P25	Norshuhani Zamin	6
	Norita Md. Norwawi	10
	Hazeem Ahmad Taslim	1
	Wan Mohd Fadhlullah Wan Mohd Rosdi	1
P26	Fan-Hsun Tseng	18
	Hsin-Hung Cho	12
	Hsin-Te Wu	12
P27	Shubo Liu	7
	Liqing Guo	3
	Heather Webb	3
	Xiao Ya	1
	Xiao Chang	1
P28	Kuldeep P. Sambrekar	1
	Vijay S. Rajpurohit	12

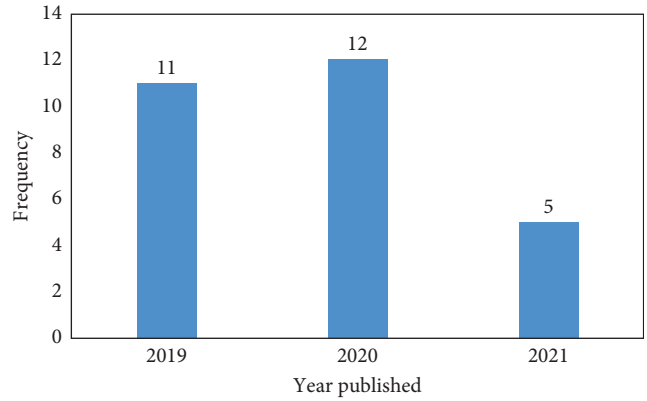

Figure 3: Year of publication of the selected studies.

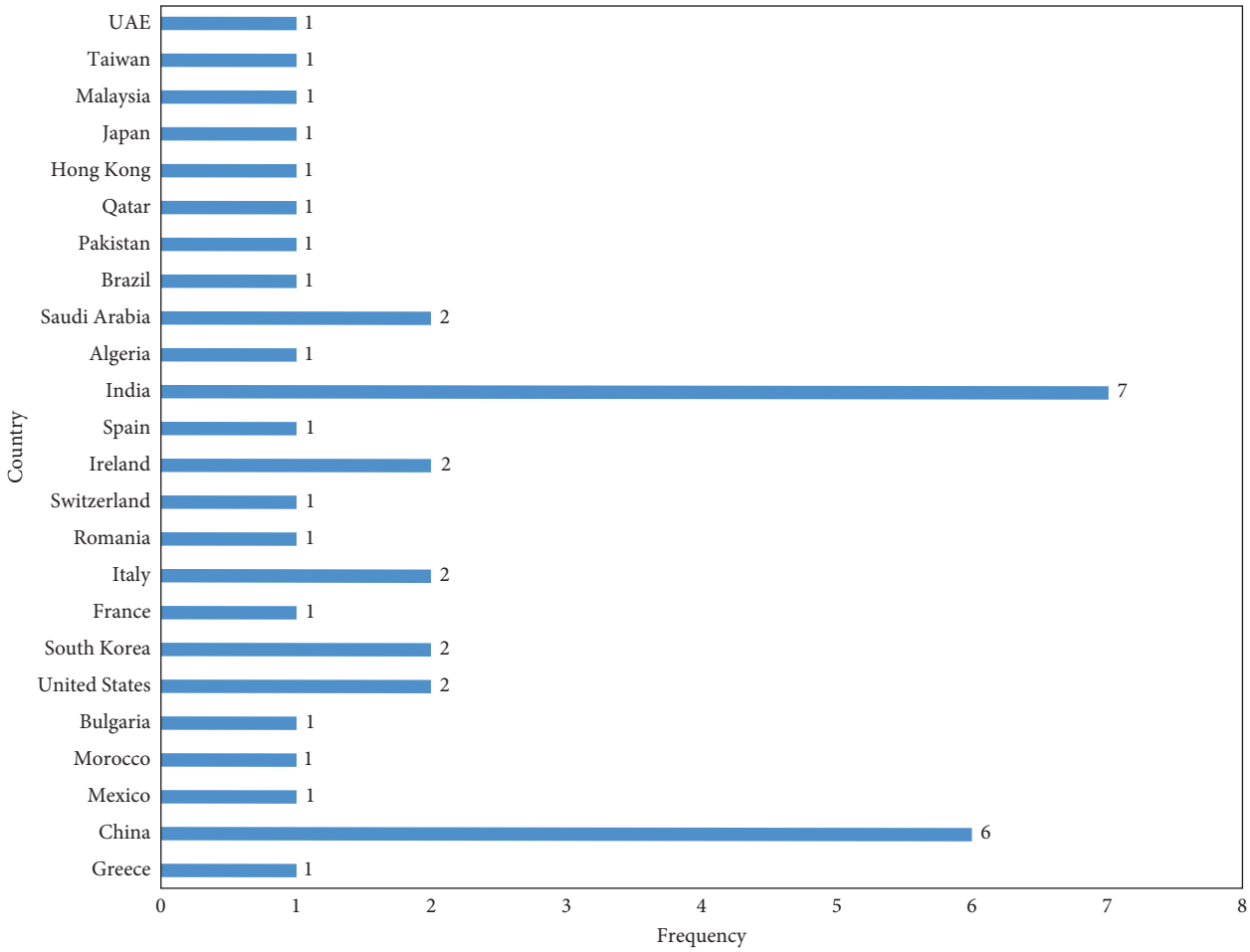

Figure 4: Number of selected studies per country.

various countries. In total, authors from 24 countries contributed to IoT and data analytics research in agriculture. The two countries that made the most significant contributions were India and China, with seven and six studies, respectively. Figure 4 illustrates the distribution by country of the selected studies.

2.7.3. Frequency of Studies Published Journal-Wise. The selected studies were sourced from a variety of journals, totaling 22. Among researchers, the four most popular journals for publication are IEEE Access and the International Journal of Innovative Technology and Exploring Engineering, each with four publications. These were followed by Computers and

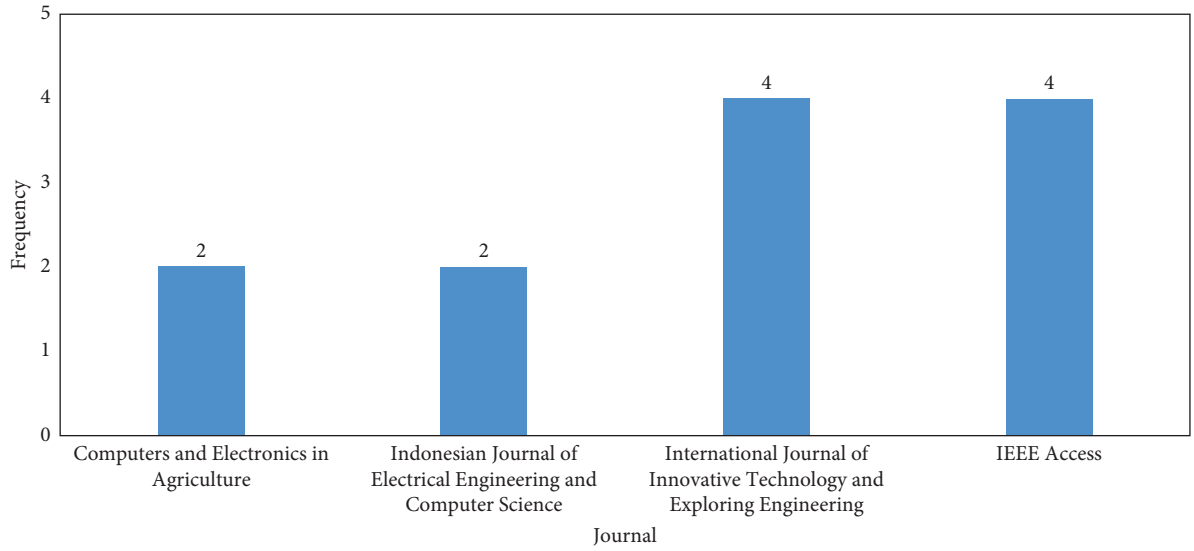

FIGURE 5: Top four publishing journals.

Electronics in Agriculture and the Indonesian Journal of Electrical Engineering and Computer Science, each with two publications. The remaining 18 journals each had one publication. Figure 5 shows the preferences of researchers for the top four journals.

2.7.4. Scopus Metrics Analysis. Two Scopus metrics, specifically cite score and *h*-index, were utilized to analyze the selected studies. The average Scopus cite score of the selected studies used is 6.40, with the highest cite score being 22.4. Among the top four publishing journals, the cite scores are as follows: Computers and Electronics in Agriculture with 13.6, Indonesian Journal of Electrical Engineering and Computer Science with 2.9, International Journal of Innovative Technology and Exploring Engineering with 0.6, and IEEE Access with 9. Figure 6 shows the Scopus cite scores of the top four preferred journals.

In terms of the *h*-index, the average among all authors involved in the selected studies was 11.73. The top five authors, ranked by their *h*-index, were Joel J.P.C. Rodrigues (89), Felix T.S. Chan (73), Ashish Khanna (49), and Deepak Gupta and Suat Irmak, each with an *h*-index of 45. Figure 7 illustrates the *h*-index values for these five authors.

3. Overview and Literature Review

3.1. IoT. IoT represents a disruptive force in the agricultural sector, offering transformative capabilities driven by its broad definition and wide-ranging application [15]. The interconnected system of various devices, encompassing basic sensors and sophisticated drones and satellites, has the potential to bring about a transformative impact on industries that extend beyond the conventional domains typically linked with digitalization [20]. The independent functioning of IoT devices, where data exchange occurs without human intervention, introduces greater complexity and potentially raises ethical dilemmas that warrant scholarly investigation [21].

3.1.1. Applications and Potential of IoT in Agriculture. The adoption of IoT technologies in agriculture has seen a steady rise, fueled by advancements in enabling technologies such as hardware improvements, enhanced connectivity, and efficiency in size and power consumption [22]. These technological advancements enable a wide range of applications aimed at enhancing agricultural productivity, quality, and sustainability [23].

IoT devices, ranging from basic sensors to sophisticated drones and satellites, serve diverse purposes tailored to specific agricultural objectives. For instance, smart poultry management systems, as demonstrated by Astill et al. [24], use biosensors to identify molecular entities indicative of avian influenza virus presence. Alternatively, crop monitoring systems employ sensors to measure soil moisture, temperature, and humidity to optimize irrigation and crop management practices [25].

This is enabled through communication technologies such as LoRaWAN [26], ZigBee [27], Wi-Fi [28], and 5G [29]. These technologies facilitate seamless connectivity and data exchange among IoT devices, enhancing operational efficiency and decision-making capabilities across agricultural operations.

3.1.2. Challenges and Ethical Considerations. Despite the promising potential of IoT in agriculture, several challenges and ethical dilemmas warrant careful consideration. Its widespread application has raised significant questions regarding the democratization of technology as well as data ownership and stewardship [30]. In agricultural settings, where data is generated autonomously, clarifying ownership rights and ensuring equitable access to data becomes imperative. The commodification of agricultural data may disproportionately impact small-scale farmers compared to large agricultural conglomerates, exacerbating existing socioeconomic disparities.

Moreover, the proliferation of IoT technologies introduces greater complexities and uncertainties. As IoT applications

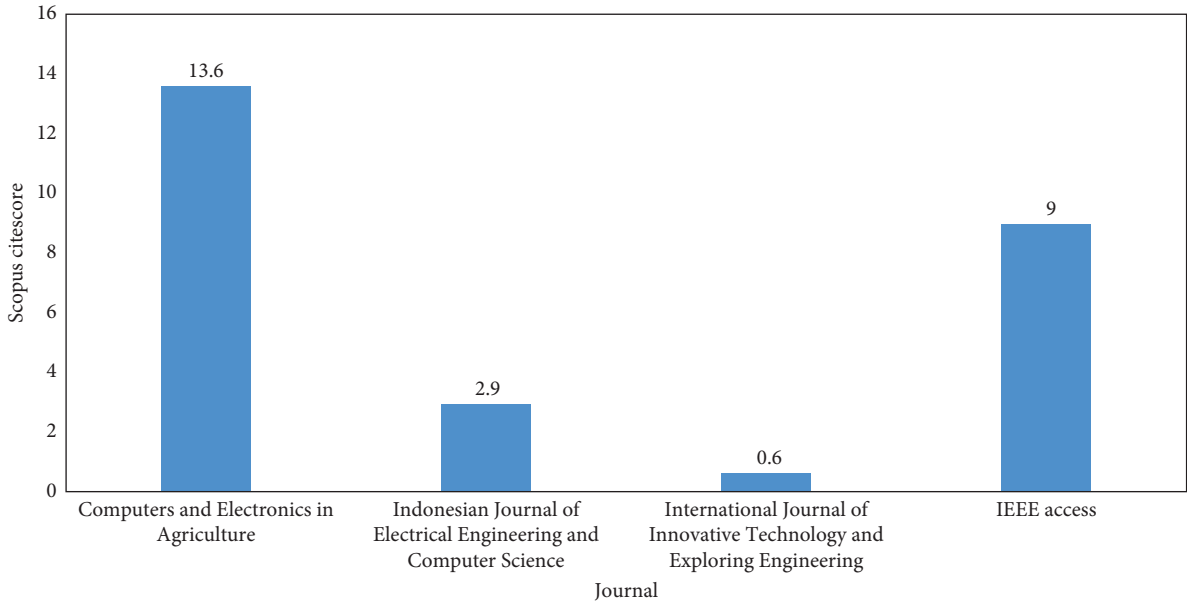

FIGURE 6: Cite score of the top four publishing journals.

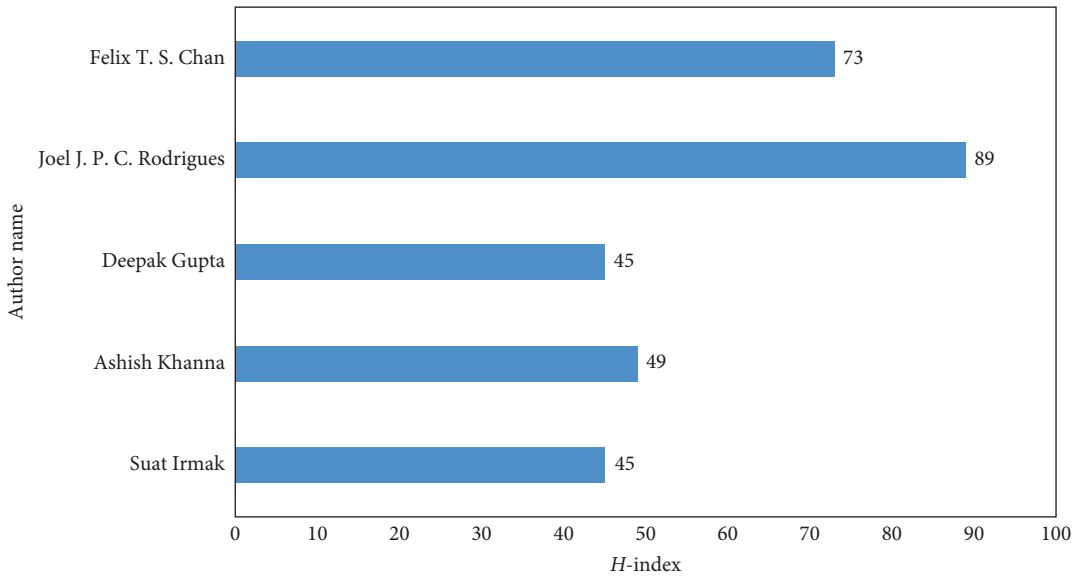

FIGURE 7: *H*-index of the top five highest-rated authors.

expand into healthcare and waste management sectors, concerns regarding patient data privacy, ethical standards in medical practice, technological obsolescence, and electronic waste generation necessitate proactive measures to mitigate adverse impacts. Consequently, this highlights that the implementation of IoT in agriculture must be approached with meticulous attention and caution.

3.1.3. Towards Responsible Implementation. Navigating the intricate landscape of IoT in agriculture requires a nuanced understanding of its capabilities, limitations, and ethical considerations. Stakeholders must prioritize responsible implementation practices, guided by interdisciplinary collaboration and ethical frameworks. By fostering transparency, accountability, and inclusivity, the agricultural sector can harness the transformative potential of IoT technologies while mitigating associated risks and ensuring sustainable outcomes.

In summary, the integration of IoT in agriculture marks a new era of innovation and efficiency, offering unprecedented opportunities to address pressing challenges and unlock new avenues for growth. However, realizing the full potential of IoT in agriculture requires a holistic approach that balances technological advancements with ethical considerations and societal impact. For illustration, Figure 8 depicts a simplified schematic diagram of the smart farm.

3.2. Data Analytics in Agriculture. Data analytics plays a pivotal role in leveraging the vast amounts of data generated by

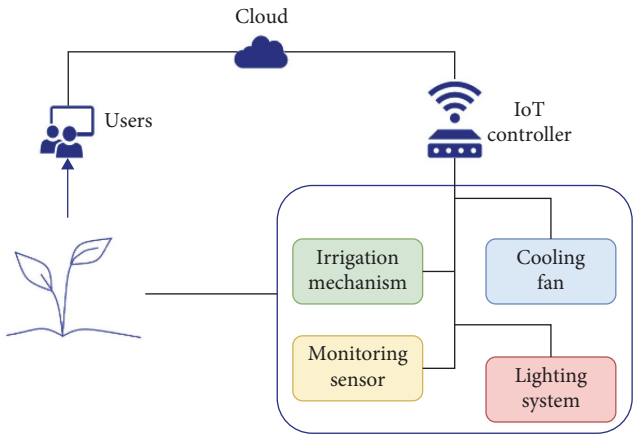

Figure 8: Simplified IoT smart farm schematic diagram.

IoT technologies in the agricultural sector [31]. The concept of big data, characterized by its extensive scale, complexity, and rapid generation, necessitates the utilization of advanced methods to integrate and analyze such data within agricultural supply chains [32, 33]. The implications are manifold, as data analytics not only provides a means for improved resource efficiency but can also redefine sustainability paradigms in agricultural production [34]. Furthermore, the substantial accumulation of data is driving a transition from decision-making models based on intuition to those driven by analytics. This section examines the methodologies and applications of data analytics, emphasizing its transformative impact on agricultural practices.

3.2.1. Methodologies of Data Analytics. Data analytics encompasses a spectrum of methodologies tailored to analyze and derive insights from complex agricultural datasets. Among these methodologies, machine learning emerges as a prominent approach [35] due to its versatility and efficacy in handling diverse datasets. Machine learning algorithms possess capabilities that go beyond basic data processing. They function as predictive and prescriptive engines, with the potential to guide agricultural strategies in real time.

Techniques such as generalized linear models (GLMs), gradient boosting machines (GBMs), deep learning (DL), and random forests (RFs) offer a diverse toolkit for agricultural data analysis [36]. DL, in particular, has gained traction owing to its ability to address the computational demands inherent in integrating IoT data [37]. By surpassing the limitations of traditional machine learning models, DL algorithms facilitate real time predictive and prescriptive analytics, thereby guiding agricultural strategies effectively. These algorithms offer valuable solutions for addressing critical concerns such as crop disease management, yield prediction, and supply chain optimization.

3.2.2. Applications of Data Analytics in Agriculture. Empirical evidence underscores the significant impact of data analytics on enhancing decision-making processes and operational efficiency in agriculture. Studies by Ang and Seng [38] demonstrate how big data analytics optimize crop planting cycles and harvest timings, thereby improving yield and resource allocation.

Innovative frameworks, such as the mobile edge computing system proposed by Gupta et al. [39], exemplify the fusion of machine learning with agricultural technology. By analyzing acoustic signals, this framework detects and classifies vehicular abnormalities in agricultural vehicles, enhancing maintenance efficiency and reducing downtime.

Moreover, data analytics contributes to proactive disease management in crops. Araby et al. [40] developed a disease detection system utilizing regression machine learning algorithms to identify late blight in potatoes. This technological advancement equips farmers with practical tools to mitigate the spread of crop diseases effectively.

3.2.3. Discussion on Data Analytics. While data analytics holds immense promise for agriculture, ethical considerations regarding data collection, privacy, and usage remain paramount. As the agricultural sector increasingly relies on analytics-driven insights, stakeholders must ensure responsible data stewardship and adhere to ethical guidelines to safeguard privacy and maintain trust among users.

In summary, data analytics emerges as a cornerstone in harnessing the potential of IoT technologies in agriculture. By employing advanced methodologies and innovative applications, data analytics enables informed decision-making, enhances operational efficiency, and fosters sustainable agricultural practices.

4. Results

The results are organized and discussed according to each research question. The comprehensive list of reviewed studies can be found in Table A1.

4.1. Current Trends in IoT and Data Analytics in Agriculture. RQ1: What are the current trends of research regarding IoT and data analytics in agriculture?

4.1.1. Smart Farming Monitoring Systems. Among the prominent trends is the development of smart farming monitoring systems. Triantafyllou et al. [41] explored this topic by leveraging emerging technologies to assist in various farming activities. These monitoring systems can be categorized into two types: crop-based agriculture monitoring systems and livestock-based agriculture monitoring systems.

Crop-based agriculture monitoring systems focus on utilizing IoT technologies to collect data on factors that affect growth, such as soil moisture, temperature, and humidity. This data is then analyzed to provide valuable information for farmers' decision-making processes. Kim et al. [42] conducted research on a smart agricultural system that exemplifies this approach. Some crop-based systems are capable of autonomous actions, where they respond to information derived from IoT sensors. Castañeda-Miranda and Castaño-Meneses [43] developed an IoT system with intelligent antifrost capabilities that activate based on temperature predictions.

Livestock-based agriculture monitoring systems focus on using IoT technologies for animal behavior analysis and health monitoring. These systems can classify animals and identify abnormal behavior. Taneja et al. [44] presented the SmartHerd system, which provides livestock farmers with decision-making

data and enhances animal welfare by alerting farmers to animals that require attention.

General agriculture monitoring systems, which encompass both crops and livestock, represent another research trend in IoT and data analytics in agriculture. Alonso et al. [45] are among those who conducted research on an agro-industry platform that validates the concept of a general agriculture monitoring system.

4.1.2. Agricultural Product Logistics Systems. Besides agriculture monitoring systems, there is a growing interest in agricultural product logistics systems. These systems aim to improve the logistics of agricultural products and address supply chain challenges using IoT and data analytics. Gao et al. [46] investigated agricultural product logistics systems. This growing interest underscores a critical need for seamless integration of supply chains, from farm to table. The real time data provided by IoT devices can drastically reduce waste and improve the efficiency of agricultural logistics. However, this also brings to light the challenge of managing and securing such vast amounts of data and ensuring it is used ethically and sustainably.

4.1.3. Algorithms for Agricultural Data Analysis. Another research trend of interest involves algorithms for agricultural data analysis. This trend emerged because of the need for efficient processing and analysis of large volumes of data obtained from agricultural IoT sensors. The research from Sambrekar and Rajpurohit [47], Ruan et al. [48], and Zhang and Zhang [49] provides insights into effective algorithms for agricultural data analysis. A closer examination of algorithms for data analysis in agriculture reveals the potential for artificial intelligence (AI) to revolutionize this field. The use of machine learning and DL can predict crop yields, detect plant diseases, and even recommend precision farming techniques. However, these opportunities also bring challenges such as the potential bias in algorithmic decision-making and the need for datasets that are representative of the diverse global agricultural environments.

4.1.4. Other Emerging Research Trends. In addition to the major trends previously mentioned, researchers have explored several other trends in IoT and data analytics within the selected agricultural literature. These encompass blockchain technology implementation in agriculture, as discussed by Ilieva et al. [50], which focuses on blockchain software tailored for agricultural stakeholders. Additionally, the concept of privacy-preserving geodistance evaluation, as introduced by Yan et al. [51], enables distance computation crucial for agricultural applications while ensuring privacy protection. Moreover, Park et al. [52] delved into employing pattern recognition techniques to determine factors influencing crop growth. Table 10 presents an overview of the current research trends in IoT and data analytics in agriculture.

4.2. Advantages of IoT and Data Analytics. RQ2: What are the advantages of utilizing IoT and data analytics in agriculture?

4.2.1. Optimization of Agricultural Product Quality. The utilization of IoT and data analytics in agriculture offers numerous advantages, including optimizing the quality of agricultural products. This is achieved through the implementation of IoT technologies, such as wireless sensor networks (WSNs), which enable efficient monitoring of various parameters that influence agricultural product quality [41]. By supervising and maintaining ideal conditions for crops or livestock, IoT and data analytics contribute to higher-quality agricultural products. This optimization not only enhances the quality but also significantly boosts the economic viability of farming practices. With the capability to monitor and adjust in real time, farmers can ensure that products meet the increasingly stringent standards required by markets and consumers.

4.2.2. Promotion of Sustainability and Environmental Impact Reduction. IoT and data analytics play a crucial role in promoting sustainability and minimizing environmental impact. IoT enables the adoption of environmentally friendly practices, such as vertical gardening, which acts as a carbon sink and mitigates the effects of global warming caused by rising carbon emissions [53]. Innovations like the RobotFarm, as presented by Angeloni [54], offer soilless cultivation and independence from external environmental conditions, contributing to environmental protection. The transformative potential of IoT and data analytics in promoting sustainability extends beyond individual farming practices to encompass the entire agricultural supply chain, offering holistic benefits.

4.2.3. Cost Reduction in Agricultural Activities. Reducing the cost of agricultural activities is another advantage of implementing IoT and data analytics. Machine learning, a powerful tool for data analytics, can effectively control the agricultural production process and minimize the occurrence of defective products [46], thus, eliminating additional costs associated with handling such products. Automated IoT technologies, such as automated irrigation systems for crops explored in the research conducted by Joshi et al. [55], have the potential to reduce management and labor costs. The economic benefits conferred by IoT and data analytics are underscored by their ability to enable precise and automated decision-making, reducing not only the direct costs associated with labor and resource management but also the indirect costs such as energy consumption and equipment wear and tear.

4.2.4. Enhanced Production Efficiency. IoT and data analytics also enhance production efficiency in agriculture by automating various agricultural processes, reducing the need for human intervention [56]. According to a study by Li and Niu [57], IoT facilitates the monitoring and control of crop growth and diseases, enabling decision-makers to develop effective plans to maximize production based on data provided by the IoT systems. The flexibility of IoT systems makes them well-suited for improving farming operations and increasing productivity, as shown by Kim et al. [42]. The enhancement in production efficiency through IoT is not just about automation but also involves optimizing resource allocation and utilization, which can lead to more sustainable farming practices. The data collected by IoT devices can be analyzed to understand crop yields

Table 10: Current research trends regarding IoT and data analytics in agriculture.

Study	Research trends							
	RT1	RT2	RT3	RT4	RT5	RT6	RT7	RT8
P1	√	—	—	—	—	—	—	—
P2	—	—	—	√	—	—	—	—
P3	√	—	—	—	—	—	—	—
P4	—	—	√	—	—	—	—	—
P5	—	—	—	—	—	√	—	—
P6	—	—	—	—	—	—	√	—
P7	√	—	—	—	—	—	—	—
P8	√	—	—	—	—	—	—	—
P9	√	—	—	—	—	—	—	—
P10	—	√	—	—	—	—	—	—
P11	√	—	—	—	—	—	—	—
P12	—	—	√	—	—	—	—	—
P13	√	—	—	—	—	—	—	—
P14	—	—	—	—	√	—	—	—
P15	√	—	—	—	—	—	—	—
P16	√	—	—	—	—	—	—	—
P17	√	—	—	—	—	—	—	—
P18	√	—	—	—	—	—	—	—
P19	√	—	—	—	—	—	—	—
P20	√	—	—	—	—	—	—	—
P21	—	—	—	—	√	—	—	—
P22	—	—	—	—	—	—	—	√
P23	√	—	—	—	—	—	—	—
P24	—	√	—	—	—	—	—	—
P25	√	—	—	—	—	—	—	—
P26	√	—	—	—	—	—	—	—
P27	√	—	—	—	—	—	—	—
P28	—	—	—	—	√	—	—	—

RT1: Crop-based agriculture monitoring system
RT2: Livestock-based agriculture monitoring system
RT3: General agriculture monitoring system
RT4: Agricultural products logistics system
RT5: Algorithms for agricultural data
RT6: Blockchain technology in agriculture
RT7: Privacy-preserving geodistance evaluation
RT8: Determination of factors affecting the growth of crops through pattern recognition techniques

in relation to different farming techniques and environmental conditions, thus, allowing for more precise farming.

4.2.5. Increased Profit Generation. Another advantage of applying IoT and data analytics in agriculture is the potential increase in profits generated. One approach to achieving this is through the optimization of crop prices using big data analytics, which analyzes the current market state and predicts prices based on the analysis [58]. The effective utilization of spatiotemporal information through precision agriculture IoT applications maximizes profits and output by determining optimal resource allocation and facilitating better decision-making [51]. The strategic application of big data and IoT not only enhances profit through optimal pricing strategies but also through the development of a more responsive and resilient agricultural supply chain. By harnessing real time data, farmers and agricultural businesses can react swiftly to market changes, supply demands, and environmental conditions, reducing waste and maximizing output. This adaptability is crucial in a sector where profit margins can be significantly impacted by factors outside a farmer's control, such as weather conditions and market fluctuations.

4.2.6. Enhanced Competitiveness Among Agricultural Producers. Improved competitiveness among agricultural producers is also a notable advantage of implementing IoT and data analytics in agriculture. Enhancing competitiveness is crucial in the agricultural sector, as it motivates producers to improve the quality of their products while simultaneously increasing production efficiency in cost-effective ways.

Introducing IoT and data analytics in agricultural production can benefit both small farmers and large landowners, enabling them to improve competitiveness through the production of higher-quality products that are cost-effective and efficient to produce [41]. This drive for enhanced competitiveness through IoT and data analytics not only democratizes access to cutting-edge technology but also promotes inclusivity within the agricultural sector. By leveling the playing field, small-scale farmers who adopt these technologies can compete more effectively with large agribusinesses, often leading to better market positions and increased bargaining power. This shift could lead to more sustainable agricultural practices that are broadly adopted across the industry due to competitive pressures.

4.2.7. Predictive Information and Risk Reduction. IoT and data analytics provide predictive information that proves valuable in various agricultural settings. For instance, these systems can predict and respond to weather, as exemplified by Castañeda-Miranda and Castaño-Meneses [43], whose intelligent frost control system allows for the prediction of frost conditions that could negatively affect crops. IoT and data analytics also facilitate the prediction of yields and harvests, even before crop planting [58]. IoT applications combined with machine learning, as demonstrated by Taneja et al. [59], can predict and detect diseases in animals, such as lameness in cows, before they become visually detectable to farmers. The utilization of predictive information for risk reduction in agriculture exemplifies a proactive approach to farming, shifting the traditional reactive models to more strategic, data-informed decision-making processes. This foresight not only enhances the efficiency and effectiveness of agricultural operations but also significantly mitigates financial risks associated with unpredictable environmental factors and health issues in livestock.

4.2.8. Reducing the Risks of Health and Safety. Moreover, IoT and data analytics help reduce health and safety risks for farmers by promoting the rational use of toxic products and pesticides [58] and reducing exposure through automation. The reduction of health and safety risks through the rational use of chemicals and automation highlights a critical shift towards safer agricultural environments. By minimizing human exposure to harmful substances and potentially dangerous tasks, IoT and data analytics not only safeguard the health of farmers but also contribute to a more sustainable approach to agriculture. This shift can lead to broader societal benefits, such as reduced healthcare costs and increased workforce productivity.

4.2.9. Enhanced Trust Between Agricultural Consumers and Producers. Last, these systems can enhance trust between agricultural consumers and producers. For instance, the SmartDairyTracer system developed by Alonso et al. [45] enables traceability of information, ensuring the quality and safety of agricultural products. Table 11 summarizes the advantages derived from using IoT and data analytics in agriculture.

4.3. Barriers to Implementing IoT and Data Analytics. RQ3: What barriers are present in implementing IoT and data analytics in agriculture?

4.3.1. Lack of Guidance Models and Frameworks. Implementing IoT and data analytics in agriculture has not yet reached its full potential because of various barriers that affect users' motivation to invest in and adopt this technology. One such barrier is the lack of sufficient models that can serve as guidance for practitioners [41]. This means that potential users do not have reliable references to understand the essential components required to develop functional IoT monitoring systems. For instance, the absence of guidelines or frameworks for implementing blockchain technology in IoT–based agricultural systems discourages users from embracing it [50].

4.3.2. Challenges in Interoperability and Communication. Another challenge in implementing IoT and data analytics is the difficulty in enabling seamless communication between components developed by different manufacturers [44]. This limitation might restrict users to purchasing components from a single manufacturer, hampering the flexibility of agricultural systems.

4.3.3. Ensuring Continuous and Efficient Sensor Functioning. Ensuring the continuous and efficient functioning of sensors within their designated environments is another barrier to implementing IoT and data analytics in agriculture. Since most sensors operate on batteries, the use of energy-efficient protocols is crucial for the long-term functionality of the system [41].

4.3.4. Presence of Long Data Queues. Furthermore, the presence of long data queues within IoT–based agricultural systems poses obstacles to their implementation. This can be attributed to the limited processing capacity of sensors or long distances for sensor communication, resulting in reduced network viability because of higher energy consumption associated with long data queues [41].

4.3.5. Misunderstanding Between System Designers and Users. Misunderstanding between system designers and intended users is identified as an issue that affects implementation. Socioeconomic, cultural, and geographic factors contribute to differences of opinion, leading to suboptimal or unsuitable agricultural systems [41].

4.3.6. High Costs and Security Concerns. High costs also pose significant barriers to implementing IoT and data analytics in agriculture. The cost of a system is primarily determined by the network topology and the quality of materials used [41]. Factors such as lack of interoperability can further increase costs for users [59]. Implementation is hindered by the need for improved security systems that facilitate data management and protect privacy. Blockchain implementation in agriculture, for example, is susceptible to fraud, cyberattacks, and opportunistic behavior of partners, reducing its acceptance among users [50].

4.3.7. Legal and Regulatory Constraints. In addition, laws and regulations can affect the implementation of IoT and data analytics in agriculture, as seen with blockchain implementation where distributed computing infrastructure is restricted [50].

Table 11: Advantages of utilizing IoT and data analytics in agriculture.

Study	Advantage								
	A1	A2	A3	A4	A5	A6	A7	A8	A9
P1	√	√	√	√	√	√	—	—	—
P2	—	√	√	√	—	—	—	—	—
P3	—	—	—	—	—	—	√	—	—
P4	—	—	√	√	√	√	√	√	—
P5	√	√	√	—	—	√	√	—	√
P6	—	—	—	—	√	—	—	—	—
P7	—	—	—	√	—	—	—	—	—
P8	—	√	—	√	—	—	—	—	—
P9	√	—	√	√	√	—	√	—	—
P10	—	√	—	√	—	—	√	—	—
P11	√	√	√	√	—	—	√	—	—
P12	—	√	—	√	—	√	√	—	√
P13	√	—	—	√	—	—	√	—	—
P14	—	—	—	—	—	—	—	—	—
P15	—	—	—	√	√	—	√	—	—
P16	—	—	—	√	—	—	—	—	—
P17	√	√	√	√	√	—	√	√	—
P18	√	√	√	√	—	—	—	—	—
P19	—	—	—	—	—	—	√	—	—
P20	—	—	—	—	—	—	√	—	—
P21	—	—	—	—	—	—	—	—	—
P22	√	—	—	√	—	—	—	—	—
P23	—	—	√	√	—	—	—	—	—
P24	—	√	√	√	—	—	√	—	—
P25	—	√	√	—	—	—	—	—	—
P26	√	—	√	√	—	—	—	—	—
P27	—	√	√	√	√	—	—	—	—
P28	—	—	—	√	—	—	√	—	—

A1: Optimizing the quality of the agricultural product
A2: Minimizing environmental impact and improving sustainability
A3: Reduce the cost of agricultural activities
A4: Enhance production efficiency
A5: Increase profit gain
A6: Increase competitiveness in production among agricultural producers
A7: Provide predictive information
A8: Reduce health and safety risks to farmers
A9: Improve trust between agricultural consumers and producers

4.3.8. Lack of User-Friendliness and Awareness. Insufficient user-friendliness of IoT systems also poses a challenge to effective implementation [54]. Users are more likely to embrace products that are accessible to them. Additionally, a low willingness to learn about new technologies also demotivates individuals from adopting IoT and data analytics because of perceived complexity. This aspect was highlighted by Suk Oh [56] in their study, which involved aging rural farmers. Furthermore, a lack of knowledge about IoT devices presents a significant barrier to implementing IoT and data analytics in agriculture. Angeloni [54] notes in her research that one reason for the limited distribution of RobotFarm, an IoT–based agricultural appliance, is because of consumers' lack of awareness about its existence.

4.3.9. Challenges in Data Processing and Connectivity. Continuous real time data processing and storage have become challenging for IoT and data analytics systems due to the large volumes of sensor-generated data [44]. The difficulty in extracting information from large amounts of agricultural data is another obstacle to implementing IoT and data analytics in agriculture. The vast volume of data collected from sensors needs to be efficiently processed to extract valuable information at acceptable computational costs [48]. Low internet

Table 12: Barriers to implementing IoT and data analytics in agriculture.

Study	Barriers													
	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14
P1	√	√	√	√	√	√	—	—	—	—	—	—	—	—
P2	—	—	—	—	—	—	—	—	—	—	—	—	—	—
P3	—	—	—	—	—	—	—	—	—	—	—	—	—	—
P4	—	—	—	—	—	—	—	—	—	—	—	—	—	—
P5	√	—	—	—	—	√	√	√	—	—	—	—	—	—
P6	—	—	—	—	—	—	√	—	—	—	—	—	—	—
P7	—	—	—	—	—	—	—	—	—	—	—	√	—	—
P8	—	—	—	—	—	—	—	—	—	—	—	—	—	—
P9	—	—	—	—	—	—	—	—	—	—	—	—	—	—
P10	—	√	—	—	—	√	—	—	—	—	—	—	—	√
P11	—	—	—	—	—	—	—	—	—	—	—	—	—	—
P12	—	—	—	—	—	—	—	—	—	—	—	—	—	—
P13	—	—	—	—	—	—	—	—	—	—	—	—	—	—
P14	—	—	—	—	—	—	—	—	—	—	—	—	—	—
P15	—	—	—	—	—	—	—	—	—	—	—	—	—	—
P16	—	—	—	—	—	—	—	—	—	—	—	—	—	—
P17	—	—	—	—	—	√	√	—	√	—	√	—	—	—
P18	—	—	—	—	—	—	—	—	—	—	—	—	—	—
P19	—	—	—	—	—	—	—	—	—	—	—	—	—	—
P20	—	—	—	—	—	—	—	—	—	—	—	—	—	—
P21	—	—	—	—	—	—	—	—	—	—	—	—	√	—
P22	—	—	—	—	—	—	—	—	—	—	—	—	√	—
P23	—	—	—	—	—	—	—	—	—	—	—	—	—	—
P24	—	√	—	—	—	√	—	—	—	√	—	—	—	√
P25	—	—	—	—	—	—	—	—	—	—	—	√	—	—
P26	—	—	—	—	—	—	—	—	—	—	—	—	—	—
P27	—	—	—	—	—	—	—	—	—	—	—	—	—	—
P28	—	—	—	—	—	—	—	—	—	—	—	—	—	—

C1: Insufficient models to act as guidance for practitioners
C2: Difficult for components from different manufacturers to communicate
C3: Continuous operation of sensors for a long time
C4: Long data queues
C5: Disconnect between system designers and intended users
C6: High cost
C7: Unsatisfactory security systems that can manage data and protect privacy
C8: Laws and regulation
C9: IoT–based solutions not user-friendly enough
C10: Continuous real-time data processing and storage
C11: Lack of knowledge of IoT devices
C12: Low willingness to learn about new technologies
C13: Difficulty in mining information from large amounts of agricultural data
C14: Low internet connectivity

connectivity presents another issue affecting implementation, particularly in geographically remote areas with limited internet access, which may discourage farmers from embracing IoT and data analytics systems that traditionally rely heavily on cloud infrastructures [44]. Table 12 summarizes the barriers present in implementing IoT and data analytics in agriculture.

4.4. Effectiveness of IoT and Data Analytics Systems. RQ4: How are the effectiveness of IoT and data analytics systems in agriculture evaluated?

4.4.1. Real-World Use Case Studies. One approach employed by scholars to measure effectiveness is the implementation of

proposed solutions in real-world use case studies. Triantafyllou et al. [41] are researchers who utilize this method to evaluate their IoT and data analytics systems. They conducted tests on their smart farming monitoring system using the drone innovation in saffron agriculture surveillance (DIAS) project platform, which aligns with their proposed architectural design. The utilization of real-world use case studies is essential in translating theoretical research into practical and measurable outcomes that reflect the true effectiveness of IoT and data analytics systems in agriculture. This method provides concrete evidence on how these technologies perform under actual working conditions, identifying both their strengths and limitations.

4.4.2. Statistical Analysis. Statistical analysis of acquired data is another method employed by researchers to evaluate the effectiveness of IoT and data analytics systems in agriculture. Castañeda-Miranda and Castaño-Meneses [43] provide an example of this approach as they used statistical analysis to assess their artificial neural network (ANN) model's effectiveness in forecasting and controlling temperature changes within a greenhouse. Zhang and Zhang [49] also employed statistical analysis to compare and verify the effectiveness of the BigDataACO with other data fusion clustering algorithms in handling agricultural datasets.

4.4.3. System Performance Evaluation. Evaluating system performance is another means of assessing the effectiveness of IoT and data analytics systems in agriculture. Taneja et al. [44] conducted field tests to evaluate their system's performance in monitoring cow behavior. Pedometers were attached to cows to track their behavior and feed data into the developed smart system, after which the test results were examined. Subahi and Bouazza [60] offer another example of utilizing system performance evaluation to assess the effectiveness of IoT and data analytics systems in agriculture. One of their evaluations involved testing the temperature response and power consumption of their greenhouse system.

4.4.4. Comparison With Expert Opinions. In addition, some scholars evaluate the effectiveness of IoT and data analytics systems by comparing the results obtained from their proposed solutions with expert opinions. Taneja et al. [59] demonstrate this approach by showcasing their system's capability to detect lameness among cows before any physical signs recognizable by farmers or animal experts emerge. Ilieva et al. [50] present another example where they compare the recommended blockchain-based software provided by their system with the recommendations from Capterra.com.

4.4.5. Plant Growth Rate. Last, one study employed the growth rate of plants as a metric to measure the effectiveness of the IoT and data analytics system they used. This study, conducted by Zamin et al. [53], compared the growth rate of water spinach produced using traditional farming methods with the growth rate of those produced using their proposed system. Table 13 summarizes how the effectiveness of IoT and data analytics systems in agriculture is evaluated.

4.5. Future Research Directions for IoT and Data Analytics Systems. RQ5: What are future research directions for IoT and data analytics systems in agriculture?

Future research directions for IoT and data analytics systems in agriculture, highlighted by scholars in related works, can be categorized into two main areas. The first category involves improving or extending existing solutions, while the second category focuses on exploring new research avenues following the breakthroughs achieved by the current work. Some researchers mention the possibility of both categories being explored in the future based on their studies, while others focus on one particular direction.

4.5.1. Improving Current Solutions. Among the future research directions aimed at improving or extending current solutions, Triantafyllou et al. [41] plan to conduct a real-time performance study of their proposed system in the DIAS project. Yan et al. [51] intend to further improve and extend the reach of their scalable and private geodistance evaluation (SPRIDE) system. Balan et al. [61] envision significant enhancements for their decision and prediction algorithms. Alonso et al. [45] aim to complete and implement their SmartDairyTracer platform more extensively. Sowmya et al. [62] suggest incorporating features from other rainfall and water control systems into their proposed system.

Furthermore, Revathi and Sengottuvelan [63] propose revalidating data for their system through the use of deep neural networks and drone-based visualization to minimize sensor disruptions. Angeloni [54] outlines several future research directions for the improvement of RobotFarm, including a comprehensive analysis of RobotFarm's technical aspects, understanding the influence of environmental and nutrient parameters on plant growth using RobotFarm, evaluating the effectiveness and controlling RobotFarm using smart devices, and optimizing nutrient solution and production technology as well as expanding the range of crops that can be grown. Latif et al. [64] plan to create a new model that combines their current model with other models to increase prediction accuracy and computational feasibility.

Additionally, Ruan et al. [48] anticipate that future research will introduce a greater number of granulation techniques to deal with complex big data and highlight the potential of granular GA-SVM predictors in parallel and cloud computation systems. Joshi et al. [55] aim to enhance their system by incorporating various technologies, such as WSN, MATLAB, and GPS. Taneja et al. [44] intend to increase system reliability by having multiple gateways coexisting within their developed infrastructure. Tseng et al. [65] propose the future implementation of AI within their suggested scheme. Liu et al. [66] plan to test their experimental design through simulations, conduct quantitative empirical studies, and apply it to a real-world scenario.

4.5.2. Exploring New Research Grounds. In the second category of future research directions, scholars who mention the possibility of exploring new research grounds include Gao et al. [46], who seek to utilize future economic theories and accumulated agricultural data from IoT systems to study and test functional requirements for modeling methods that promote big

Table 13: How the effectiveness of IoT and data analytics systems in agriculture are evaluated.

Study	Evaluation method				
	EM1	EM2	EM3	EM4	EM5
P1	√	—	—	—	—
P2	√	—	—	—	—
P3	—	√	—	—	—
P4	—	—	—	—	—
P5	—	—	—	√	—
P6	—	—	√	—	—
P7	—	—	—	—	—
P8	—	√	√	—	—
P9	—	√	—	—	—
P10	—	√	√	√	—
P11	—	√	—	—	—
P12	√	—	√	—	—
P13	—	√	—	—	—
P14	—	√	—	—	—
P15	—	√	—	—	—
P16	—	—	√	—	—
P17	—	—	—	—	—
P18	—	—	√	—	—
P19	—	√	—	—	—
P20	—	√	—	—	—
P21	—	√	—	—	—
P22	—	√	—	—	—
P23	—	—	√	—	—
P24	—	√	√	—	—
P25	—	—	—	—	√
P26	—	√	—	—	—
P27	—	—	—	—	—
P28	—	√	√	—	—

EM1: Use case study approach
EM2: Statistical analysis of data
EM3: Evaluation of system performance
EM4: Comparison of obtained result with expert opinion
EM5: Plant growth rate

Table 14: Future research directions for IoT and data analytics systems in agriculture.

Study	Future research directions		
	FR1	FR2	FR3
P1	√	—	—
P2	—	√	—
P3	—	—	√
P4	—	√	—
P5	—	—	√
P6	√	—	—
P7	—	—	—
P8	√	—	—
P9	—	√	—
P10	—	√	—
P11	—	—	—
P12	√	—	—
P13	√	—	—
P14	—	—	—
P15	—	—	—
P16	√	—	—
P17	√	—	—
P18	—	—	—
P19	—	—	—
P20	√	—	—
P21	√	—	—
P22	—	—	√
P23	√	—	—
P24	—	—	√
P25	—	—	—
P26	√	—	—
P27	√	—	—
P28	—	√	—

FR1: Improving or extending the current solutions
FR2: Exploring new research grounds after breakthrough generated by current work
FR3: Improving current solutions and exploring new research grounds

data analysis in agriculture. Rabhi et al. [58] propose a metamodel of big data analytics applicable to smart farms and aim to investigate agricultural use cases related to digital and connected agriculture. Li and Niu [57] plan to utilize classification technologies capable of analyzing and predicting the output of specific agricultural products. Taneja et al. [59] aim to research and evaluate additional clustering techniques, along with exploring distributed analytics and distributed learning. Sambrekar and Rajpurohit [47] are considering developing a cost-effective and multilevel cloud storage architecture for an agriculture management system and are also attempting to obtain real-time agricultural data.

4.5.3. Combining Improving Current Solutions and Exploring New Research Grounds. Last, some researchers mention both categories of future research directions. Castañeda-Miranda and Castaño-Meneses [43], besides wanting to improve their current research methodology, also intend to explore new meteorological datasets using neural networks for temporary processing to identify areas of interest. Ilieva et al. [50] plan to develop new hybrid methods for evaluating blockchain software and expand upon the proposed mechanism for ranking blockchain alternatives. Park et al. [52] express interest not only in verifying the effectiveness of their proposed strategies for improving tomato yield but also in developing a smart farming system that automates the management of environmental and growth factors. Table 14 provides an overview of the future research directions for IoT and data analytics systems in agriculture. A summary of the analysis results is provided in Figure 9.

5. Towards a Conceptual Framework

A dual-model approach has been adopted in this study to synthesize the findings of the SLR. This includes both a user-

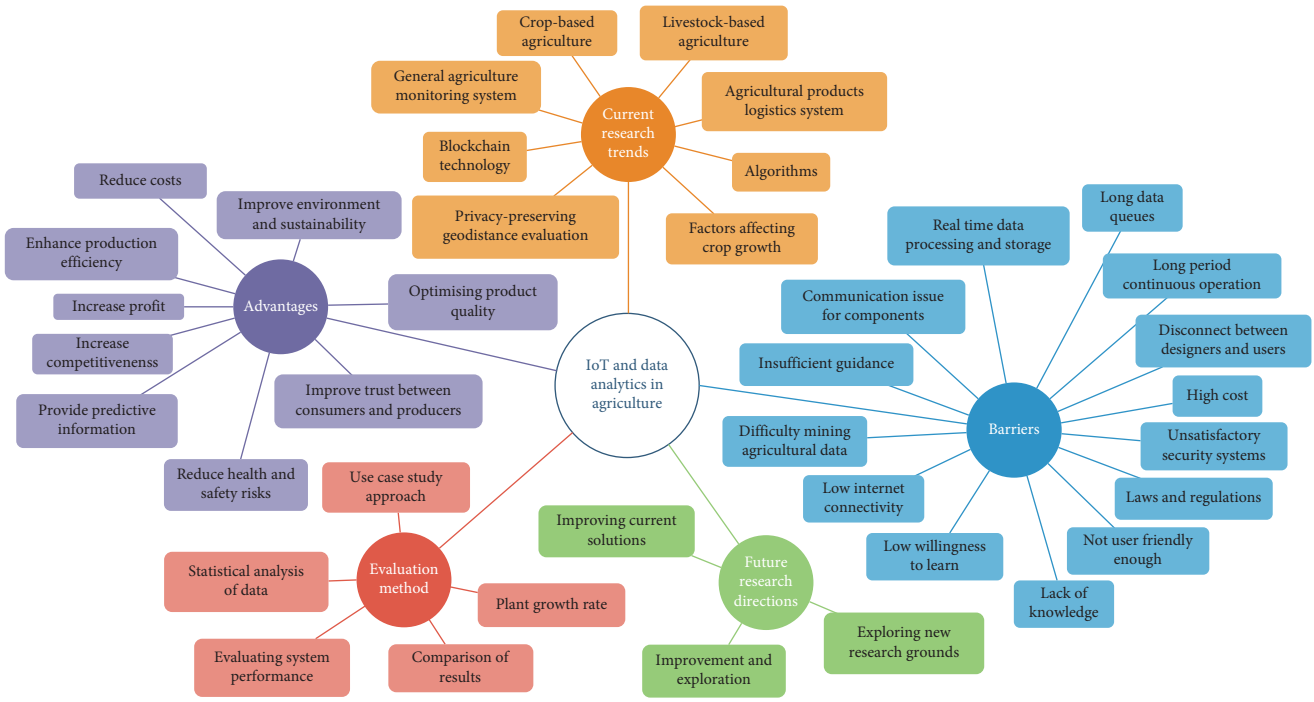

Figure 9: Analysis of IoT and data analytics in agriculture.

centric conceptual model and a technical-operational framework, each serving distinct yet complementary purposes in understanding the integration of IoT and data analytics in agriculture.

5.1. Conceptual Model for User Acceptance of IoT–Based Agricultural Systems. The first model, based on the technology acceptance model (TAM), focuses on explaining and predicting stakeholders' acceptance of such systems. TAM evaluates users' perceptions of usefulness and ease of use, making it a suitable lens for assessing the adoption potential of IoT and data analytics technologies in agricultural contexts [67]. The philosophical conceptualization of this model follows the approach by Meredith [68], involving the integration and extension of existing literature with similar themes. The external variables in the adapted TAM are shaped by the challenges identified in the reviewed studies and are assumed to impact user perceptions of ease of use and usefulness. Figure 10 presents the adapted TAM model, incorporating these external factors, while Table 15 defines each external variable identified from the literature.

Based on Table 15, 13 external variables have been derived from the challenges in implementing IoT and data analytics systems in agriculture identified in the literature review. The list of challenges can be found in Table 12.

The first external variable is system quality. High system quality refers to a system that performs well without being error-prone or constantly malfunctioning. Challenges that inspired this variable are C5 and C9, which could cause diminished system quality. A lower system quality may dissuade users from using the system, as they are unlikely to engage with one that functions poorly, highlighting the significance of system quality in user acceptance of IoT and data analytics systems in agriculture.

The second external variable is information quality. High information quality means that a system can consistently provide understandable, accurate information relevant to user needs. Similar to system quality, challenges that led to the creation of this variable are also C5 and C9, as they could also contribute to lower information quality. Substandard information quality could be detrimental to users if the system provides inaccurate information that may cause users to make incorrect decisions. This underscores the importance of information quality in the adoption of IoT and data analytics in agriculture.

The third external variable is computer self-efficacy. Individuals with high computer self-efficacy would be able to confidently use the technology provided to them to perform tasks and solve necessary problems. The challenge related to this variable is C11. This is because a lack of knowledge of relevant digital technologies would result in lower computer self-efficacy levels, negatively affecting user perception of the technology. This highlights the value of computer self-efficacy when dealing with user acceptance of IoT and data analytics in agriculture.

The fourth external variable is individual innovativeness. High individual innovativeness implies that users are more inclined to explore and adopt new technologies. This variable was inspired by the Challenge C12. This is because having a low willingness to learn about new technologies would have a negative effect on individual innovativeness, subsequently affecting

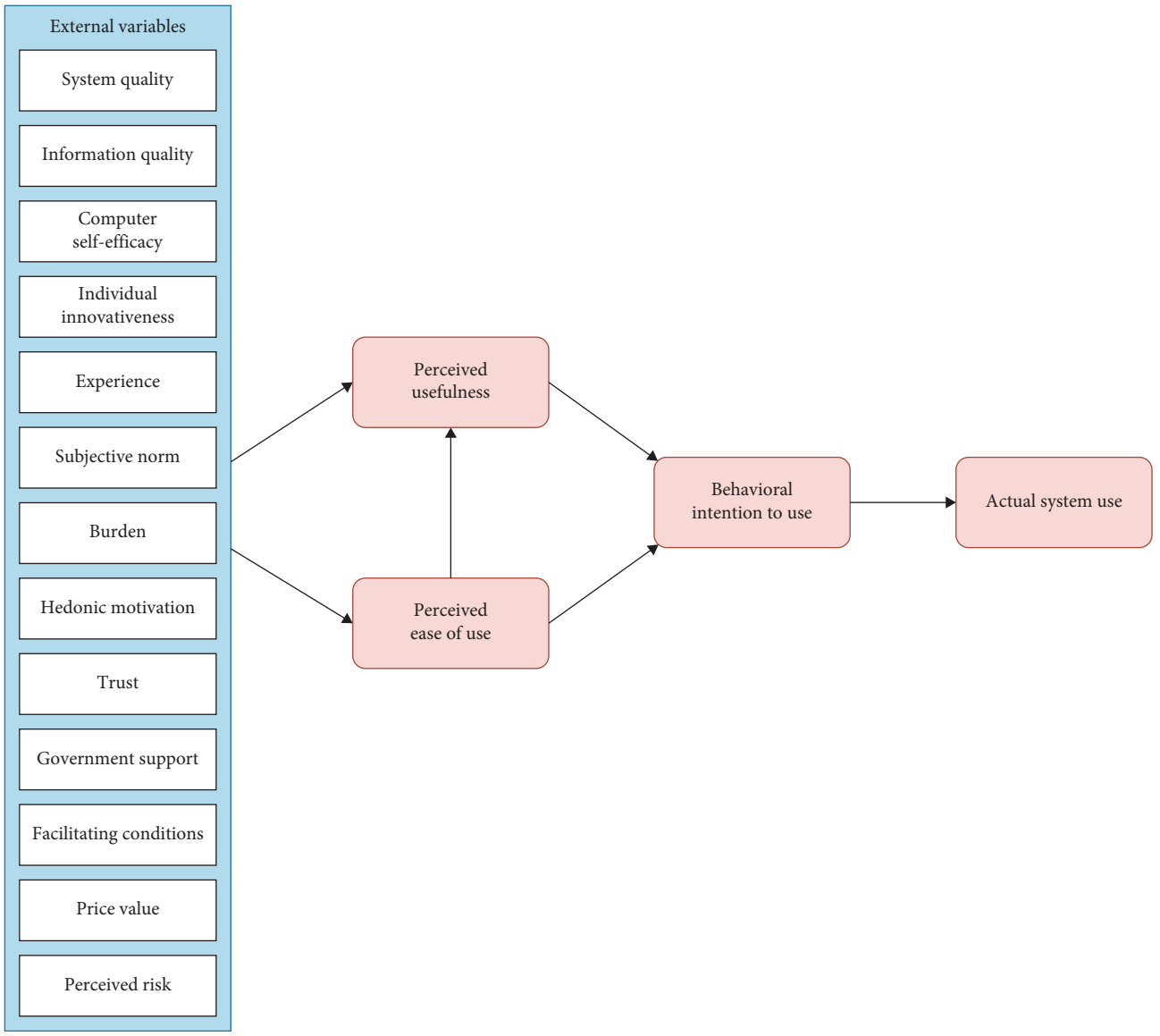

Figure 10: Conceptual model of factors influencing the adoption of IoT and data analytics systems in agriculture, based on the technology acceptance model (TAM).

the acceptance of new systems such as IoT and data analytics. This shows the relevance of individual innovativeness to the uptake of new IoT and data analytics systems in agriculture.

The fifth external variable is experience. Extensive experience would mean that users have amassed considerable knowledge of similar technologies and can apply them to currently used technologies. Challenge C11 is related to this variable. The lack of knowledge of digital technologies implies a low level of self-efficacy with currently used technology and a lack of experience with similar devices in the past. The deficiency in experience would adversely affect users' acceptance of the technology because it hinders their ability to efficiently learn and adapt to the new technology compared to those with prior experience. This demonstrates that experience could influence the acceptance of IoT and data analytics systems in agriculture.

The sixth external variable is subjective norm or social influence. The effects of this variable should not be underestimated as having a supportive or discouraging community can significantly influence whether a user embraces or disregards new innovative technologies. Challenge C12 is closely associated with this variable, as low willingness to learn about new technologies among users can be attributed to subjective norms. If a community consistently discourages the adoption of new technologies, then most members are likely to refrain from adoption as it is against the norm of society. This emphasizes the role of subjective norms in the successful adoption of IoT and data analytics systems in agriculture.

The seventh external variable is burden. A technology that is burdensome to use will face greater challenges in gaining acceptance among users even if they are capable of doing the

Table 15: Definition of the external variables used in the adapted TAM.

External variable	Definition
System quality	Quality of system characteristics such as usability and reliability
Information quality	Quality of the information produced by the system in terms of relevance and accuracy
Computer self-efficacy	Confidence in knowing how to complete tasks and solve problems using the technology
Individual innovativeness	Personal desire to explore new technology
Experience	Knowledge after previous interactions with similar technologies
Subjective norm	Social pressure to either engage in or abstain from a particular action
Burden	Perceived level of effort required to utilize the technology
Hedonic motivation	The degree to which the technology leads to satisfaction or enjoyment
Trust	Confidence in the technology
Government support	Attention and help provided by the government for the adoption of the technology
Facilitating conditions	Infrastructure and support to help in using the technology
Price value	Cognitive trade-off between the perceived value of the technology and the cost of acquiring or utilizing them
Perceived risk	Concerns that the technology might bring adverse effects

required tasks. The challenge related to this variable is C9, as systems lacking user-friendliness would increase the burden on users during the learning and usage process. Consequently, users may abandon the system after encountering prolonged difficulties. This shows the significance of burden in the implementation of IoT and data analytics in agriculture.

The eighth external variable is hedonic motivation. Technologies that appeal to the hedonic motivation of users are generally better received compared to those that overlook this aspect. Challenge C9 is associated with this variable, as technologies that are not user-friendly can dampen users' hedonic motivation and prompt them to swiftly abandon the technology due to a lack of enjoyment. Therefore, hedonic motivation is a crucial variable to consider when seeking to promote IoT and data analytics acceptance in agriculture.

The ninth external variable is trust. Technologies that are trusted by users are far more likely to be accepted compared to those that have not gained trust. The challenges that motivated the creation of this variable are C5 and C7. First, a disconnection between system designers and intended users may lead to the development of systems that fail to meet user expectations, consequently eroding trust in both the system designers and the developed systems. Second, inadequate security in the used systems can undermine users' trust in digital solutions, especially if adopting the technology poses risks to data integrity and privacy. The erosion of trust among users towards such technologies may lead to their abandonment and could even dissuade further exploration of innovative solutions. This shows that trust is an important factor to consider in the adoption of IoT and data analytics in agriculture.

The tenth external variable is government support. Government support plays a key role in incentivizing users to embrace new technologies, as they are likely to feel more confident in doing so with formal support from a trusted authoritative body. The challenge that inspired the formation of this variable is C8. This is because laws and regulations, determined by the government, can either encourage or discourage users from adopting technologies depending on how they are formulated. This illustrates the importance of government support in the implementation of IoT and data analytics in agriculture.

The eleventh external variable is facilitating conditions. Favorable facilitating conditions attract numerous users towards using new technology, as they can receive necessary assistance for learning and utilizing the technology through robust support systems. Moreover, they can feel more confident in their investment decisions due to the presence of well-established infrastructure supporting the technology. Challenges associated with this variable are C1, C2, C4, C10, C13, and C14. C1 is related to the absence of proper models for user guidance, which can discourage adoption as users lack avenues for assistance when encountering issues. C2, C4, C10, C13, and C14 are related to infrastructure weaknesses, which can impede the acceptance of the technology by hindering optimal performance. This shows that facilitating conditions are a critical variable to consider for IoT and data analytics acceptance in agriculture.

The twelfth external variable is price value. Technologies offering good price value are often more readily adopted. This is because they not only save users money that can be invested in other areas but also efficiently perform the tasks they were designed for, satisfying their owners. Challenges that motivated the addition of this external variable are C3, C4, and C6. These challenges share a common aspect, and that is a significant investment is needed to acquire and maintain the operation of the utilized technologies. Despite the known benefits of these technologies, users may hesitate to adopt them due to the substantial capital needed for effective utilization, thereby impacting user acceptance. This highlights that price value is important when it comes to the utilization of IoT and data analytics systems in agriculture.

The thirteenth and final external variable is perceived risk. Users are less inclined to adopt technologies they perceive as potentially harmful, whether physically or financially. The challenge that relate to this external variable is C3. Prolonged operation of sensors in their intended environment carries the

risk of hardware damage, which could subsequently impact users' finances, particularly those from less affluent backgrounds. Cases such as this could diminish users' motivation to embrace these innovative technologies. This showcases the significance of perceived risk in the adoption of IoT and data analytics systems in agriculture.

5.2. Conceptual Framework for IoT and Data Analytics Integration in Agriculture. Complementing the user-centric model, a second framework—developed from the technological synthesis of the 28 reviewed studies—is introduced to illustrate the layered integration of IoT and data analytics systems in agriculture. This multilayered conceptual framework captures the full system life cycle, from data acquisition and transmission to analytics, application, and real-world impact. It serves to guide researchers and system designers in understanding the technical architecture and flow of information within agricultural IoT ecosystems. Figure 11 illustrates this layered framework, which not only addresses gaps identified in existing reviews but also provides a holistic structure to inform future development and implementation efforts.

5.2.1. Layer 1: Data Acquisition Layer. The data acquisition layer encompasses all IoT-enabled devices deployed in agricultural environments to collect real-time field data. These devices include a range of sensors such as soil moisture probes, temperature and humidity monitors, pH sensors, livestock wearables, smart cameras, drones, and RFID–based animal trackers. The continuous monitoring of environmental, soil, and biological parameters facilitates precise data gathering across spatial and temporal dimensions. This layer is critical for ensuring that raw and unprocessed data is available for subsequent analysis, enabling site-specific and crop-specific decision-making.

5.2.2. Layer 2: Data Transmission Layer. This layer refers to the communication infrastructure responsible for transmitting sensor data to processing hubs or cloud platforms. It incorporates both short-range (e.g., ZigBee, Wi-Fi, and Bluetooth) and long-range communication technologies (e.g., LoRaWAN, NB-IoT, Sigfox, and LTE-M), selected based on coverage area, power consumption, and bandwidth requirements. The role of this layer is to enable uninterrupted and energy-efficient data transfer between edge devices and centralized data repositories. Robust connectivity at this layer ensures that agricultural monitoring and control operations remain responsive and reliable.

5.2.3. Layer 3: Data Processing Layer. The data processing layer is tasked with filtering, aggregating, and storing the vast streams of incoming data. This is achieved through a combination of edge computing nodes, fog gateways, and cloud platforms. Raw data collected from IoT devices is preprocessed to remove noise, correct anomalies, and organize it for efficient retrieval. The use of distributed computing resources at this stage helps to reduce latency, conserve bandwidth, and support scalability. This layer acts as the bridge between data collection and actionable insights, preparing data for advanced analytical procedures.

5.2.4. Layer 4: Analytics and Decision-Making Layer. At this level, advanced analytical methods such as machine learning, DL, and statistical modeling are employed to generate predictive and prescriptive insights. Algorithms process cleaned datasets to identify patterns, predict crop yields, detect plant and livestock diseases, or anticipate equipment failures. Decision-support systems within this layer enable precision interventions by correlating multisensor data and generating intelligent recommendations. This layer transforms data into knowledge, directly influencing operational strategies in the field.

5.2.5. Layer 5: Application Layer. The application layer comprises end-user interfaces and automation systems that operationalize insights generated from analytics. These include smart irrigation controllers, livestock health dashboards, mobile farming applications, and logistics management platforms. This layer connects the analytical outputs to physical actions through actuators, alerts, and visual dashboards. By translating digital intelligence into tangible interventions, this layer empowers farmers and stakeholders to optimize productivity, reduce input waste, and ensure product quality.

5.2.6. Layer 6: Impact Layer. The final layer, the impact layer, represents the broader outcomes derived from implementing IoT and data analytics in agriculture. These include improved sustainability through reduced chemical usage, enhanced economic returns due to increased yields and efficiency, improved animal welfare, and strengthened consumer trust through traceability and transparency. This layer encapsulates the long-term societal, environmental, and economic effects, aligning digital agriculture with global goals such as food security, climate resilience, and smart rural development.

6. Discussion

6.1. Current Research Trends. This systematic review identifies eight trends in the integration of IoT and data analytics in agriculture, providing crucial insights into efforts aimed at addressing agricultural challenges such as productivity, resource efficiency, and sustainability. Understanding these trends is essential not only for improving farming methods but also for guiding future research and policymaking.

The dominant trend revolves around crop-based agriculture monitoring systems, with 19 studies highlighting the application of IoT and data analytics to monitor crop conditions. This focus is driven by the vital role crop agriculture plays in global food security and the significant challenges it faces, such as climate change and resource limitations. The integration of IoT and data analytics enables precise monitoring and management of factors like soil moisture, temperature, and crop health, enhancing productivity and sustainability.

Livestock-based agriculture monitoring systems, represented by two studies, also hold promise for improving the productivity and welfare of livestock through digital technologies. Although less represented in the literature, this area is gaining momentum, particularly in the use of IoT and data analytics to monitor animal behavior and health in real-time.

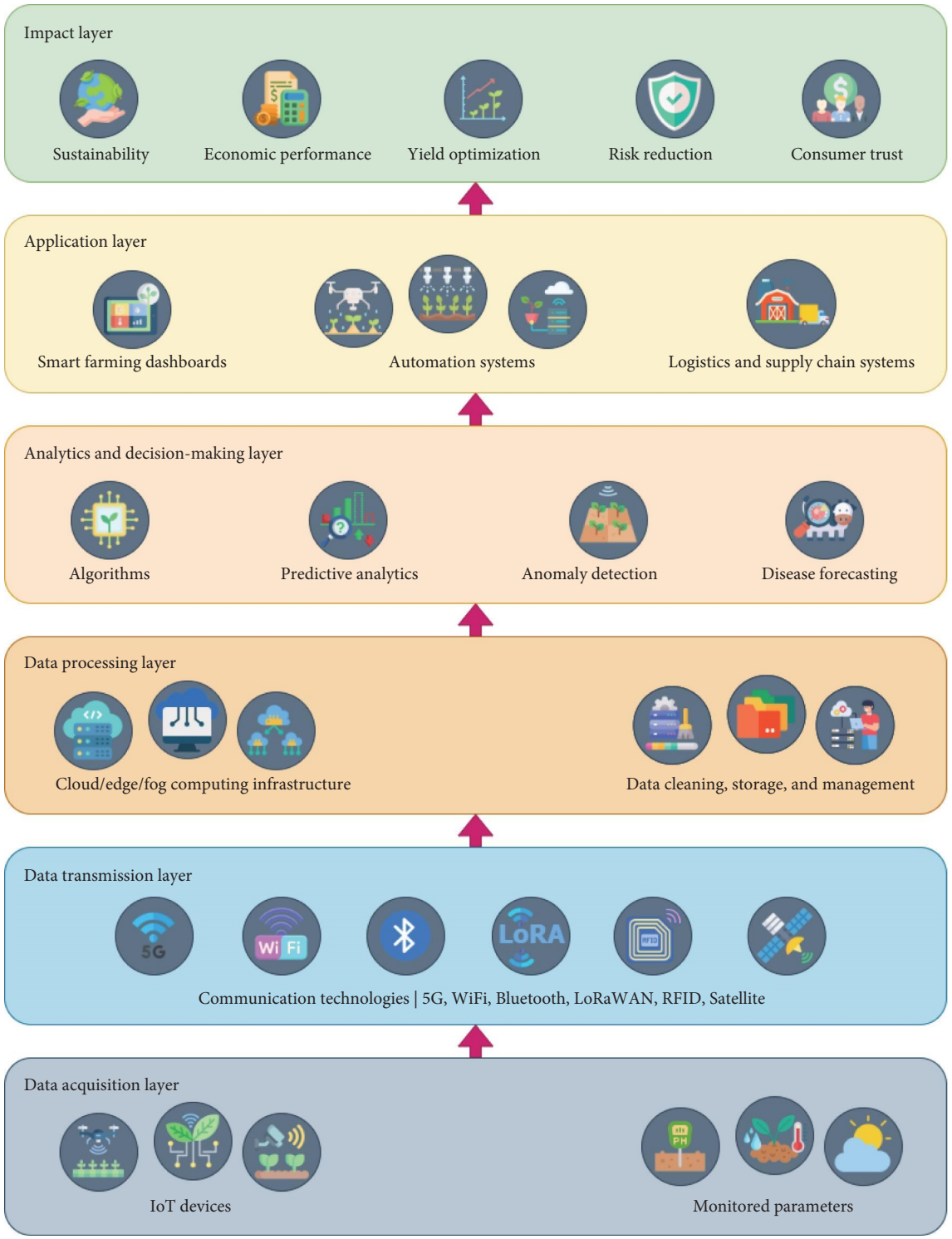

Figure 11: A layered conceptual framework for integrating IoT and data analytics in digital agriculture.

This has the potential to enhance livestock management and improve food supply chains.

General agriculture monitoring systems and agricultural product logistics systems are also emerging, addressing broader aspects of farming, including mixed farming as well as the movement and storage of agricultural products. The integration of data analytics into logistics has the potential to revolutionize supply chains by optimizing routes, reducing waste, and improving traceability. Additionally, combining insights from both crop and livestock monitoring can enable optimized resource use, such as water and feed, and improve decision-making across mixed farms.

Other notable trends include algorithms for agricultural data, which are pivotal for processing large datasets and enabling predictive analytics in farming. These algorithms allow for more accurate forecasting of crop yields, resource needs, and environmental impacts, helping farmers make data-driven decisions to optimize their operations. The refinement of these algorithms is crucial as it enhances the efficiency and reliability of IoT-driven systems in agriculture, especially in managing big data from sensors and other digital tools.

Blockchain technology is another emerging field, highlighted for its role in ensuring transparency, security, and traceability within agricultural systems. By creating immutable records of every transaction or process within the agricultural supply chain, blockchain helps build trust among stakeholders, mitigates fraud, and improves the accountability of food production systems. Additionally, blockchain can streamline supply chain logistics, reduce inefficiencies, and ensure the integrity of data related to agricultural products, which is especially critical for addressing issues like food safety and counterfeiting.

Last, studies addressing privacy-preserving geodistance evaluation and pattern recognition techniques reflect the growing interest in safeguarding data privacy and optimizing crop growth through advanced computational methods. Privacy-preserving techniques are essential as the use of IoT in agriculture involves sensitive data related to geographical locations and farming practices. Ensuring data privacy fosters trust in these systems while maintaining compliance with legal regulations. Meanwhile, pattern recognition techniques help identify and analyze complex factors affecting crop growth, such as climate variables, soil conditions, and pest infestations, enabling farmers to implement more precise and effective interventions. These advancements are integral to increasing both productivity and sustainability in modern agriculture.

6.2. Added Value of IoT and Data Analytics in Agriculture. The integration of digital technologies offers substantial value to the agricultural sector, including but not limited to enhancing productivity, resource efficiency, and environmental sustainability. IoT and data analytics can significantly improve the agility of farm operations by enabling real-time surveillance and responsive decision-making based on precise environmental data. For example, farmers can react swiftly to changes in soil moisture or pest outbreaks, preventing crop loss and improving yield.

Moreover, these technologies facilitate resource use efficiency by optimizing the application of water, fertilizers, and pesticides, leading to both economic and environmental benefits. By automating processes such as irrigation and fertilization, farmers can achieve significant time and cost savings, reducing manual labor while improving operational efficiency.

The environmental benefits of IoT and data analytics are also profound. By reducing the need for harmful inputs like pesticides and nitrogen fertilizers, they support greener agricultural practices. Additionally, the use of real-time monitoring tools enhances the sustainability of farming by enabling farmers to adopt climate-resilient practices that reduce their carbon footprint.

Digital platforms utilizing IoT and data analytics also enhance asset management, allowing farmers to monitor equipment and farm properties in real-time, improving maintenance and preventing costly breakdowns. Additionally, by ensuring product safety and improving traceability, technologies like blockchain when implemented with IoT and data analytics can help prevent fraud and ensure the quality and authenticity of agricultural products.

6.3. Challenges and Roadblocks in Agricultural Digitization. The widespread adoption of IoT and data analytics in agriculture is still met with notable difficulties. A major barrier is the cost and complexity associated with implementing advanced technologies, particularly in small-scale farms. The cost of sensors, IoT devices, and data analytics infrastructure can be prohibitive, especially in developing regions. Moreover, the complexity of integrating these technologies into existing agricultural systems, which involve living organisms and unpredictable environments, remains a key challenge.

Scalability is another issue, as large-scale farms require robust systems capable of handling vast amounts of data and maintaining real-time connectivity across distributed environments. Interoperability between different IoT systems, devices, and platforms is a persistent technical challenge, and the lack of standardization complicates the seamless exchange of data. Furthermore, data security and privacy remain major concerns, with the increasing digitization of farms exposing sensitive agricultural data to cyberattacks and unauthorized access.

Additionally, digital literacy and accessibility also impact the integration of IoT and data analytics in agriculture. Many farmers, particularly small-scale and older farmers, struggle with understanding how these technologies work or how they can benefit their operations. The lack of clear guidance from technology providers and governments further exacerbates this issue, leaving users uncertain about how to implement these tools effectively. Moreover, insufficient awareness campaigns limit the spread of knowledge about the advantages of digital agriculture, slowing down adoption rates. Finally, IoT and data analytics systems are still not user-friendly enough, making them difficult to operate for those without technical expertise.

Addressing these roadblocks will require coordinated efforts at the technical, regulatory, and policy levels. Overcoming these challenges will accelerate the adoption of smart farming technologies and contribute to the broader goals of sustainability and food security.

6.4. Future Research Directions. From the systematic review, future research directions are categorized into three different types which are improving current solutions, exploring new research grounds, and a combination of those two. Every future research direction will be analyzed to determine their significance and potential impact. Analyzing these may lead to more benefits and innovation in agriculture.

6.4.1. Improving Current Solutions. Triantafyllou et al. [41] propose a real-time performance study of their saffron cultivation monitoring system, aiming to enhance saffron yield. This would advance knowledge in the agricultural field related to

methods of increasing crop production and profits earned. Next, Yan et al. [51] seek improvements in their privacy-focused SPRIDE system. Improving this system would allow it to be integrated into other applications of IoT that include yield management, planting, and irrigation, subsequently improving the data security related to agricultural activity. Balan et al. [61] plan to enhance decision and prediction algorithms for fertilization strategies, ensuring more accurate information for farmers. Alonso et al. [45] aim to complete and implement their SmartDairyTracer platform, leveraging IoT and AI for comprehensive dairy industry improvements.

Sowmya et al. [62] recommend enhancing their system by incorporating features from other works, improving predictions made based on agrometeorological data, and therefore, refining farmers' decision-making. Revathi and Sengottuvelan [63] suggest revalidating data using deep neural networks and drone-based visualization for paddy field irrigation scheduling. Following their suggestions would ensure that the system gets accurate data and will be less prone to wrongful decisions. Angeloni [54] aims to improve the RobotFarm appliance for hydroponic cultivation. Enhancing this appliance would allow it to better serve consumers and provide a sustainable platform for the production of crops. Latif et al. [64] propose integrating their convolutional neural network (CNN) model with others for better frost event predictions and improved computational costs. Ruan et al. [48] focus on improving their granular GA-SVM predictor for big data in agricultural cyber–physical systems. Refinement of this predictor will enable the processing of more complex big data and improve overall efficiency, benefiting the computation of agricultural big data.

Joshi et al. [55] plan to upgrade their crop irrigation system through the integration of GPS, MATLAB, and WSN, which expands the system's functionalities for improved productivity. Taneja et al. [44] consider enhancing system reliability by incorporating multiple gateways. Improving the reliability would ensure that there will be fewer events that can cause data loss and corruption for their animal behavior and health monitoring system. Tseng et al. [65] recommend integrating AI into their smart IoT equipment for farm environmental monitoring. It would improve result analysis and allow for automatic environmental control and cultivation. Liu et al. [66] aim to validate their experimental approach using simulations and real-world implementation for modern agriculture systems. Validation of the experimental approach would demonstrate the feasibility of their proposed solution and identify opportunities for improvement. This could benefit the agricultural field since it can be used as a guideline to design agricultural systems.

6.4.2. Exploring New Research Grounds. Gao et al. [46] emphasize leveraging economic theories and agricultural IoT data for enhancing big data analysis in agriculture. Their recommendations would make it possible to investigate and evaluate functional requirements relevant to modeling methods to advance the application of agricultural big data analysis. Rabhi et al. [58] propose a big data analytics meta-model for smart farms, exploring digital and connected agriculture use cases. This can serve as a guideline for constructing smart farms that rely on IoT and data analytics. Li and Niu [57] plan to use classification technologies for analyzing and predicting specific agricultural product outputs. This will benefit the data mining aspect of agricultural greenhouse systems and allow for better predictions.

Taneja et al. [59] express interest in further researching clustering techniques, distributed analytics and learning methods for IoT–based lame cattle detection. This will cause improvement in the detection of lame cattle, reducing the number of wrongful identification. Sambrekar and Rajpurohit [47] focus on developing a cost-effective multilevel cloud storage architecture for agricultural management systems, emphasizing real-time agricultural data analysis. Their work improves classification models for the analysis of agricultural data and solidifies their validity.

6.4.3. Combining Improving Current Solutions and Exploring New Research Grounds. Castañeda-Miranda and Castaño-Meneses [43] aim to enhance their research methodology and discover new meteorological datasets using neural networks for temporary processing, contributing to intelligent frost control in smart farming greenhouses. Their recommendation would strengthen the system by making it much more smarter and accurate in predictions. Ilieva et al. [50] plan to devise novel hybrid methods for assessing blockchain software, as well as enhance the multicriteria selection of blockchain software, which could lead to the selection of suitable blockchain software that could work in tandem with IoT and data analytics technology. Park et al. [52] express dual interests in both validating currently proposed strategies for improving tomato yield and developing a new smart farming system for automating environmental and growth factor management. Their planned actions hold potential for broader agricultural applications beyond greenhouses, offering possibilities for automating plant growth management, which includes but is not limited to tomatoes.

6.5. Comparative Evaluation of Reviewed Studies. To complement the thematic findings and the conceptual frameworks, a comparative evaluation matrix was developed to synthesize the technological and functional characteristics of the 28 selected studies. This matrix offers a synthesized view of the studies' application domains, technology stacks, maturity levels, scalability, evaluation methods, barriers, benefits, and overall scoring. The table for the comparative evaluation matrix can be viewed in Table A2.

The synthesized matrix reveals that a majority of the reviewed studies concentrate on crop monitoring, highlighting it as the most extensively explored and prioritized domain within IoT and data analytics in agriculture. This emphasis underscores a strong research and development focus on enhancing crop yield, health assessment, and environmental monitoring. In contrast, other areas such as logistics, livestock monitoring, general agricultural monitoring, blockchain integration, precision agriculture, and broader agricultural data analytics receive comparatively less attention. The predominance of crop monitoring suggests that these other domains remain underexplored, thereby presenting valuable opportunities for future research to address existing gaps and diversify the scope of technological innovation in agriculture.

In terms of technologies utilized across the studies, IoT, AI, and big data emerge as the most prominent, with frequent implementation of sensor networks, machine learning algorithms, and big data platforms such as Hadoop. This trend suggests that these technologies are becoming foundational components in the development of smart agriculture systems, emphasizing data collection, intelligent analytics, and scalable processing. Additionally, technologies such as GPS and GIS, mobile applications, and data fusion techniques are also commonly employed. This indicates a growing inclination towards multimodal technological integration to enhance spatial awareness, field-level decision-making, and real-time responsiveness within agricultural environments.

Regarding system maturity, fewer than one-third of the studies have progressed to the final stages of development, namely, pilot deployment or production-ready implementation. The majority remain at the conceptual stage or within early to mid-stage prototype development. This trend underscores a research-to-practice gap in digital agriculture, where many promising technologies have yet to achieve real-world application at scale. The prevalence of conceptual models and preliminary prototypes indicates a predominant focus on system design, feasibility analysis, and proof-of-concept, rather than on empirical validation or widespread deployment. The lack of mature systems implies a significant gap in empirical evaluation and practical deployment, highlighting the need for more robust testing, scalability studies, and performance evaluations in real agricultural environments. This maturity imbalance presents an opportunity for future research to focus on transitioning from prototypes to deployment, particularly by addressing scalability, reliability, user adoption, and cost-effectiveness.

For system scalability, the majority of studies were assessed as having moderate to high scalability. This suggests that many of the proposed systems are designed with growth, adaptability, and broader deployment in mind, even if they have not yet been fully implemented. The findings suggest that scalability is a key consideration during the system design phase, with researchers actively addressing factors such as data volume management, interoperability, and infrastructure flexibility. The widespread use of cloud computing, big data, and modular architectures contributes to this scalability rating, enabling systems to expand across different farm sizes, geographic regions, and crop types. This emphasis on scalable design reflects a forward-thinking approach within the research community, signaling strong potential for wider adoption and long-term impact once implementation challenges are overcome.

Evaluation methods varied across the studies, with some employing multiple approaches to assess their proposed systems. The majority relied on statistical analysis and system performance testing, indicating a strong preference for data-driven evaluation focused on quantifiable outcomes such as accuracy, efficiency, and reliability. In contrast, only a minority incorporated expert opinion, assessed plant growth rates, or utilized use case studies. This underutilization of contextual and real-world evaluation methods highlights a gap in practical validation, which is essential for assessing the systems' effectiveness in actual agricultural environments. The limited engagement with user-centric and stakeholder-driven evaluations such as expert feedback and use case implementation raises concerns about the adoptability and real-world relevance of such systems. Furthermore, the absence of agronomic indicators such as plant growth limits the ability to showcase the tangible benefits of these systems in real-world agricultural contexts. To enhance the practical value and acceptance of smart agriculture technologies, future research should integrate comprehensive evaluation metrics that align technological performance with agronomic outcomes and end-user needs.

The comparative evaluation matrix highlights several key implementation barriers that continue to impede the adoption of IoT and data analytics systems in agriculture. A key challenge is the lack of interoperability, with multiple studies highlighting difficulties in achieving seamless communication between components from different manufacturers. High implementation costs also remain a significant obstacle, particularly in settings with limited financial resources. Technical immaturity is also evident in the widespread concerns over data security and privacy, indicating inadequate mechanisms for protecting sensitive information. The difficulty in mining and processing large volumes of agricultural data, especially in real time, represents a technological bottleneck that compromises the timeliness and effectiveness of data-driven decision-making in the field. The absence of clear, practitioner-oriented implementation models further reflects a disconnect between research and real-world application. Additionally, nontechnical barriers such as limited willingness to adopt new technologies and poor internet connectivity highlight underlying issues related to digital infrastructure, user awareness, and education. These findings suggest that overcoming these barriers will require not only technological advancements but also supportive infrastructure, standardization efforts, user training, and policy interventions.

The most commonly reported benefits of IoT and data analytics applications in agriculture center around both economic and environmental gains. A majority of studies highlight improvements in product quality, production efficiency, and profitability, indicating a strong focus on enhancing the productivity and financial viability of farming operations. At the same time, several studies also emphasize the role of these technologies in reducing environmental impact and promoting sustainable agricultural practices, reflecting a growing concern for ecological responsibility. Additionally, the emergence of predictive capabilities across multiple studies points to a shift toward data-driven decision-making, enabling farmers to anticipate issues and optimize resources more proactively. Collectively, these benefits demonstrate the transformative potential of digital technologies in modern agriculture, offering not only operational improvements but also long-term sustainability.

Each study was also evaluated and assigned a score reflecting the current development level of its proposed system. The scoring framework was based on three key criteria, which were system maturity, technological integration, and scalability. A lower score indicates a system of limited quality or readiness, whereas a higher score reflects greater quality and development maturity. The scoring process began with an assessment of

system maturity. Systems that were outdated, incomplete, or poorly validated were rated below 5. Systems in the conceptual or early prototype phase were typically assigned a score of 6 or 7, while those in the mid-stage or end-stage prototype phase received scores of 7 or 8. Systems in the end-stage prototype, pilot deployment, or production-ready phase were rated between 9 and 10. This initial maturity-based score served as the baseline. It was then adjusted upward or downward based on the system's scalability and technological integration. For example, the inclusion of robust scalability features or advanced technologies could raise the score, whereas limited scalability or reliance on outdated technologies could lower it.

Based on the evaluation matrix, it can be seen that all studies achieved a score above 5, indicating that none of the proposed systems were of very low quality or readiness. Most studies scored 7, suggesting that the majority of systems were in the conceptual or early prototype stage, with some reaching mid-stage development. This was followed by scores of 8, which generally reflect mid-stage to end-stage prototypes with stronger technological integration or scalability features. A smaller number of studies scored 6, representing early-phase systems with limited validation, while a few reached 9, indicating pilot deployment or near-production readiness. Notably, none of the studies achieved the highest score of 10, highlighting that fully mature and production-ready solutions with groundbreaking technologies remain rare in this domain. Overall, the distribution of scores suggests that while there is steady progress in system development, most solutions remain in early to mid-level stages, with significant scope for advancement in scalability, technological sophistication, and real-world deployment.

In summary, the comparative evaluation matrix provides an integrated view of the current state of IoT and data analytics in agriculture, covering application domains, technologies, system maturity, scalability, evaluation practices, benefits, and barriers. The results show notable strengths in the dominance of crop monitoring, the widespread use of IoT, AI, and big data, and the emphasis on scalability in system design. However, challenges remain, including limited system maturity, insufficient real-world evaluation, and a narrow focus on certain domains. The scoring analysis indicates that most systems are still in the conceptual to mid-prototype stages, with few nearing deployment. These findings suggest that future progress will depend on advancing scalability, strengthening technological integration, expanding evaluation approaches, and closing the gap between research and practice to achieve impactful and production-ready solutions.

6.6. Research Gaps and Avenues for Further Exploration. This SLR has identified gaps worth exploring based on the analysis of the 28 selected studies. Table 16 displays the identified gaps in the literature along with relevant research questions for those gaps.

6.7. Study Limitations. The study's limitations primarily stem from its reliance on a constrained set of academic databases, namely, Scopus and WoS. This focused approach, while beneficial for in-depth analysis, potentially omits significant contributions from other scholarly databases and publications that could offer additional insights or alternative viewpoints on the intersection of IoT and data analytics in agriculture. Such an exclusion risks a narrowed perspective, potentially overlooking emerging trends, novel methodologies, or critical evaluations that exist outside these selected databases.

Furthermore, the study predominantly focuses on published academic literature, which inherently limits the scope of analysis to perspectives that have undergone the formal publication process. This approach may inadvertently exclude gray literature, such as industry reports, government publications, and unpublished academic work, which could provide practical insights, real-world applications, and policy implications that enrich the understanding of IoT and data analytics in agriculture.

Additionally, the temporal range of the literature reviewed could impose constraints. As technology rapidly evolves, especially in fields like IoT and data analytics, recent developments or ongoing research might not be adequately represented in the review. This time lag could lead to a snapshot that, while comprehensive for its period, may not fully capture the most current advancements and trends in the field.

In essence, while the systematic review provides a robust analysis within its defined parameters, its findings must be contextualized within these methodological boundaries to fully appreciate the breadth and depth of the rapidly evolving domain of IoT and data analytics in agriculture.

Moreover, the conceptual model has not yet been validated to determine whether the external variables suggested ultimately impact users' intentions to use IoT and data analytics systems in agriculture. This presents an interesting topic for future studies, which could employ comprehensive quantitative methods.

6.8. Implications. The implications of the study are manifold and extend to various stakeholders involved in agriculture, as well as to the advancement of knowledge in agricultural technology, particularly in the realms of IoT and data analytics. By reviewing and analyzing current trends in IoT and data analytics in agriculture, this study contributes to the theoretical understanding of how these technologies are shaping agricultural practices. The insights gained from the analysis can enrich existing theories on technology adoption, innovation diffusion, and agricultural development.

From a practical point of view, agricultural stakeholders, including farmers, agricultural extension workers, policymakers, and technology developers, stand to benefit from the findings of this study. Understanding the advantages of IoT and data analytics in agriculture can inform decision-making processes related to technology adoption, resource allocation, and investment strategies. Moreover, insights into the barriers to implementing these technologies can guide the development of targeted interventions and support mechanisms to overcome challenges faced by stakeholders.

Additionally, policymakers and regulatory authorities can leverage the findings of this study to formulate policies and regulations that promote the adoption and integration of IoT and data analytics in agriculture. Addressing the identified barriers and facilitating the effective evaluation of IoT and

Table 16: Identified gaps and research questions.

Theme	Gaps	Potential research questions (RQs)
Current research trends in IoT and data analytics in agriculture	Sustainability and environmental impact	RQ1: How can IoT and data analytics be leveraged to optimize water usage in agriculture while minimizing environmental impact?
		RQ2: What strategies can be implemented to quantify and mitigate the carbon footprint of agricultural practices using IoT and data analytics?
	User-centric design and adoption	RQ3: How can user-centric design principles be applied to IoT devices and interfaces to enhance usability and acceptance among farmers with varying levels of technological literacy?
		RQ4: What are the key factors influencing the adoption of IoT and data analytics tools among different segments of agricultural stakeholders and how can these barriers be addressed?
	Regulatory and policy implications	RQ5: What are the key regulatory challenges and policy gaps hindering the widespread adoption of IoT and data analytics in agriculture and how can they be addressed?
		RQ6: How do existing agricultural policies and regulations impact the collection, sharing, and use of data generated by IoT devices and what reforms are needed to foster innovation while safeguarding privacy and security?
	Integration with traditional knowledge	RQ7: How can IoT and data analytics systems be designed to effectively integrate traditional agricultural knowledge and practices, ensuring their relevance and applicability in modern farming contexts?
		RQ8: What mechanisms can facilitate knowledge exchange and collaboration between traditional farmers and technology developers to cocreate IoT–based solutions that align with local agricultural traditions and needs?
	Capacity building and training	RQ9: What are the most effective approaches for designing and delivering training programs to build the digital skills and literacy necessary for farmers to effectively utilize IoT and data analytics tools?
		RQ10: How can partnerships between educational institutions, agricultural extension services, and technology providers be leveraged to scale up capacity-building efforts and reach underserved farming communities effectively?
Advantages of IoT and data analytics in agriculture	Labor optimization	RQ1: How do different types of IoT-enabled technologies impact labor efficiency and productivity in various agricultural settings?
		RQ2: What are the socioeconomic implications of labor optimization through IoT and data analytics in agriculture, particularly concerning employment patterns and rural livelihoods?
	Energy conservation	RQ3: What are the most effective strategies for utilizing IoT and data analytics to optimize energy usage in diverse agricultural operations, such as irrigation, livestock management, and crop cultivation?
		RQ4: How do factors such as farm size, geographic location, and technological infrastructure influence the feasibility and effectiveness of energy conservation measures facilitated by IoT and data analytics?
	Disease and pest detection	RQ5: How can IoT sensors and data analytics algorithms be integrated to enhance the accuracy and timeliness of disease and pest detection in crops and livestock?
		RQ6: What are the barriers to the adoption of IoT–based disease and pest monitoring systems among farmers and how can these barriers be addressed to facilitate widespread implementation?
	Disaster resilience	RQ7: What role can IoT sensors and predictive analytics play in improving agricultural resilience to natural disasters such as floods, droughts, and extreme weather events?

Table 16: Continued.

Theme	Gaps	Potential research questions (RQs)
		RQ8: How can multistakeholder collaborations be leveraged to develop and implement disaster resilience strategies that incorporate IoT and data analytics technologies at the farm and community levels?
	Carbon footprint reduction	RQ9: What are the most significant contributors to agricultural carbon emissions and how can IoT and data analytics solutions target these sources for reduction?
		RQ10: How do farm-level carbon footprint reduction initiatives enabled by IoT and data analytics align with broader sustainability goals and policies, and what are the potential trade-offs and synergies?
Barriers to implementing IoT and data analytics systems in agriculture	Inconsistent performance of IoT sensors under extreme weather conditions or in remote rural areas	RQ1: How can IoT sensor technologies be improved to ensure reliable performance in diverse weather conditions prevalent in agricultural settings?
		RQ2: What are the most effective strategies for deploying and maintaining IoT sensor networks in remote rural areas with limited infrastructure and connectivity?
	Ethical considerations surrounding the collection, use, and sharing of agricultural data in IoT ecosystems	RQ3: What ethical frameworks and guidelines are needed to ensure responsible data collection, use, and sharing practices in agricultural IoT deployments?
		RQ4: How do farmers and other stakeholders perceive and navigate ethical dilemmas related to data privacy, ownership, and consent in IoT-enabled farming environments?
	Challenges in quantifying the return on investment (ROI) and economic benefits of IoT adoption in agriculture	RQ5: What methodologies and metrics can be employed to accurately assess the economic impact and ROI of implementing IoT technologies across different types of farms and agricultural operations?
		RQ6: How do socioeconomic factors such as farm size, location, and market dynamics influence the cost-effectiveness and financial viability of IoT adoption in agriculture?
	Lack of robust disaster recovery and backup mechanisms for IoT-generated agricultural data	RQ7: What are the best practices for designing and implementing disaster recovery and backup systems tailored to the unique data requirements and constraints of agricultural IoT deployments?
		RQ8: How can distributed ledger technologies such as blockchain be leveraged to enhance the resilience and integrity of agricultural data storage and recovery systems in IoT ecosystems?
	Challenges in quantifying and managing the environmental impacts of IoT-enabled farming practices	RQ9: What methodologies and indicators can be used to assess the environmental footprint of IoT-enabled agricultural activities, including resource usage, emissions, and ecosystem impacts?
		RQ10: How can IoT and data analytics be integrated into holistic sustainability assessment frameworks to enable farmers and policymakers to make informed decisions about the environmental implications of adopting IoT technologies in agriculture?
Effectiveness of IoT and data analytics systems in agriculture	Comparative studies between IoT-equipped farms and control groups using traditional methods	RQ1: How do key performance indicators such as crop yield, resource usage efficiency, and profitability differ between farms utilizing IoT and data analytics compared to those employing traditional farming methods?
		RQ2: What are the specific factors contributing to the observed differences in agricultural outcomes between IoT-equipped farms and control groups and how do these factors vary across different agricultural contexts?
	Simulation modeling of IoT and data analytics implementation in farms	RQ3: How accurately do simulation models predict the expected outcomes of implementing IoT and data analytics solutions in agriculture, including changes in crop yield, resource utilization, and economic returns?
		RQ4: What are the most critical variables and assumptions that influence the reliability and validity of simulation models used to

Table 16: Continued.

Theme	Gaps	Potential research questions (RQs)
		simulate the effects of IoT and data analytics adoption in agricultural systems?
	Livelihoods impact assessments to measure the socioeconomic benefits of IoT adoption	RQ5: What are the socioeconomic impacts of adopting IoT and data analytics technologies on farmers' livelihoods, including changes in income levels, employment opportunities, and overall well-being?
		RQ6: How do factors such as access to markets, technological literacy, and support infrastructure influence the magnitude and distribution of socioeconomic benefits derived from IoT adoption in agriculture?
	Usage analytics to understand farmer engagement and interaction with IoT platforms	RQ7: What are the patterns of farmer engagement with IoT platforms, including frequency of use, features utilized, and duration of interactions?
		RQ8: How do user feedback and interaction data collected from IoT platforms inform the design and refinement of user interfaces and features to enhance farmer adoption and satisfaction?
	Resource quantification to measure the efficiency gains achieved through IoT-driven resource management	RQ9: What are the quantifiable gains in resource efficiency, such as water, energy, and inputs, achieved through the implementation of IoT-driven resource management systems?
		RQ10: What are the key performance metrics and benchmarks used to quantify the efficiency gains achieved through IoT-driven resource management practices, and how do these metrics vary across different agricultural production systems and regions?

data analytics systems can foster an enabling environment for innovation and technology-driven growth in the agricultural sector.

Moreover, the identification of future research directions provides a road map for scholars and researchers to explore new avenues and address unanswered questions in the field of IoT and data analytics in agriculture. By highlighting areas such as the measurement of effectiveness and emerging trends, this study lays the groundwork for further inquiry and innovation, driving continuous advancements in agricultural technology.

Overall, the implications of this study extend beyond academic circles to have practical benefits for agricultural stakeholders and policymakers alike. By shedding light on the current state and prospects of IoT and data analytics in agriculture, this study contributes to the sustainable development of the agricultural field and the enhancement of agricultural digital technologies, particularly those related to IoT and data analytics.

7. Conclusion and Future Work

7.1. Summary of Findings. The current study implemented a rigorous SLR to explore the relationship between IoT and data analytics in the agricultural industry. A comprehensive examination was conducted on a curated collection of 28 influential works, utilizing the PRISMA framework as a guiding structure. The aforementioned scholarly contributions were thoroughly analyzed to extract significant insights that address five key research inquiries. These inquiries encompass the examination of current trends, inherent benefits, common barriers, approaches for evaluating effectiveness, and potential directions for future research in agricultural IoT and data analytics. The review facilitated a thorough examination of the existing body of literature, leading to the consolidation of research outcomes and the development of a conceptual framework. This framework serves as a guide for the creation of widely accepted IoT and data analytics systems in agriculture. The comprehensive analysis conducted in this study, together with the conceptual model and framework, provides valuable insights that contribute to a more nuanced understanding of the current academic discourse, thereby enhancing the fundamental understanding in the realm of IoT and data analytics within the agricultural sector.

7.2. Recommendations for Future Research. For future research, it is essential to widen the scope of this review by incorporating a more diverse array of databases beyond Scopus and WoS, which would enhance the empirical robustness of findings by covering a broader spectrum of literature. Key areas for further study include a detailed examination of the specific technologies underpinning IoT and data analytics in agriculture, focusing on their attributes, functionalities, and practical limitations. Additionally, an in-depth analysis of the influence of governmental policies on the deployment of these technologies is crucial, as understanding regulatory frameworks and socioeconomic factors can highlight barriers and facilitators to their adoption. Finally, investigating the environmental impact of these technologies is imperative, particularly their energy use, waste production, and emissions, in the context of global environmental concerns such as climate change and resource depletion.

7.3. Emerging Opportunities and Strategic Implications. The findings of this review, coupled with the proposed conceptual frameworks and comparative evaluation matrix, highlight

several emerging opportunities and strategic directions for the evolution of IoT and data analytics in agriculture. First, the growing availability of cost-effective IoT hardware and cloud-based analytics platforms presents a unique opportunity to scale smart agriculture systems beyond experimental prototypes. As more open-source and interoperable solutions emerge, the barriers related to system integration and vendor lock-in are expected to diminish, particularly in resource-constrained environments. This opens the door for modular and customizable agricultural IoT systems that can be adapted to varying scales, from smallholder farms to industrial operations.

Second, the convergence of AI with edge computing offers a path toward more autonomous and real-time decision-making in agricultural operations. A majority of the reviewed studies still rely heavily on cloud infrastructure. Future systems are likely to feature decentralized intelligence where data is processed and acted upon closer to the source, leading to reduced latency, enhanced resilience in areas with poor connectivity, and improved energy efficiency. Third, the integration of blockchain technologies with IoT and data analytics introduces new opportunities for enhancing transparency, traceability, and trust within agri-food supply chains. While adoption is currently limited, the conceptual potential for decentralized data validation, smart contracts, and tamper-proof provenance records is considerable, especially for certification, compliance, and export-focused agriculture.

Furthermore, the intersection of environmental sustainability and precision agriculture is poised to become a critical focal point. Climate-smart agricultural systems that leverage predictive analytics to reduce input waste, optimize water usage, and minimize chemical application will align closely with emerging policy incentives and sustainability standards. Strategically, stakeholders, including policymakers, system developers, and academic researchers, must prioritize the development of cross-disciplinary frameworks that incorporate not only technical viability but also usability, ethics, and institutional readiness. Efforts should also be made to establish standardized evaluation metrics for system performance, impact, and scalability.

Collectively, these opportunities suggest a shift from isolated technological implementations toward integrated and data-driven agricultural ecosystems. By addressing systemic barriers and capitalizing on emerging technological trends, the agricultural sector can move closer to achieving resilient, efficient, and sustainable food production systems for the future.

Appendix A

Table A1: Reviewed studies.

Study	Author and year	Title
P1	Triantafyllou et al. [41]	Precision agriculture: a remote sensing monitoring system architecture
P2	Gao et al. [46]	Intelligent circulation system modeling using bilateral matching theory under Internet of Things technology
P3	Castañeda-Miranda and Castaño-Meneses [43]	Internet of things for smart farming and frost intelligent control in greenhouses
P4	Rabhi et al. [58]	A functional framework based on big data analytics for smart farming
P5	Ilieva et al. [50]	Blockchain software selection as a fuzzy multicriteria problem
P6	Yan et al. [51]	Scalable privacy-preserving geodistance evaluation for precision agriculture IoT systems
P7	Oh [56]	Smart urban farming service model with IoT based open platform
P8	Balan et al. [61]	Smart multisensor platform for analytics and social decision support in agriculture
P9	Li and Niu [57]	Design of smart agriculture based on big data and Internet of Things
P10	Taneja et al. [59]	Machine learning–based fog computing assisted data-driven approach for early lameness detection in dairy cattle
P11	Kim et al. [42]	A smart, sensible agriculture system using the exponential moving average model
P12	Alonso et al. [45]	An intelligent Edge-IoT platform for monitoring livestock and crops in a dairy farming scenario

Table A1: Continued.

Study	Author and year	Title
P13	Sowmya et al. [62]	Data analytic techniques for developing decision support system on agrometeorological parameters for farmers
P14	Zhang and Zhang [49]	A big data mining and blockchain-enabled security approach for agricultural based on Internet of Things
P15	Tatapudi and Suresh Varma [69]	Prediction of crops based on environmental factors using IoT and machine learning algorithms
P16	Revathi and Sengottuvelan [63]	Real-time irrigation scheduling through IoT in paddy fields
P17	Angeloni [54]	Domo Farm 4.0
P18	Subahi and Bouazza [60]	An intelligent IoT–based system design for controlling and monitoring greenhouse temperature
P19	Keswani et al. [70]	Improving weather dependent zone specific irrigation control scheme in IoT and big data enabled self driven precision agriculture mechanism
P20	Latif et al. [64]	Integration of Google Play content and frost prediction using CNN: scalable IoT framework for big data
P21	Ruan et al. [48]	A granular GA-SVM predictor for big data in agricultural cyber–physical systems
P22	Park et al. [52]	Determination on environmental factors and growth factors affecting tomato yield using pattern recognition techniques
P23	Joshi et al. [55]	WSN hardware prototype for irrigation control and multiparameter plant growth monitoring using IoT
P24	Taneja et al. [44]	SmartHerd management: a microservices-based fog computing–assisted IoT platform towards data-driven smart dairy farming
P25	Zamin et al. [53]	KLIKTani: a concept of a smart edible garden using IOT for Indigenous community in Malaysia
P26	Tseng et al. [65]	Applying big data for intelligent agriculture-based crop selection analysis
P27	Liu et al. [66]	Internet of Things monitoring system of modern ecoagriculture based on cloud computing
P28	P. Sambrekar and S. Rajpurohit [47]	Fast and efficient agro data classification model for agriculture management system using hierarchical cloud computing

Table A2: Comparative evaluation matrix.

Study	Application type	Technology stack	System maturity	Scalability	Evaluation method	Barriers	Benefits	Evaluation score
P1	Crop monitoring	• IoT • Unmanned aerial vehicles (UAVs) • FIWARE orion context broker • Big data tools • AI	Early-stage prototype	High	Use case	C1, C2, C3, C4, C5, C6	A1, A2, A3, A4, A5, A6	8
P2	Logistics	• IoT • Remote sensing and GIS technologies • AI	Mid-stage prototype	Moderate to high	Use case	NA	A2, A3, A4	8
P3	Crop monitoring	• IoT • AI	End-stage prototype	Moderate	Statistical analysis	NA	A7	8
P4	General agriculture monitoring	• IoT • Big data tools • AI • Data visualization tools	Conceptual	High	NA	NA	A3, A4, A5, A6, A7, A8	6
P5	Blockchain in agriculture	• Blockchain technology • Decision support systems • AI	Conceptual	Moderate to high	Expert comparison	C1, C6, C7, C8	A1, A2, A3, A6, A7, A9	6
P6	Precision agriculture technology	• IoT • GPS and GIS technologies	Mid-stage prototype	High	System performance	C7	A5	7
P7	Crop monitoring	• IoT	Conceptual	Moderate to high	NA	C12	A4	6
P8	Crop monitoring	• IoT • AI	End-stage prototype	High	Statistical analysis + system performance	NA	A2, A4	8
P9	Crop monitoring	• IoT • Big data tools • AI	Conceptual	Moderate	Statistical analysis	NA	A1, A3, A4, A5, A7	6
P10	Livestock monitoring	• IoT • Fog computing • AI • Microservices	Pilot deployment	High	Statistical analysis + system performance + expert comparison	C2, C6, C14	A2, A4, A7	9
P11	Crop monitoring	• IoT • Mobile devices • AI	Early-stage prototype	Low to moderate	Statistical analysis	NA	A1, A2, A3, A4, A7	6
P12	General agriculture monitoring	• IoT • Edge computing • Blockchain technology • AI	Pilot deployment	High	Use case + system performance	NA	A2, A4, A6, A7, A9	9
P13	Crop monitoring	• AI	Early-stage prototype	Moderate	Statistical analysis	NA	A1, A4, A7	7
P14	Agricultural data analytics	• IoT • Blockchain technology • Data fusion + big data technology • AI	Early-stage prototype	Moderate to high	Statistical analysis	NA	NA	7

Table A2: Continued.

Study	Application type	Technology stack	System maturity	Scalability	Evaluation method	Barriers	Benefits	Evaluation score
P15	Crop monitoring	• IoT • AI	Early-stage prototype	Moderate	Statistical analysis	NA	A4, A5, A7	6
P16	Crop monitoring	• IoT • Big data technology • AI	Early-stage prototype	Moderate to high	System performance	NA	A4	7
P17	Crop monitoring	• IoT	Production ready	Moderate	NA	C6, C7, C9, C11	A1, A2, A3, A4, A5, A7, A8	8
P18	Crop monitoring	• IoT • Energy efficient technology • Big data technology	Conceptual	High	System performance	NA	A1, A2, A3, A4	7
P19	Crop monitoring	• IoT • Big data technology • Decision support systems • AI	Pilot deployment	High	Statistical analysis	NA	A7	9
P20	Crop monitoring	• IoT • AI • Mobile devices	Early-stage prototype	Moderate to high	Statistical analysis	NA	A7	7
P21	Agricultural data analytics	• IoT • Big data technology • AI	Early-stage prototype	Moderate to high	Statistical analysis	C13	NA	8
P22	Crop monitoring	• IoT	Pilot deployment	Moderate	Statistical analysis	C13	A1, A4	8
P23	Crop monitoring	• IoT	Mid-stage prototype	Moderate	System performance	NA	A3, A4	7
P24	Livestock monitoring	• IoT • Fog computing • Microservices • AI	Pilot deployment	High	Statistical analysis + system performance	C2, C6, C10, C14	A2, A3, A4, A7	9
P25	Crop monitoring	• IoT • Mobile apps	Early-stage prototype	Moderate	Plant growth rate	C12	A2, A3	7
P26	Crop monitoring	• IoT • Big data technology	Pilot deployment	High	Statistical analysis	NA	A1, A3, A4	9
P27	Crop monitoring	• IoT • Big data technology • AI • Mobile apps	Conceptual	High	NA	C13	A2, A3, A4, A5	7
P28	Agricultural data analytics	• IoT • Big data technology	Mid-stage prototype	High	Statistical analysis + system performance	NA	A4, A7	8

Abbreviation: NA, not available.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Disclosure

After using ChatGPT, the authors reviewed and edited the content as needed and took full responsibility for the content of the publication.

Conflicts of Interest

The authors declare no conflicts of interest.

Author Contributions

Zulfadli Hazim Zul Azlan: data curation, formal analysis, visualization, investigation, methodology, writing – original draft, writing – review and editing. **Syahrul Nizam Junaini:** conceptualization, methodology, project administration, supervision, validation, funding acquisition, writing – review and editing. **Adnan Shahid Khan** and **Wan Azani Mustafa**: writing – review and editing.

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