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Leveraging Internet of Things and Artificial Intelligence in Smart Agriculture to Enhance Food Security and Sustainable Farming: A Systematic Review

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Abstract.
Purpose: Achieving global food security while maintaining environmentally sustainable agricultural systems remains a critical challenge amid population growth, climate variability, and resource constraints. Artificial Intelligence (AI) and the Internet of Things (IoT) have emerged as transformative technologies that support data-driven agricultural practices. This study systematically examines the applications, opportunities, challenges, and adoption factors of AI-IoT integration in smart agriculture, with particular emphasis on its potential contributions to food security and sustainable farming.
Methods: A systematic literature review (SLR) was conducted following the PRISMA 2020 guidelines. Publications were retrieved from Scopus, IEEE Xplore, and ScienceDirect covering the period 2020-2024. From an initial 431 records, 17 empirical studies met the inclusion criteria and were analysed using narrative and thematic synthesis.
Result: The review shows that AI-IoT technologies are primarily applied in crop disease detection, precision agriculture, environmental monitoring, yield prediction, and livestock health monitoring. These technologies enable real-time decision support, early disease detection, productivity improvement, and resource optimisation. However, challenges remain, including data limitations, infrastructure constraints, integration complexity, and high deployment costs.
Novelty: The study proposes a layered smart agriculture framework linking technological infrastructure, application domains, adoption conditions, operational outcomes, and sustainability impacts. The findings highlight key factors necessary for successful implementation, including infrastructure readiness, affordability, technological reliability, and capacity development for farmers. Crucially, the review demonstrates that the field of AI-IoT smart agriculture is technically advanced but socio-technically incomplete: the evidence base is dominated by proof-of-concept studies from Asia, with no empirical representation from Africa or the Americas, creating what this study terms an AI-IoT agricultural equity gap that fundamentally limits the technology's contribution to global food security. The five-layered framework introduced here provides the first inductively derived organising structure that explicitly connects AI-IoT infrastructure to SDG-aligned food security outcomes, offering a replicable analytical scaffold for future empirical and policy research in this domain.

Keywords: Internet of Things (IoT), Artificial Intelligence (AI), Sustainable Development Goal (SDG 2), Marginalized Economies, Smart Agriculture, Precision Farming, Sustainable Farming, Food Security
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INTRODUCTION

Agriculture continues to be an important aspect of the global food production system, livelihood, and economy [1]. However, agricultural operations have started facing several difficulties due to increasing population, climate change, exhaustion of resources, and destruction of natural environments [2], [3]. The demand for food worldwide is expected to increase drastically in view of the anticipated 9-10 billion world population in 2050 [4]. This will place a great deal of pressure on global agricultural production systems and the environment. Ensuring continued global food production in this situation has become the central concern of development discussions and scientific studies at present [5], [6]. With this backdrop, modern technologies like those of the fourth industrial revolution, such as artificial intelligence (AI) and Internet of Things (IoT), have become increasingly appreciated and studied as forces of change within agricultural production systems [7], [8].

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AI and IoT have emerged as key technologies in the emerging fields of "smart agriculture" and "precision agriculture"[9]. With the help of IoT technology, farmers can monitor environmental parameters such as soil moisture and temperature, as well as the activities of crops and animals, using sensors [10], [11], [12]. AI technology, on the other hand, has the potential to analyze data generated by IoT sensors and provide predictions and recommendations for agricultural management [11]. The growing trend of integrating AI-IoT technology in agriculture aligns with the world's Sustainable Development Agenda [11], [13], [14]. More specifically, the application of AI-IoT technology in the field of agriculture has the potential to contribute to the achievement of some of the United Nations Sustainable Development Goals (SDGs), such as the eradication of hunger (SDG 2), the development of innovation infrastructure (SDG 9), and the promotion of sustainable consumption (SDG 12) [15], [16], [17]. The application of AI-IoT technology in agriculture has the potential to advance sustainable agriculture, eradicate hunger, and drive the development of innovative infrastructure [15], [18].

Despite the increasing number of publications on the application of digital technology in agriculture, some gaps remain in the literature. More specifically, the majority of the publications on the application of digital technology in the field of agriculture are focused on the development of individual machine learning technologies for the detection of diseases [19], [20], [21], [22], [23], [24], [25] rather than examining the application of AI-IoT technology in agriculture. Moreover, most of the publications are focused on the technical performance of the technology [26], [27], [28], [29], rather than examining the opportunities and challenges associated with the application of AI-IoT technology in the field of agriculture. More specifically, the infrastructure, availability of data, scalability of the technology, and the technological readiness level are some of the issues that are often associated with the application of AI-IoT technology in the field of agriculture [30]. The socio-technical factors influencing the adoption of AI-IoT technology in agriculture are not adequately conceptualized in most publications.

These gaps are particularly noteworthy given the uneven global distribution of technological innovation in agriculture. Indeed, most of the existing empirical work on AI-IoT-enabled agriculture has been produced from technologically advanced or emerging digital economies, while the parts of the world where the most critical food security challenges are being faced, particularly in Africa and the developing world, are underrepresented in the existing body of work [31], [32], [33]. These are particularly noteworthy given the broader question of how emerging technologies may address the challenges faced by agricultural systems operating in resource-scarce environments. To understand the role of AI-IoT in supporting food security and sustainable agriculture, a more integrated approach is needed to analyze the applications, benefits, and challenges of these emerging technologies.

The current study conducts an SLR of empirical studies on AI and IoT technologies employed in smart agriculture and their implications for food security and sustainability. This means that the research seeks to find answers to the following fundamental questions: As far as the authors are aware, the present study provides one of the first systematic literature reviews examining the application of integrated AI-IoT in agriculture from multiple perspectives, such as empirical performance, socio-technical conditions for adoption, and food security effects aligned with SDGs. Although prior reviews have examined the potential of AI or IoT applications in agriculture, or the entire set of smart agriculture technologies, there has been no attempt to integrate all three into a single structured synthesis.

1. How are AI and IoT technologies currently applied across different domains of smart agriculture?
2. What opportunities and operational challenges emerge from the integration of AI–IoT technologies in agricultural systems?
3. What factors shape the adoption and implementation of AI–IoT technologies within agricultural production systems?

METHODS

Review design and reporting framework

This research is based on the SLR design methodology, which conforms to the PRISMA 2020 standards [34]. This paper aims to conduct a systematic analysis of the literature concerning the application and deployment of AI-IoT technologies for food security and sustainability in smart agriculture.

Data sources and databases

Three renowned databases, Scopus, IEEE Xplore, and ScienceDirect, were thoroughly explored in this study. The reason these databases were selected is their broad scope of relevant research papers in computing and technology. The search process took place on the 12th of December 2024 within the time frame of 2020-2024 due to increased digitalization in the field of agriculture. As a result of the search procedure, a total of 431 studies were obtained from Scopus (147), ScienceDirect (59), and IEEE Xplore (225).

Search strategy

A carefully crafted search query was tailored to the specific syntax rules of each database. The following search terms related to AI, IoT, smart agriculture, food security, and sustainability were used:

("Internet of Things" OR IoT) AND ("Artificial Intelligence" OR AI) AND ("smart agriculture" OR "precision farming" OR "digital farming" OR "smart farming") AND ("food security" OR "food production") AND ("sustainable farming ")

Justification of the Search Strategy and Sample Size

It is acknowledged that the search string used for this review is deliberately very specific, requiring that all the keywords mentioned above (AI, IoT, smart agriculture, food security, sustainable farming) appear in a single article. There was no mistake; this level of specificity is purposeful from a methodological perspective. It is worth noting that the goal of the current systematic literature review is not to provide a comprehensive overview of research on the use of AI or IoT in agricultural settings; rather, the aim is to identify evidence specifically addressing the integration of AI-IoT solutions, food security issues, and sustainable farming practices. Therefore, research projects that consider AI or IoT individually (not together as a combined solution), and articles discussing agricultural productivity without mentioning food security and sustainability are considered irrelevant here. In other words, they do not meet inclusion criterion number six (relevant to food security and/or sustainable farming) and two exclusion criteria (the first is about the isolated usage of AI or IoT, and the second concerns non-empirical papers). Thus, the result of the filtering process described in the previous section can be considered as a corpus of high-level precision and relevance. Although 17 studies may seem like a small number, they have passed the quality appraisal test in accordance with Section 2.7, indicating that each achieved a minimum methodological score of 6 out of 10, with five studies having a strong evidence status. This number is fully consistent with the general approach to data analysis in an SLR.

Inclusion and exclusion criteria

The inclusion criteria (IC) were defined as follows:

- IC1: Publications in English
- IC2: Peer-reviewed journal articles or conference proceedings
- IC3: Publications between 2020 and 2024
- IC4: Studies focusing on agricultural applications integrating both AI and IoT
- IC5: Empirical studies involving experiments, system implementation, simulation, or field deployment
- IC6: Explicit relevance to food security and/or sustainable farming

The exclusion criteria (EC) were:

- EC1: Studies addressing AI or IoT in isolation
- EC2: Conceptual, theoretical, review, or secondary studies
- EC3: Studies outside the agricultural domain

- EC4: Absence of empirical evaluation
- EC5: Lack of explicit smart-agriculture application

Eligibility and screening process
Following PRISMA 2020 procedures, the 431 retrieved records were first consolidated. A total of 30 records were deleted before proceeding with the screening process due to duplication and irrelevance, namely 13 duplicates and 17 irrelevant records. Thus, 401 titles were screened for potential inclusion. From the title and abstract screening process, 290 titles and abstracts were deemed unsuitable for this study and were therefore excluded from further screening based on the inclusion criteria (IC1 to IC5). Consequently, 111 documents were identified as suitable and needed full-text searches. Of the 111 identified documents, 12 could not be found, leaving 99 full-text documents for inclusion/exclusion screening. During the full-text screening phase, 82 documents were excluded based on the exclusion criteria (EC1–EC5). This means that out of 99 full-text articles screened, 17 articles fulfilled all inclusion criteria and were, therefore, selected for this review. To clarify the selection criteria, below is a summary of the number of articles excluded during the title and abstract screening stages, along with the reasons for exclusion. Approximately 118 records (41%) were excluded because they failed to satisfy IC4, as they involved AI or IoT individually without considering their integration into an agricultural system. Approximately 74 articles (26%) were excluded because they did not address food security and sustainability and made no mention of these issues (IC6). Approximately 52 articles (18%) were excluded because they failed to fulfil IC5: they had no empirical evidence and were instead review articles or position papers. Additionally, 31 documents (11%) failed to meet IC3 criteria because they fell outside the 2020-2024 period. The remaining 15 documents (5%) failed to fulfil IC1 and IC2.

Data extraction process
To make sure that the data extraction was reliable and consistent, a standardized data extraction form was employed. The extracted data include citation details, methodology employed, conceptual/theoretical framework, field of application, AI/IoT technologies utilized, advantages, disadvantages, determinants of adoption, and empirical findings. In particular, the focus was on the adopted architecture, the evaluation strategy employed, the realism of the deployment scenario, and food security/sustainable agriculture considerations.

Quality appraisal and risk of bias
Following the guidelines for the risk of bias within studies specified in the updated PRISMA 2020 checklist [34] quality assessment was performed to establish the internal validity and reliability of the selected literature. Studies were assessed against five quality domains, which include: (i) clarity of research purpose and scope of the proposed system, (ii) rigor of the proposed AI-IoT architecture and its realization, (iii) quality of data used and validity of the metrics of evaluation, (iv) realism of the deployment scenario and consideration of scalability, and (v) relevance to food security and sustainable agriculture. Each quality dimension was assigned one of three ordinal values: "0" indicates not addressed, "1" indicates partially addressed, and "2" indicates clear addressing of the quality dimension in question. Hence, the maximum score possible for each study was 10. A cut-off point of at least 6 was established to select only studies with sufficient methodological rigour.

Accordingly, the level of evidence was classified into high (8-10 points), moderate (6-7 points), and low (≤5 points). Five studies have been classified as having strong evidence due to clear evidence of an integrated AI-IoT architecture, a robust evaluation strategy, and links to productivity and sustainability [35], [36], [37], [38], [39]. Seven studies qualified as evidence of moderate level with credible experimental or prototype implementations but limited evidence in temporal, contextual or scalability evaluations [40] [41], [42], [43], [44], [45], 2023, [46]. A low evidence level was attributed to five studies that mainly provide evidence from deep learning experiments in limited deployment scenarios or evaluation contexts [47], [48], [49], [50], [51].

Based on aggregate scores, studies were categorized into high (8-10), medium (6-7), and low (≤5) levels of evidence. Five studies were rated as high evidence, demonstrating integrated AI-IoT architectures, robust evaluation strategies, and explicit links to productivity and sustainability outcomes [35], [36], [37], [38], [39].Seven studies were classified as medium evidence, reflecting sound experimental or prototype-based implementations, but limited temporal, contextual, or scalability evaluation [40], [41], [42], [43], [44], [45], 2023, [46]. Five studies were rated as low evidence, typically reporting proof-of-concept deep learning experiments with constrained deployment realism or narrow evaluation settings [47], [48], [49], [50], [51]. According to the PRISMA 2020 guidelines, the risk of bias was evaluated using a narrative assessment approach. A risk of data bias emerged in the excessive reliance on carefully curated datasets. Such problems were even more severe when considering image-based deep learning, where data overfitting occurred. There was a risk of evaluation bias in relying primarily on accuracy metrics to assess the system's performance, without considering robustness and other operational considerations. The risk of deployment bias was indicated by the fact that most studies reported on prototype experiments with short-term deployments. The risk of contextual bias was evident in the failure to properly account for socio-economic, infrastructural, and environmental considerations.

Data synthesis strategy
Given heterogeneity in design, applied technologies, datasets, and outcome measures, a quantitative meta-analysis was not possible. Thus, narrative synthesis and thematic synthesis approaches were considered to analyze the data.

Handling of study heterogeneity
Study heterogeneity was observed across methodological approaches, fields of application, AI approaches, and deployment environments. To address study heterogeneity, a narrative synthesis approach was combined with clustering by methodological approach, field of application, and evidence level.

RESULTS AND DISCUSSIONS
The following section provides a description of the synthesized findings from the 17 empirical studies covered in the literature review. The synthesized findings are presented in this section in a well-structured manner, highlighting methodological aspects, the area of implementation, technologies used, identified opportunities and drawbacks, and factors affecting the adoption of AI-IoT-based solutions in agriculture. The 17 empirical studies covered in the literature review are briefly discussed in Table 1. This table presents critical features of each empirical study. These features include authors and their nationalities, methodology, theory, research scope, technology drivers, strengths, problems encountered, and types of AI-IoT technologies used. The consolidated representation enables researchers to compare different studies and identify common patterns in the construction, use, and testing of agricultural AI-IoT systems. The table presents both technical and contextual information to help researchers identify current research patterns and gaps, as well as the extent of research on food security and sustainability goals.

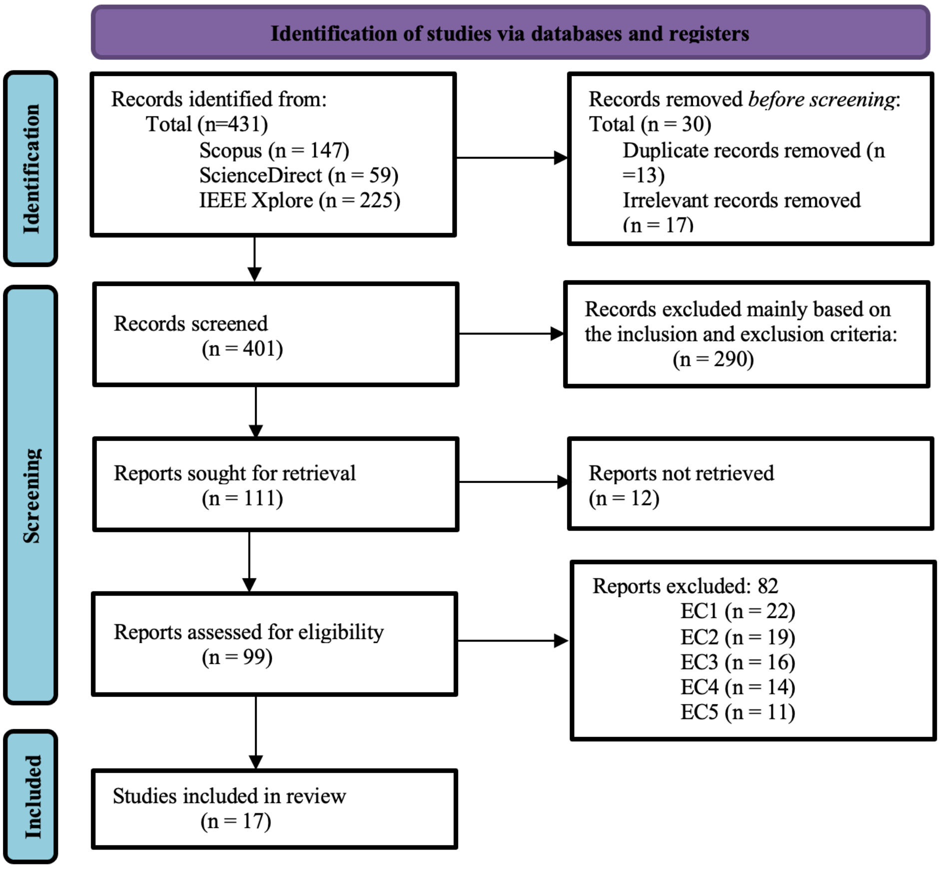

Figure 1. PRISMA workflow

Table 1. Summary of the studies included

Author(s) & year	**Country of origin**	**Methodology used**	**Theoretical framework**	**Factors influencing adoption**	**Application areas**	**Benefits**	**Challenges**	**Techniques/tools/ technologies**	**Key findings**
[52]	India	Experimental DL comparison	None explicitly stated	Accuracy/ Model efficiency	Precision agriculture	Improved pest detection	High computation	VGG16/ IoT/ DL	Hybrid DL improves detection accuracy
[53]	India	Multicloud architecture/ Experiments	Cloud computing paradigm	Scalability/ Latency	Smart agriculture platforms	High availability	Cloud integration	DL/ Multicloud/ IoT	Multicloud improves robustness
[41]	Germany	Gateway prototyping	Edge computing	Interoperability/ Latency	AI-ready agriculture	Reduced response time	Deployment complexity	IoT gateway/ AI modules	Gateway enables AI integration
[47]	India	DL image classification	None stated	Data quality	Cotton disease diagnosis	Early detection	Dataset dependency	CNN/ Image processing	Accurate cotton disease diagnosis
[40]	India	IoT system implementation	Smart farming concept	Cost/ Sensor reliability	Crop yield monitoring	Productivity gains	Infrastructure cost	IoT/ AI analytics	Yield increased via monitoring
[45]	India	Robotic field experiment	Cyber-physical systems	Automation readiness	Leaf disease detection	Reduced labour	Hardware upkeep	Robot/CNN/ IoT	Robotic diagnosis effective
[38]	Italy	Framework design	AIoT architecture	Edge latency	Precision agriculture	Real-time decisions	Integration issues	Edge AI/ IoT	AIoT improves responsiveness

Table 1. (Continued)

Author(s) & year	Country of origin	Methodology used	Theoretical framework	Factors influencing adoption	Application areas	Benefits	Challenges	Techniques/tools/ technologies	Key findings
[51]	Greece	CNN experimentation	None stated	Model accuracy	Plant disease diagnosis	Early detection	Training data	CNN/ IoT robot	CNN effective in diagnosis
[37]	Saudi Arabia	Empirical synthesis	Sustainable smart agriculture	Policy/ Cost/ Skills	Sustainable farming	Emission reduction	Adoption barriers	AI/ IoT/ UAVs	AI-IoT boosts sustainability
[44]	India	ML prediction modelling	Smart city agriculture	Climate/ Data quality	Yield prediction	Improved forecasting	Climate variability	ML/ IoT	ML improves yield prediction
[48]	India	DL image classification	None stated	Dataset size	Leaf disease detection	High accuracy	Overfitting	CNN/ Image datasets	DL outperforms classical ML
[39]	India	Edge-AI experimentation	Edge intelligence	Real-time processing	Wildlife crop protection	Reduced crop loss	Edge hardware cost	Edge AI/ DL/ IoT	Edge AI detects threats
[43]	Malaysia	IoT–Fuzzy system testing	Fuzzy logic control	Sensor precision	Plant monitoring	Efficient automation	Rule tuning	IoT/ Fuzzy logic	Fuzzy logic improves decisions
[42]	Pakistan	IoT-ML livestock study	Smart livestock farming	Wearable acceptance	Livestock health	Early illness detection	Device cost	IoT/ ML/ Wearables	Improved health monitoring
[46]	Saudi Arabia	ML model evaluation	Data-driven agriculture	Data availability	Smart monitoring	Resource optimisation	Data imbalance	IoT/ ML	ML improves efficiency
[54]	China	Hybrid DL experiment	AIoT integration	Image quality • Compute	Rice disease detection	High accuracy	Large data needs	DC-GAN/ ResNet/ IoT	Hybrid DL outperforms baselines
[50]	India	IoT system deployment	Smart farm management	Infrastructure readiness	Farm automation	Operational efficiency	Network reliability	IoT/ Cloud	Automation improves management

Regional frequency summary

An analysis of the geographical distribution of the studies, based on the affiliations of the corresponding authors, reveals a strong regional concentration of empirical research on AI-IoT smart agriculture in Asia, which accounts for most studies. Figure 2 summarizes the geographical distribution of studies. Among these, there are a considerable number of studies from India alone, considering the strong participation in smart farming and precision agriculture research. There are fewer studies from the Middle East, mainly from Saudi Arabia. The number of studies from Europe is also scarce. What is alarming is that there are no empirical studies from Africa or America, given the authors' affiliations.

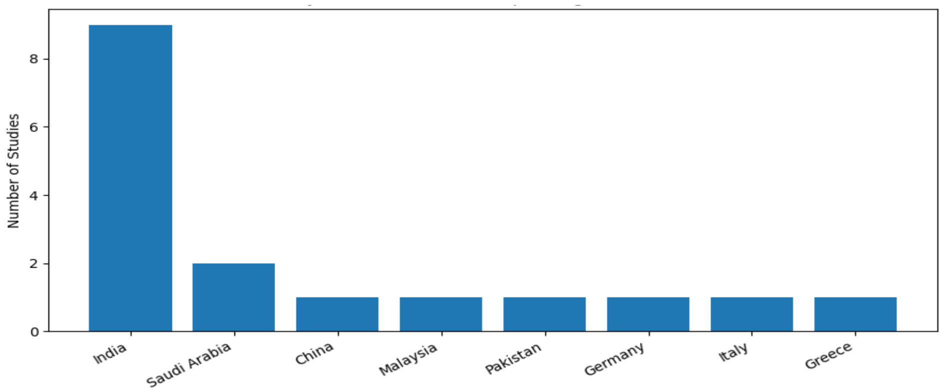

Figure 2. Distribution of corresponding authors by country across the included studies

From the geographic distribution of the included studies, there is a clear concentration of empirical research on AI-IoT smart agriculture in a small number of countries. Most of the 17 studies are from India, accounting for 9. The second in terms of number is Saudi Arabia, which has 2. China, Malaysia, Pakistan, Germany, Italy, and Greece, on the other hand, have only one study each. In terms of continents, most of the research conducted comes from Asia, at 13 studies. Europe, on the other hand, only has 3. More worryingly, there are no studies from Africa, North America, South America, or Oceania. This may seem trivial, but it has a significant implication for SDG 2: Zero Hunger, which seeks to enhance agricultural productivity and food security worldwide. The fact that the number of studies is highly concentrated in Asia suggests that experiments are being conducted with digital agricultural technologies. It is equally concerning that no empirical research has been conducted in Africa and other vulnerable regions, which means there are geographic limitations on what research can achieve in applying AI-IoT smart agriculture to resilient food systems. This pattern constitutes what this review terms the AI-IoT agricultural equity gap: a structural misalignment between where AI-IoT smart agriculture research is being produced and where it is most urgently needed. The risk embedded in this gap is not merely academic. If the trajectory of AI-IoT agricultural research continues to be shaped primarily by the priorities of digitally advanced economies, the resulting technologies, frameworks, and deployment models will be calibrated to conditions: reliable power, high connectivity, large farm operations, and well-labelled datasets that do not reflect the realities of smallholder farming in sub-Saharan Africa, where the majority of the world's food-insecure populations reside. Closing the AI-IoT agricultural equity gap must therefore be treated not as an aspirational goal but as a prerequisite for the technology's meaningful contribution to SDG 2.

Methodological approaches adopted in the adoption of AI and IoT in agriculture

The methodological approaches adopted across the included studies reflect a predominantly experimental and system-oriented research landscape. This is summarized in Table 2.

Table 2. Methodological and technological approaches adopted in AI-IoT smart agriculture studies

Methodological approach	Number of studies	Percentage (%)	Representative studies
Deep learning experimentation (CNN, hybrid DL, image classification)	7	41.2%	[52]; [47]; [48]; [50]; [54]
IoT system implementation/deployment	4	23.5%	[40]; [43]; [53]; [39]
Machine learning modelling & evaluation (non-DL)	3	17.6%	[44]; [46]; [42]
Edge-AI experimentation	2	11.8%	[38]; [54]
Robotic field experimentation	2	11.8%	[51]; [45]
IoT–Fuzzy/rule-based system testing	1	5.9%	[43]
Framework design / architectural modelling	1	5.9%	[37]
Empirical synthesis / cross-system evaluation	1	5.9%	[54]
Gateway prototyping	1	5.9%	[41]
Multicloud architecture experimentation	1	5.9%	[53]

Deep learning and machine learning techniques have been extensively used in research studies to detect crop diseases in images and predict yield. The research works usually comprised training and testing various machine learning algorithms, such as convolutional neural networks, on the specified agricultural datasets. Some of the studies focused on IoT system development, namely sensor design, data acquisition, and AI-powered analysis for real-time farm monitoring. Others addressed system architecture and framework development, including edge AI, multicloud, and AIoT system environments, to increase the system's scalability and responsiveness. Robotic experiments, UAVs, and fuzzy logic have been utilised in other studies to enhance the system's responsiveness. It should be noted that the prevalence of deep learning experimentation (41.2% of studies) is not accidental. CNN-based architectures including VGG16 and ResNet became very popular among the 17 analysed studies because of the possibility to fine-tune their pre-trained weights based on big image datasets (ImageNet) to relatively small domain-specific agricultural datasets. Therefore, these architectures are quite easy to use for researchers who work with limited labelled agricultural datasets, a common issue in the studies discussed. VGG16's simplicity and high performance in feature extraction, together with the availability of the open-source implementation, explain the popularity of this architecture for leaf and crop disease classification. ResNet residual connections prevent gradient vanishing in the deep architecture and provide an advantage in recognizing fine-grained differences between healthy and affected tissue in disease pattern recognition tasks. Edge computing implementation appears quite rare in the studies (explicitly mentioned in 3 out of 17 analysed studies) because it imposes extra requirements for deploying the algorithm, such as the presence of edge devices, on-device inference optimisation, and connectivity management, that go beyond proof-of-concept agriculture studies. Thus, the lack of edge AI presence can be attributed to the limitations of the current research scope, not to its impracticability.

Techniques, tools, and technologies in the adoption of AI and IoT in agriculture
From the analyzed literature, it is evident that there is a significant reliance on integrated AI-IoT technology stacks to support intelligent agriculture applications. At the sensing and connectivity layer, IoT infrastructure plays a significant role in collecting real-time agricultural data using sensors, gateways, and monitoring devices deployed across the farming ecosystem. The collected data is then analysed using AI technologies, with a specific focus on implementing techniques such as deep learning and machine learning. Convolutional neural networks are commonly used in image-based applications, such as plant disease detection and crop monitoring. Machine learning techniques are also used for yield prediction and decision-making. Some of these applications also involve edge AI, which enables faster data processing by performing analytics closer to the data sources. Other technologies, such as robots, unmanned aerial vehicles, fuzzy logic, wearable livestock sensors, and cloud technologies, also play a significant role in supporting AI-IoT. All these technologies contribute to the development of intelligent agriculture applications that can respond to real-time events. This is summarized in Table 3.

Table 3. The technologies, tools and techniques used

Technique/technology	Functional role in agriculture	Studies using the technology (author, year)
IoT (sensing, communication, platforms)	Real-time data acquisition, monitoring, and system integration	[40]; [51]; [41]; [42]; [43]; [44]; [38]; [48]; [53]; [45]; [47]; [52]; [50]; [37]; [54]; [46]; [39]
Deep learning (general)	Pattern recognition and predictive analytics	[47]; [48]; [52]; [50]; [54]; [39]; [53]
CNN-based architectures	Image-based plant disease and health detection	[47]; [48]; [52]; [45]; [50]; [54]
VGG16	Feature extraction for leaf disease classification	[47]
ResNet	Deep feature learning for plant disease detection	[50]
DC-GAN	Synthetic data generation to address data scarcity	[50]
Machine learning (non-DL)	Yield prediction, data-driven decision support	[44]; [46]; [42]; [50]
Edge AI / Edge computing	Low-latency, on-device inference	[38]; [39]; [54]
Cloud/multicloud computing	Scalable data storage and analytics	[53]; [37]
IoT gateways	Data aggregation and protocol management	[41]
Robotics (AI-enabled)	Automated crop inspection and monitoring	[51]; [45]
UAVs (Drones)	Aerial crop monitoring and analysis	[54]
Fuzzy Logic Systems	Rule-based decision support from sensor data	[43]
Wearable sensors	Livestock health and behaviour monitoring	[42]

Application areas of AI and IoT in agriculture
The reviewed studies show the wide applicability of AI-IoT in contemporary agriculture. A significant part of the literature focuses on crop health monitoring and disease detection, enabling early identification of crop diseases through deep learning techniques integrated with IoT. Other studies pertain to precision agriculture, where AI-IoT solutions enable real-time monitoring of crop development, the environment, and soil conditions. Other applications of AI-IoT technology include yield prediction and improvement, in which machine learning approaches predict crop yields from agricultural data. The last type of application includes animal disease detection, wildlife intrusion detection, and smart agriculture monitoring. As can be seen, all of the analyzed studies indicate the diverse range of possible applications of AI-IoT technologies in agriculture (see Table 4). Most studies focus on crop disease detection (10 of 17 studies involved some

form of disease/health detection). This situation is explained by three structural reasons: Firstly, as crop diseases exhibit their symptoms visually, they are suitable for image-based deep learning; Secondly, public datasets related to plant diseases (such as PlantVillage) are available; Thirdly, disease losses pose a tangible threat to smallholder food security. On the contrary, limited interest shown towards livestock health monitoring (one study) and wildlife intrusion detection (one study) is justified by increased hardware complexity and less favourable environmental conditions. Therefore, while there is potential for AI-IoT implementation in other areas, it is obvious that currently developed applications reflect the maturity gap between vision-based diagnosis of plant diseases and other subfields of AI-IoT applications in agriculture. From this perspective, the contribution of the discussed AI-IoT technologies to SDG 2 is insufficient, while crop disease detection is important, a more holistic approach to food security is needed, including supply chain monitoring, reducing post-harvest losses, and addressing social issues related to smallholder access.

Table 4. Application areas

Application area	**Description of application**	**No. of studies**	**Representative studies (from the 17 papers)**
Precision agriculture	Data-driven optimization of farming practices using sensors and AI analytics	5	[40]; [53]; [54]; [37]; [39]
Smart agriculture platforms	Integrated AI–IoT platforms for monitoring, analytics, and decision support	4	[53]; [37]; [54]; [41]
AI-ready agriculture	Architecture and frameworks designed to support AI-enabled farming systems	2	[37]; [54]
Crop/yield monitoring	Continuous monitoring of crop conditions and productivity indicators	3	[40]; [44]; [46]
Yield prediction	Machine learning–based forecasting of crop yields	2	[44]; [46]
Leaf disease detection	Image-based detection of leaf-level crop diseases	5	[47]; [48]; [50]; [54]; [52];
Plant disease diagnosis	Diagnosis of plant diseases using AI models and IoT data	4	[48]; [50]; [54]; [52]
Cotton disease diagnosis	AI-based detection of cotton plant diseases	1	[47]
Rice disease detection	Machine learning and IoT-based diagnosis of rice crop diseases	1	[50]
Plant monitoring	Sensor-based monitoring of plant growth and health	2	[43]; [40]
Livestock health monitoring	Monitoring animal health and behavior using IoT and ML	1	[42]
Wildlife crop protection	Edge AI systems for detecting and deterring wildlife intrusion	1	[39]
Smart monitoring	Real-time monitoring systems integrating sensors and analytics	3	[43]; [45]; [54]
Farm automation	Automation of inspection and monitoring using robotics and AI	2	[51]; [45]
Sustainable farming	AI–IoT applications aimed at efficiency and sustainability outcomes	3	[40]; [37]; [53]

Factors influencing the adoption of AI and IoT in agriculture

Several determinants influencing the adoption of AI and IoT technologies in an agricultural context have been identified through analysis of the selected sources. First, technological performance and, specifically, the accuracy and reliability of the AI models constitute important adoption factors because farmers' trust in the technology can be built only based on evidence of the technology's performance. The presence of required data is another key issue, as machine learning and deep learning algorithms depend heavily on the availability of large volumes of accurate data to make accurate predictions. The readiness of the infrastructure is a key factor in the feasibility of implementing the AI-IoT system in the agricultural domain. Finally, economic factors often constrain the adoption of AI-IoT systems due to the high costs of implementation and operation. Another set of factors that affects the success of adopting the technology in question includes the solution's scalability, latency characteristics, and integration capabilities. However, the list provided above is not exhaustive, and the successful adoption of an AI-IoT system depends on a wide range of different factors. All mentioned factors that influence the adoption of AI-IoT systems are outlined in Table 5. Importantly, the aforementioned factors are not independent of one another and are structurally related; thus, adoption-related factors constitute an interrelated cascade of enabling factors for technology adoption. Infrastructure availability is considered the first prerequisite for successful implementation: without access to connectivity, a stable power supply, and sensors, neither data collection nor model application is possible. Thus, infrastructure availability is a crucial condition for data quality and availability, which is another prerequisite of success. Indeed, poor connectivity conditions lead to data incompleteness, noise, and low data volume. The latter, in turn, degrades model performance and reduces prediction precision, which can undermine farmers' confidence in AI-IoT and thereby hamper the technology adoption process. Economic factors further complicate the situation by increasing the costs of implementing and operating the technology, which limits its use in developing countries with smallholder farmers; at the same time, low data volumes reduce system scalability and increase per-unit maintenance costs for installed hardware. The relationship between user skills/awareness and other factors is also bidirectional: when skills are low, farmers cannot work with the system; conversely, systems not adapted for use by low-skilled users produce output that can be distrusted even by technically aware farmers. Automation readiness and device acceptance are determined by economic and skill-related constraints: if farmers cannot afford or use the devices, there is little chance they will accept them, regardless of their performance.

Table 5. Factors influencing the adoption of AI-IoT technologies in agriculture

Adoption factor	Description	Studies reporting
Technological accuracy and model performance	Reliability and predictive accuracy of AI models influence farmer confidence in smart agriculture systems	[52]; [47]; [48]; [54]
Data quality and availability	Access to large, well-curated datasets is essential for training effective AI models	[50]; [48]; [44]
Infrastructure readiness	Availability of sensors, connectivity, and digital infrastructure supports IoT system deployment	[40]; [50]
Cost of technology	Initial investment in IoT devices, sensors, and computing systems affects adoption decisions	[40]; [37]
System scalability and latency	Performance and responsiveness of AI–IoT platforms influence practical implementation	[53]; [41]
Integration capability	Ability to integrate AI algorithms with IoT devices and agricultural platforms	[38]
Automation readiness	Farm readiness to adopt automated technologies and robotics	[45]
User skills and technological awareness	Technical expertise and digital literacy among farmers affect adoption	[37]
Environmental and climate conditions	Climate variability influences data reliability and system performance	[44]
Device and wearable acceptance	Farmer acceptance of wearable or monitoring technologies in livestock farming	[42]

Opportunities identified in the adoption of AI and IoT in agriculture

The results identify opportunities created by integrating AI and IoT technologies into the agricultural sector, summarized in Table 6.

Table 6. Opportunities for AI-IoT applications in agriculture

Opportunity	Description	Studies reporting
Early detection and monitoring	AI models detect plant diseases, pests, or livestock illness at early stages	[52]; [47]; [48]; [50]; [54]
Productivity improvement	Smart monitoring systems enhance crop yield and production efficiency	[40]; [44]
Real-time decision support	IoT sensors and AI analytics enable rapid responses to environmental changes	[38]; [41]
Automation and labour reduction	Robotics and automated monitoring reduce manual farm operations	[45]; [43]
Operational efficiency	Data-driven farm management improves efficiency and workflow	[50]; [46]
Resource optimisation	AI–IoT systems optimise resource use and reduce waste	[37]
Forecasting and predictive analytics	Machine learning improves crop yield prediction and planning	[44]
Sustainability benefits	Smart agriculture systems contribute to reduced emissions and improved environmental management	[37]

The first identified opportunity is the potential of intelligent monitoring systems to detect diseases, pest infestations, and animal health conditions early. The second opportunity is real-time sensing and analytics, enabling farmers to monitor environmental conditions. Various studies have also identified opportunities created by the integration of AI and IoT in the agricultural sector, such as automating agricultural processes, minimising labour requirements, and maximising process efficiency. The integration of smart agriculture platforms also creates opportunities to optimise resource use and minimise environmental impacts. Thus, the identified opportunities highlight the potential of AI and IoT technologies in the agricultural sector.

Challenges identified in the adoption of AI and IoT in agriculture

While the reviewed studies demonstrate the potential of AI-IoT technology in the agricultural domain, they also identify certain challenges. This is depicted in Table 7.

Table 7. Challenges of AI-IoT applications in agriculture

Challenge	Description	Studies reporting
High computational requirements	Deep learning models require significant processing power	[52]; [47]
Dataset limitations	AI models rely on large and well-curated datasets	[48]; [50]
Infrastructure and deployment cost	IoT infrastructure and hardware devices can be expensive	[40]
Hardware maintenance	Sensors, robots, and edge devices require continuous upkeep	[45]
Integration complexity	Integrating AI algorithms, IoT devices, and cloud systems remains challenging	[41]; [38]
Cloud and edge architecture challenges	Managing distributed computing environments introduces technical complexity	[53]
Data imbalance and overfitting	Machine learning models may suffer from biased datasets	[54]
Adoption barriers	Skills, policy support, and technological readiness influence adoption	[37]
Network reliability	Connectivity issues affect real-time system performance	[50]
Environmental variability	Climate variability can reduce model reliability	[44]

For example, the excessive use of deep learning for developing surveillance and disease detection models has been noted in many of the papers examined. However, the problem here is that training models this way requires considerable computational power. Another problem with the technology is its high cost. There are costs associated with constructing the necessary infrastructure and other systems for the technology to function properly. The problems that arose during implementation include its integration. The technology has to be integrated smoothly into the diverse context of its usage. In agriculture, AI models, sensors, and cloud/edge computing platforms are expected to cooperate.

DISCUSSION

These findings imply considerable progress in integrating AI and IoT into the agricultural sector. While the findings demonstrate positive developments in both technology and its use, the numerous benefits of applying AI and IoT across different fields of agriculture are tempered by certain implementation limitations and challenges to the sustainable development of such solutions. In this regard, the next chapter will elaborate on the relationship between these findings and the research questions posed, as well as their contributions to discussions on smart agriculture, Industry 4.0, and food security.

AI-IoT applications in agriculture

In summary, the results demonstrate that AI-IoT applications in agriculture are primarily focused on crop disease detection, environmental monitoring, and yield prediction. Specifically, AI for disease detection is the most mature application field in agriculture, owing to high classification accuracy reported by multiple researchers using deep learning methods combined with IoT-based image acquisition technologies. At the same time, the use of AI-IoT for environmental monitoring and yield prediction demonstrates the potential of IoT sensor networks, in collaboration with AI analytics, to support the decision-making process in agriculture [55]. Meanwhile, AI-IoT in livestock monitoring and farm security represents an emerging application field for AI-IoT in agriculture, indicating growth in the number of application domains. In terms of food security implications, the results imply that AI-IoT applications in agriculture play a more significant role in protecting and optimizing crop yield compared to their role in agricultural value chain transformation. In particular, the results show that AI-IoT applications in agriculture are primarily focused on metrics and models rather than on holistic management and socio-economic change. The measurement trap of AI-IoT smart agriculture refers to such a tendency: researchers tend to focus on the outcomes of their work which can be easily measured, namely classification accuracy, speed of detection, and crop yield, instead of food security-related outcomes, such as nutrition, market access, income stability of smallholders, and adaptation to climate stress. In turn, the measurement trap is self-reinforced since the easier-to-measure outcomes are more attractive for investment in research and publication. Thus, the socio-economic aspects of food security are typically excluded from the scope of AI-IoT agricultural research. To avoid the measurement trap, researchers must purposefully incorporate socio-economic impact indicators into the study design alongside performance indicators.

The analysis above indicates that the application of AI and IoT technologies is mostly centred on crop disease detection, environmental monitoring, and yield prediction. More specifically, it is indicated that AI for detecting plant diseases is currently the most mature application area, with many studies showing that, by combining deep learning algorithms with IoT, very high levels of accuracy can be achieved [55]. Similarly, the application of AI and IoT in environmental monitoring and yield prediction showcases how IoT is useful for sensing and gathering information to support decision-making in the agricultural sector. It is important to note that AI-IoT in livestock monitoring and farm security is a new application field in agriculture. Regarding food security, the application of AI-IoT in agriculture serves more to optimize yield than to change the value chain in agriculture. What is more, from a food security point of view, it is notable that the application of AI and IoT in agriculture focuses more on measurements and modeling than on helping farmers with holistic management and changing the socio-economic landscape of agriculture. This paper highlights that such a concentration represents what the authors call a "measurement trap". Specifically, it means that there is a tendency in the field to focus on what can be measured in terms of technical performance: classification accuracy, detection speed, and yield quantities. However, socio-economic impacts, which are crucial for food security, include nutrition, market access, farmers' stable incomes, and resilience to climate conditions. The more easily quantifiable indicators attract more funding and research efforts and produce more publications, reinforcing the measurement trap in the AI-IoT agriculture literature.

Opportunities and challenges of leveraging AI-IoT in agriculture

Based on the results of the above-mentioned studies, there is room for the utilisation of AI and IoT technologies, especially for early detection, efficiency, and response speed. The AI and IoT technologies are efficient tools used to provide an early response that contributes significantly to minimizing crop losses and enhancing productivity. Edge AI is also useful for providing rapid responses with limited connectivity, as reported in [56] and [57]. It should be noted that, although many opportunities arise from applying the technologies in the cited studies, the process can be hindered by certain challenges. Such challenges range from infrastructure and energy availability to connectivity and sensor lifetime. Despite the high technical performance of some technologies, some other concerns, including scalability, maintenance, and technical support, have been raised. Such challenges are common in small-scale farming and play a key role due to the costs involved. The technical support mentioned in [58] and [59] is an important consideration.

Adoption of AI and IoT as Industry 4.0 technologies in agriculture

While explicit adoption frameworks are not evident in the literature review, the results enable the identification of critical adoption factors from the implementation experience. For instance, technical reliability in terms of accuracy, responsiveness, and robustness emerges as a critical factor for the adoption of AI and IoT as Industry 4.0 technologies in agriculture [60], [61]. Systems perceived as inaccurate and unreliable in the field will not be adopted. Infra readiness is also critical for adoption. In this regard, the availability of connectivity options, power, and hardware platforms is critical to adoption. While edge computing addresses some connectivity issues to some extent, it does not negate the need for infrastructure readiness for data aggregation and updates. Economic factors also emerge as critical factors for adoption. For instance, the system's cost is perceived as a critical factor in adoption, as noted in [58]. Adoption is constrained for smallholder farmers due to the high cost of maintaining the systems. While the results do not directly address human factors related to usability, the overall experience suggests that systems providing actionable recommendations to farmers will be adopted more widely. Training support for farmers is also critical for adoption, as noted by [62].

Furthermore, the results suggest that the adoption of AI-IoT systems in the agricultural sector is a multi-dimensional process shaped by various factors. While the results do not provide explicit information about the adoption framework, the overall experience suggests this is a critical area requiring further research.

The overall experience suggests that the adoption framework cannot be generalized due to the limited availability of explicit adoption frameworks in the literature, a fact concurred by [58]. Synthesizing the results from the three research questions suggests that the field is technically advanced but socio-technically incomplete. Specifically, the results suggest that AI-IoT systems demonstrate strong technical performance in targeted agricultural applications, particularly in monitoring and detection tasks. However, translating these technical results into the adoption and sustainability of these systems for food security remains limited.

This suggests that the next step in the development of smart agriculture will need to move from a primarily technology-driven approach to a more socio-technically integrated approach to address issues of adoption, sustainability, and scaling. Failure to do so will mean that the potential of AI-IoT to make a meaningful contribution to sustainable agriculture and food security will be only partially harnessed. In addressing Research Question 3 specifically, the synthesis of findings across the 17 studies reveals that adoption factors cannot be understood as an independent checklist but must be interpreted as a relational system. Infrastructure readiness is the foundational enabler: it determines what data can be collected, which in turn shapes the models that can be trained, and ultimately the performance outcomes that farmers experience. Economic accessibility gates entry into this system entirely for smallholder farmers who represent the majority of food producers in food-insecure regions. Skills and digital literacy then moderate the extent to which technically functional systems are used in practice. The implication is that AI-IoT adoption strategies that focus narrowly on improving model accuracy without simultaneously addressing infrastructure, cost, and capacity will not translate into the food security outcomes anticipated by SDG 2. Coordinated, multi-factor interventions are therefore the minimum effective unit of action in this domain.

IMPLICATIONS

The implications were grouped into theoretical, practical, and policy implications.

Theoretical implications

This systematic review contributes to the theoretical debate on smart agriculture and Industry 4.0 by showing that current empirical research on the integration of AI and IoT is largely technology-focused and does not consider well-established theories of technology adoption and innovation. Although the investigations provide strong evidence of the technical feasibility of integrating AI and IoT across various agricultural applications, the lack of a theoretical foundation limits the development of scientific knowledge. The current study highlights the need to include socio-technical adoption theories, such as Technology, Organisation, Environment (TOE), Diffusion of Innovations (DOI), and Unified Theory of Acceptance and Use of Technology (UTAUT), in the study design to investigate the adoption of AI and IoT in agriculture. The determinants of technology adoption, such as infrastructure readiness, economic viability, ease of use, and trust, have always been around but usually implicitly. The inclusion of these elements in the analysis will enable scholars to go beyond analysing the efficiency of integrating AI and the IoT and to construct a theoretical framework that includes these variables. Furthermore, the results of the study confirm that the theoretical framework for considering AI and IoT in smart agriculture needs to go beyond merely analysing technology and to view both as a socio-technical system. In other words, this theoretical framework advances the discussion by integrating the adoption of these technologies into the concepts of sustainable agriculture and food security. The relevance of the theoretical frameworks mentioned above can be illustrated as follows. For instance, the TOE framework considers the technology adoption process from three different dimensions. The first one is technological (it relates to the features of the technology itself). The second dimension is organizational (it relates to the organization adopting technology, i.e., the characteristics of farms). The last dimension includes the environment (industry and political factors affecting adoption). All these variables are present among the factors identified across all 17 articles analyzed in this paper, even though none of them applies TOE in their methodology. However, their application would enable a more theory-oriented analysis rather than purely contextualized, specific findings. For instance, technological readiness refers to accuracy, reliability, and latency performance; organisational capacity refers to farmers' digital literacy, education, and the availability of resources; and the environment refers to the availability of infrastructure, support, and policy. UTAUT framework includes four factors: Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions. Performance Expectancy is implied by the focus on higher model accuracy as the determinant of farmers' confidence. Effort Expectancy is indicated by recurring usability issues and a complicated integration process. Finally, Facilitating Conditions refer to all infrastructure readiness and technical factors considered by the reviewed authors. In other words, had the framework been applied, scholars would have conducted analytical rather than descriptive assessments of the barriers and enablers to technology adoption. Additionally, DOI theory helps explain the concentration of AI-IoT research in Asia (particularly India), since innovations were adopted further along the diffusion curve than in Africa, where people remained at the awareness and persuasion stages. Further empirical research should incorporate one or several of these theories from the very beginning.

Practical implications

The findings offer a variety of actionable implications for practitioners, including farmers, agribusinesses, and technology developers. First, the substantial body of empirical evidence supporting AI-IoT applications for disease detection, monitoring, and yield prediction suggests potential to derive value from these applications. However, it is imperative to highlight that these applications should be tailored to specific situations that offer high-impact benefits. Second, the findings highlight the need for reliability, usability, and maintainability of AI-IoT applications. Although high-performance AI-IoT applications contribute to the development of AI-IoT, their value is limited if they are not usable. Therefore, it is imperative that designers of AI-IoT applications use user-centred design approaches to ensure their output aligns with existing farming practices. Third, the findings suggest that edge computing is instrumental in improving the performance of AI-IoT applications. For instance, AI-IoT applications could be useful for resource-constrained farmers. Finally, the findings suggest that deriving value from AI-IoT applications in smart agriculture depends on capacity-building training for farmers. Therefore, it is imperative that training be integral to the sustainability of AI-IoT applications in smart agriculture. A core practical principle that emerges from this review is that technical performance is a necessary but not sufficient condition for value creation in smart agriculture. An AI model that achieves 95% disease detection accuracy in a laboratory setting delivers zero food security benefit if the farmer cannot afford the sensor hardware required to generate the input images, cannot interpret the system's output recommendations, or operates in a context without the connectivity infrastructure to run the model in real time. Practitioners and technology developers must therefore adopt a context-first design philosophy, beginning with the operational, economic, and infrastructural realities of the target farming context, and working backwards to identify which AI-IoT configurations are feasible, rather than adapting high-performance systems developed for different contexts and expecting adoption to followThis notion becomes especially important when considering technological efforts in agriculture aimed at small-scale farmers in developing countries, where this disparity is more pronounced.

Policy implications

From a policy perspective, the review has underscored the need to create an enabling environment that supports the effective adoption of AI-IoT technologies in the agricultural sector. It is imperative that the government recognizes that technological readiness does not necessarily imply adoption, especially in the agricultural sector. There is an urgent need to invest in both physical and digital infrastructure to address structural constraints affecting the adoption of AI-IoT technologies in the agricultural sector. At the same time, it is imperative that the government consider initiatives that make the technology accessible to small-scale farmers. A critical insight for policymakers that emerges from this review is the innovation-without-inclusion risk: when AI-IoT agricultural technologies are developed and deployed without deliberate policy mechanisms to ensure equitable access, they are likely to widen rather than narrow existing agricultural inequalities. Farmers with larger landholdings, better connectivity, and higher digital literacy will capture the productivity and market benefits of AI-IoT first, while smallholders who face the sharpest food security pressures remain excluded. This risk is compounded by the geographic concentration of AI-IoT research documented in this review: when the evidence base is built on studies from digitally advanced agricultural economies, the policy recommendations that flow from it will reflect those contexts rather than the conditions of food-insecure regions. Governments and development agencies should therefore treat investment in AI-IoT agricultural research from and for sub-Saharan Africa and South Asia not merely as a research priority, but as a food security and equity imperative.

Based on the literature review results above, it is necessary for the government to develop initiatives to ensure an enabling environment for the adoption of AI-IoT technologies in agriculture. First, it is important to note that agricultural extension services can be instrumental in facilitating technology adoption in the agricultural sector. Second, the review results indicate a need for initiatives to promote data security in the agricultural sector. There is a pressing need for the government to develop initiatives to ensure data security in agriculture as AI-IoT technologies are adopted.

LAYERED AI-IOT SMART AGRICULTURE FRAMEWORK FOR FOOD SECURITY AND SUSTAINABLE FARMING

In particular, the proposed framework analyses the existing literature in the context of the 17 empirical studies reviewed and demonstrates how AI/IoT facilitates the development of smart agriculture systems that help achieve food security goals and promote sustainable farming practices. It consists of five layers of interrelated components: (1) technology infrastructure; (2) agricultural fields for implementation; (3) adoption determinants and barriers; (4) operational effects; and (5) implications for sustainability and food security, including such SDGs as SDG 2, SDG 9, and SDG 12. As demonstrated in Figure 3, the model's upward direction reflects the connections among technical aspects, their practical applications in agriculture, the adoption process, and operational results.

The framework has been developed through inductive research, based on a thematic synthesis of results from the 17 studies included in the systematic review. The studies were coded using a variety of analytical groups, including technological architectures, application domains, operational benefits, implementation challenges, and adoption determinants. Level 1 of the framework represents the technology infrastructure for AI-IoT systems, including the various digital technologies identified in the studies. Level 2 of the framework represents the application domains of AI-IoT technology in the broader agricultural domain, including crop disease detection, precision farming, crop yield forecasting, livestock monitoring, and farm automation. Level 3 of the framework represents the adoption conditions for AI-IoT technology, where the technological, infrastructural, economic, and human factors identified in the literature converge in real-world AI-IoT applications in the agricultural domain. Level 4 of the framework represents the operational benefits of AI-IoT technology, including disease detection, productivity enhancement, automation, and optimization. The highest level of the framework addresses the potential impacts of AI-IoT technology on food security and sustainability, including its contributions to global development agendas, particularly SDG 2 - Zero Hunger, SDG 9 - Industry, Innovation and Infrastructure, and SDG 12 - Responsible Consumption and Production.

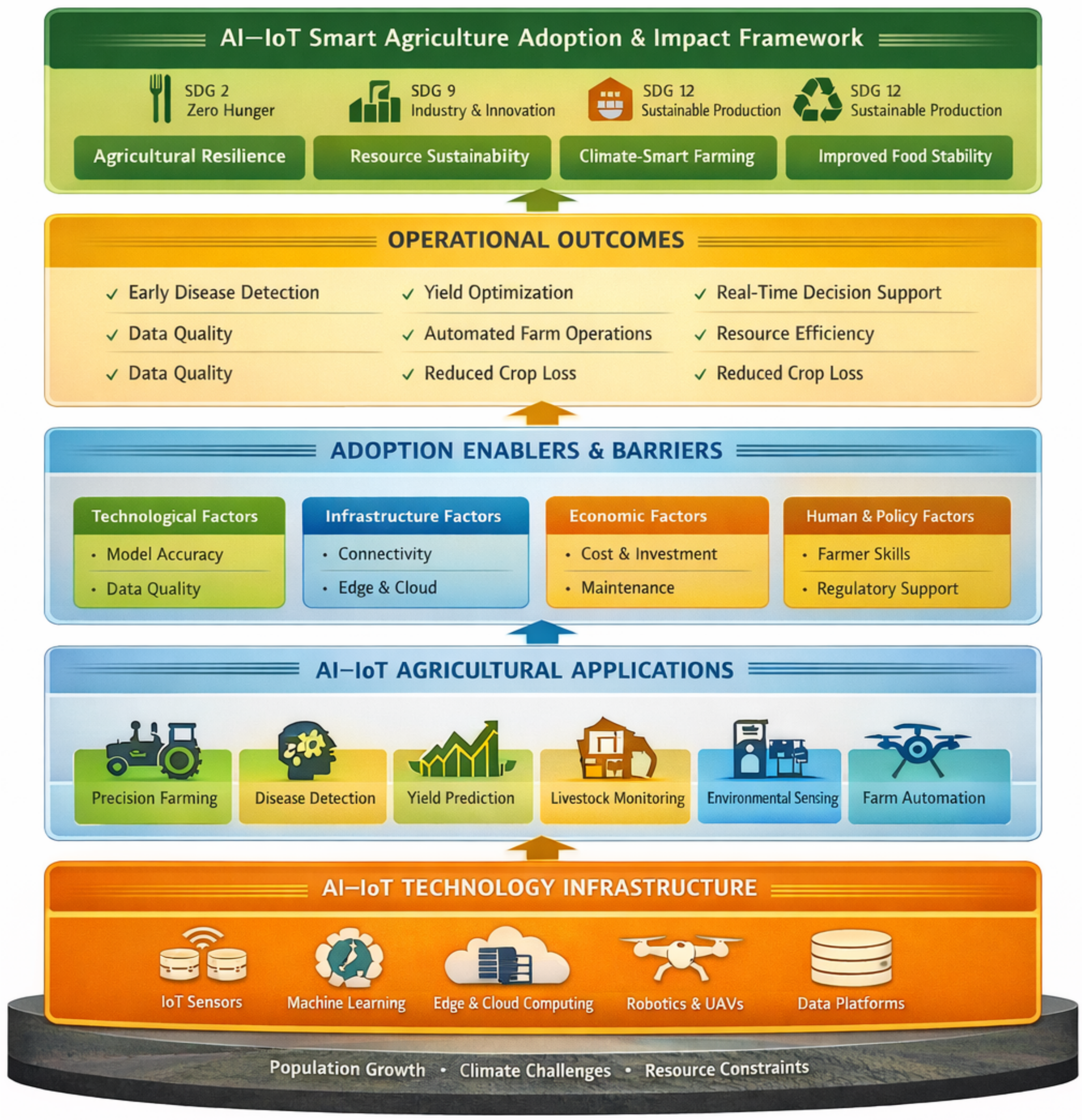

Figure 3. AI-IoT Smart Agriculture framework for enhancing food security and sustainable farming

While the five layers are presented sequentially, they interact dynamically, and understanding these interactions is critical to the framework's practical utility. The relationship between Layer 1 (infrastructure) and Layer 2 (application domains) is enabling yet constraining: the types of AI-IoT applications that can be deployed in a given context are bounded by the available infrastructure. For example, deep learning-enabled disease recognition models (Layer 2) rely on high-resolution imaging, constant power, and adequate computational capacity (Layer 1): prerequisites that are easy to meet in technologically sophisticated agriculture but are formidable challenges in subsistence agriculture in sub-Saharan Africa or South Asia. Most crucially, the relationship between Layer 3 (adoption conditions) and Layer 2 is especially important. The cost of infrastructure (a Layer 3 parameter) limits application domains (Layer 2) accessible by resource-constrained farmers. Edge computing deployment, although technically superior for low-latency tasks in precision agriculture, requires dedicated edge devices that, because they are relatively expensive, are currently unaffordable for most poor farmers in developing countries. In other words, some technically valid Layer 2 applications may fail to produce Layer 4 outcomes due to insufficient attention to Layer 3 variables. Similarly, moving from Layer 4 (operational effects) to Layer 5 (sustainability outcomes) does not always occur naturally. Technological solutions proven to be operationally efficient in experiments and field trials are often insufficient to ensure sustainable improvements in food security, especially when studies are conducted under optimal conditions. In turn, the framework implicitly requires a supportive environment, i.e., policies designed and implemented at Layer 3 that connect operational success (Layer 4) with sustainability effects (Layer 5). Such policies may include extension services, government subsidies, training, and a regulatory framework. In sum, the framework proposed here provides researchers with a tool for diagnosing problems in smart agriculture development at each identified level; any gaps at any level signal possible areas for intervention. More generally, failure to proceed from Layer 4 to Layer 5 in the context of developing countries implies that, while the technology works, the socio-technical system remains immature. It is important to emphasize that the five-tier framework outlined above represents a theoretical conceptualization of smart agriculture based on a thematic review of the 17 empirical papers reviewed above. Consequently, the framework was inductively developed through thematic analysis of the studies and not empirically validated via expert panel ratings, case study evaluations, or stakeholder surveys across different agricultural contexts. The framework should be seen as a theoretically well-grounded organizing principle, which helps to conceptualize the links between technological performance, adoption conditions, and sustainability effects in smart agriculture, but is not yet a validated predictive or prescriptive instrument. Therefore, one of the key objectives of future research should be the empirical validation of the framework outlined above, both to further refine it and to support its practical use in policy and decision-making.

LIMITATIONS AND FUTURE RESEARCH AGENDA

There are certain limitations that are inherent to the study presented here. For instance, the systematic review uses only a modest number of empirical studies (N = 17) as its base, indicating that the area of AI–IoT integration in agriculture is still in development. Secondly, all studies reviewed focus on relatively short-term experimentation and/or prototyping, thereby limiting understanding of the scalability, sustainability, and practicality of AI-IoT systems in actual agricultural settings. The third limitation concerns the geography of the empirical studies used. They mostly come from China, and only rarely include examples from other countries, which limits the generalization of results to countries experiencing food shortages such as those in Africa. In addition, many studies do not explicitly employ any theoretical frameworks to analyze their results, which limits the scope of possible conclusions.

Taking these limitations into account, several directions for future research may help address the identified issues. Firstly, it seems relevant to use proven technology adoption theories (e.g., Theory of Planned Behaviour, DOI, and UTAUT to study AI-IoT adoption and use cases. It will help obtain the necessary theoretical background and enhance the generalizability of future research. Moreover, longitudinal field validation of the systems is needed to establish their reliability. This implies that the next stage of research will need to focus on multi-seasonal and multi-location testing to better understand their actual functioning under various conditions. Moreover, further research will need to address the economic feasibility of the systems discussed in this paper. While the systems' performance has been thoroughly researched (their accuracy, latency, etc.), their economic feasibility is not yet known.

Finally, as decision-making processes in agriculture become more reliant on AI, issues of explainability, human-AI interaction, and the usability of AI-powered recommendation engines become increasingly relevant. In addition, it is necessary to focus on data quality, data bias, and model generalization. Transfer learning, federated learning, and domain adaptation techniques can be applied for this purpose. Edge AI, cybersecurity, and institutional factors, such as agricultural extension services, are also important considerations. Another specific suggestion for future research is to conduct empirical validation of the five-layered AI-IoT Smart Agriculture Framework, developed from the results of thematic synthesis. As it was stated above, this conceptual framework was derived inductively from the analysis of 17 empirical studies. Future research should subject the framework to rigorous validation through multiple complementary methods: (i) expert panel review involving agricultural technology specialists, policymakers, and extension practitioners to assess the framework’s face validity and practical utility; (ii) case study application in contrasting agricultural contexts including technologically advanced settings (such as those represented by the included studies) and resource-constrained smallholder settings in sub-Saharan Africa and South Asia, to assess its transferability and contextual relevance; and (iii) survey-based empirical testing using quantitative methods to measure the relationships between the framework’s layers and test whether the proposed directional influences (e.g., from infrastructure to application domains, or from adoption conditions to operational outcomes) hold across diverse real-world agricultural environments. Until such validation is undertaken, the framework should be applied as a structured analytical and diagnostic lens rather than a prescriptive deployment guide..

CONCLUSION

This systematic review of 17 empirical studies yields five findings of enduring significance for the field of AI-IoT smart agriculture. Firstly, the existing empirical literature on AI-IoT smart agriculture has reached a high level of technological maturity but remains limited in terms of geography and contextual diversity; thus, the lack of empirical research from other regions and continents, namely Africa and the Americas, calls into question its applicability beyond India/Asia. Secondly, the field faces an issue of measuring what is easy to measure, in essence, accuracy, latency, and detection speed, while the measures of importance for food security, such as smallholder income, health outcomes, and resilience, remain largely unexplored. Thirdly, the field's adoption framework consists of a cascade of interrelated variables: infrastructure determines data quality, data quality leads to reliable models, and reliable models determine farmers' trust and, consequently, adoption; hence, any solution targeting a single variable may prove futile. Fourthly, the lack of theoretically informed studies based on frameworks such as TOE, UTAUT, or DOI prevents the field from explaining how and why technologically proven solutions fail to get adopted and, moreover, from formulating effective theories that will inform intervention. Lastly, the multi-layered framework of AI-IoT smart agriculture outlined in the literature review provides structure to the field's research agenda and aligns well with SDGs 2, 9, and 12. In conclusion, although the technological capabilities of AI and IoT have long since surpassed the boundaries of their potential contributions to food security, the biggest problem in the field today is a lack of theoretically sound, contextually grounded research, interventions, and technology deployments.

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