



Artificial Intelligence in Precision Agriculture: A Systematic Survey of Technologies, Applications, and Future Research Directions

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Abstract. This study uses the Technology Acceptance Model (TAM) and Diffusion of Innovation to analyze the rapidly growing literature on precision agriculture (PA) AI applications. Data-driven agricultural decision-making using artificial intelligence is increasingly vital as agricultural systems are expected to enhance productivity without compromising environmental sustainability or resource efficiency. PRISMA 2020 is used to evaluate 150 peer-reviewed publications from Scopus, Web of Science, and IEEE Xplore from 2015 to 2025. To detect research trends and clusters, we used CiteSpace-based bibliometric analysis on chosen papers. We classified AI and agriculture using Braun and Clarke's theme analysis. AI-driven precision agricultural research is 55% deep learning, 8% machine learning, 11% IoT systems, and 6% robots and automation. Deep learning models forecast 92% accuracy in image-based applications like plant disease diagnosis and crop monitoring, compared to 85% for traditional machine learning. Most common applications include crop monitoring (35%), yield prediction (5%), and pest and disease detection (18%). Data interoperability, infrastructure, scale, and acceptance remain issues, especially in developing agriculture. Combining smart farming ecosystem models with DOI theory, expanding TAM to include infrastructure availability as a critical factor in AI adoption, and presenting an AI-precision agriculture framework that links technical capacities with agricultural decision-making procedures expands knowledge. These results may help academics, policymakers, and agricultural stakeholders digitalize sustainable agriculture.

Keywords: Artificial Intelligence; Precision Agriculture; Deep Learning; Smart Farming; Internet of Things; Sustainable Agriculture; Systematic Literature Review

1 INTRODUCTION

Maintaining global economic growth and providing food security for a world population that is rapidly growing are both fundamentally influenced by agriculture. Population increase, environmental deterioration, resource scarcity, and climatic unpredictability are just a few of the fundamental obstacles that modern agricultural systems must contend with. In order to keep up with the expected rise in food consumption due to a predicted world population of 9.7 billion by 2050, agricultural productivity would need to see a significant boost, according to the Food and Agriculture Organization [1]. Simultaneously, soil erosion, dwindling biodiversity, water shortages, and climate-induced interruptions to crop production are growing threats to agricultural output [2]. All the more reason to find creative technical answers to these problems so that farming may become more efficient without compromising the environment in the long run. Precision agriculture (PA) has arisen as a paradigm shift in contemporary agricultural systems as a reaction to these difficulties. With the use of cutting-edge technology, precision farmers are able to track the geographical and temporal variability of their fields, allowing them to make the most efficient use of inputs like seeds, fertilizer, irrigation water, and pesticides [3]. Precision agriculture uses site-specific management to increase crop yield and reduce environmental impact and production costs. Precision agriculture has made several technological advances. Yield monitoring technologies, GIS, and GPS drove early 1990s innovation. This enables farmers to collect location-specific agricultural data [3]. After that, sensor networks, cloud computing, and remote sensing improved precision agriculture's analytical capabilities, spawning digital agriculture and smart agricultural ecosystems [4]. Digital agriculture's technological ecosystem includes IoT networks, UAVs, remote sensing technologies, and advanced data analytics platforms [4]. Farmers can accurately assess soil health, environmental conditions, crop growth, and other variables using this technology. Thus, data-driven and predictive management systems are replacing experience-based agricultural decision-making. In this fast-changing technological context, AI technologies enable the extraction of meaningful insights from complex agricultural datasets. Agriculture corporations may evaluate satellite pictures, soil measurements, temperature observations, and crop phenotyping using AI-powered analytical algorithms. More precise projections and efficient agriculture are conceivable [5]. Sustainable, climate-resilient, and resource-efficient agriculture is becoming possible with AI-integrated precision agriculture.

1.1 Emerging Role of Artificial Intelligence in Smart Agriculture

AI-enabled predictive modeling and automated decision-support systems are transforming how farmers use data. Machine learning, deep learning, computer vision, and reinforcement learning are AI computing approaches. These technologies enable intelligent computers to predict, learn, and detect patterns without programming [5]. In agriculture, these advancements make it simpler to examine massive data from sensors, drones, satellites, and farm equipment. AI is used in agriculture to diagnose crop diseases and monitor plant health. Deep learning models, especially CNNs, can swift-

ly diagnose plant illnesses from leaf pictures and remote sensing data [6]. Early disease detection may minimize crop losses and pesticide usage, enhancing agricultural sustainability. Also important is machine learning-based agricultural production forecast. Random forests, gradient boosting algorithms, and support vector machines predict agricultural outputs from temperature, rainfall, soil quality, and crop growth [7]. Projections may affect planting, irrigation, and resource allocation. AI technologies significantly improve soil health monitoring and precision irrigation through real-time predictive analytics. Farmers can monitor soil moisture, nutrient content, and weather using AI-powered sensors. These devices can adjust irrigation and fertilizer rates to save water and reduce agrochemical pollution [8]. Agriculture is also using more autonomous equipment and AI-powered robots. Autonomous tractors, robotic harvesters, and smart spraying systems can plant, weed, and harvest crops without human intervention. Labor shortages are reduced and operational efficiency is improved [9].

1.2 Timeliness of an Updated Review

Recent technical advances have improved precision agricultural systems' analytical capacities, necessitating a comprehensive literature study despite the plethora of AI in agriculture literature. First, transformer and foundation model improvements have improved agricultural AI systems' analytical abilities. Transformer-based models, originally developed for NLP, are increasingly used for multimodal agricultural data including satellite images, meteorological measurements, and crop monitoring data [10]. With these models, even the most complicated and massive agricultural information may be better predicted and analyzed for patterns. Secondly, processing data in real-time on farms is now possible because to the widespread use of edge computing technology. Reducing latency and allowing real-time decision-making in precision agriculture situations, edge AI systems enable agricultural data to be analyzed directly on field equipment like sensors and drones [11]. Thirdly, advances in generative AI have opened up new possibilities for automated agronomic advising systems in agricultural decision-support systems. Synthesizing data from many sources, generative AI models may then provide tailored suggestions for irrigation timing, pest control methods, and crop management [12]. Previous studies primarily focused on early machine learning applications in agriculture, with limited attention to integrated AI-driven smart farming ecosystems [5] and [7]. It mostly dealt with the first uses of machine learning in farming. Therefore, a revised review of studies looking at how AI is changing precision agricultural ecosystems is required due to the fast development of AI.

1.3 Theoretical Framing of Research Gaps

Previous assessments of machine learning and deep learning in agriculture are dispersed across technical, socio-economic, and sustainability factors. While most research focused on algorithmic performance, few addressed technological adoption hurdles, infrastructure inequities, and integrated smart agricultural ecosystems. Few studies have integrated AI-enabled precision agriculture utilizing multi-level theoreti-

cal views incorporating behavioral, institutional, and ecological dynamics. TAM, DOI, and Systems Theory are combined in this research to fill these gaps. Several significant conceptual and theoretical voids persist in the current literature on AI-driven agriculture, despite the expanding amount of research in this area. Many algorithmic performance studies ignore socio-technical systems, creating a techno-centric divide. Agriculture ecosystems include human decision-making, institutional support, and technology infrastructures, but AI algorithms are often evaluated. Second, agricultural technology literature lacks theory. The technological Acceptance Model (TAM) has been used to analyze how farmers adopt digital technology, although most studies have focused on technical value and usability. Few studies have studied how data governance, agricultural extension, and internet availability affect adoption. Third, nothing is known about how existing and new farms employ technology. Digital literacy, budgetary restrictions, and infrastructure availability vary by place, yet research assumes all agricultural systems adapt the same manner. Filling these gaps requires conceptually solid technical, institutional, and socio-economic literature evaluations.

1.4 Research Questions

This study addresses these gaps with three research questions:

- RQ1: Why do precision agriculture domains use AI technology differently?
- RQ2: How can AI technologies help agricultural efficiency and the environment?
- RQ3: In established and developing agricultural environments, how do hurdles to adoption of AI technology differ?
- RQ4: In theory, how can smart farming ecosystems benefit from the integration of new AI technologies?

1.5 Research Objectives

This research integrates technology architectures, adoption dynamics, infrastructural constraints, and sustainability implications in AI-enabled precision agricultural ecosystems, unlike earlier review studies that focused on discrete AI approaches. To address these research questions, this study pursues the following objectives:

1. The primary objective is to catalogue and categorize all forms of AI that are used in precision agriculture.
2. To investigate the most important areas of AI use in agricultural production systems.
3. Revisiting current practices and future directions in AI-powered smart agricultural research on a worldwide scale.
4. To determine the most important obstacles that are preventing the use of AI in farming.
5. To provide a plan for future research that will help develop more sustainable and intelligent farming systems.

The critical realist epistemology that this analysis is based on recognizes that social, institutional, and infrastructure settings influence the adoption and effect of AI technologies, despite the fact that these technologies have objective technological capabilities. Studying AI-enabled agricultural systems fits well within this paradigm since these systems are complex socio-technical interactions between technology innovation, human decision-making, institutional regulations, and environmental factors.

1.6 Contributions of the Study with Transition to Theoretical Framework

This study improves smart and digital agriculture three ways. Starting with data governance and infrastructure availability, AI-specific preconditions affect agricultural technology adoption and perceived value in the Technology Adoption Model (TAM). Second, the study uses smart farming ecosystem models and DOI theory to demonstrate how institutional infrastructures and technological interdependencies affect AI in agriculture. Third, the article shows how technical configurations, institutional contexts, and technology adoption stages impact agricultural production using an AI-enabled precision agriculture contingency paradigm. Systems theory, the Technology Acceptance Model (TAM), and the Diffusion of Innovation (DOI) theory are used to examine macro-level dynamics in smart farming ecosystems, micro-level adoption behavior, and meso-level technology diffusion in agricultural networks. These perspectives provide a multi-tiered precision agricultural AI analytical framework. This section synthesizes previous studies after evaluating literature and theory.

2 THEORETICAL FRAMEWORK AND LITERATURE REVIEW

2.1 Theoretical Foundations

AI in precision agriculture (PA) is changing technology, institutions, and decision-making. System-level technological integration, diffusion dynamics, and technology adoption need transdisciplinary theory to explain this transition. Thus, this study uses sustainability transition, systems theory, the Technology Acceptance Model (TAM), and the diffusion of innovations theory. Systems Theory sheds light on the macro-level dynamics of technological ecosystems, TAM on the micro-level behavior of adoption, DOI on the meso-level diffusion processes, and sustainability frameworks on the long-term environmental and socio-economic impacts of AI-enabled precision agriculture systems. Taken together, these theories offer a multi-level analytical perspective for studying these systems.

2.1.1 Technology Acceptance Model (TAM). The Technology Acceptance Model (TAM) developed by [13] is still one of the best-known models for analyzing how people utilize new technology. According to TAM, people's behavioral intentions to embrace new technologies are shaped by two important cognitive constructs: perceived utility and perceived ease of use. These constructs play a significant role in

technology adoption choices. A number of studies have used TAM to explain why farmers are using digital farming technologies including AI-based decision-support systems, IoT sensor networks, and automated agricultural equipment within the framework of precision agriculture. If farmers believe that digital technologies would increase their productivity, operational efficiency, and economic performance, then they are more inclined to use them, according to empirical research [14]. According to new Agriculture 4.0 adoption study, training programs, agricultural extension services, and technical support systems improve farmers' views of digital technology's value [15]. Many obstacles hinder AI-based agricultural technology from being deployed. Risky economic returns, high implementation costs, technical inexperience, and poor digital infrastructure are obstacles [16]. Farmers' faith in AI is also deteriorating due to new data ownership, privacy, and cybersecurity issues in agricultural data networks [16]. TAM shows how contextual variables impact perceived usefulness and helps explain the behavioral and cognitive characteristics that drive AI adoption in agriculture.

2.1.2 Diffusion of Innovation (DOI) Theory. Technology Adoption Model (TAM) analyzes why individuals utilize specific technologies, whereas Diffusion of Innovations (DOI) theory explores the social environment in which these innovations spread [17]. The five-step knowledge-persuasion-decision-implementationconfirmation (DOI) model defines innovation dissemination. Farmer, agricultural consultant, research institution, technology supplier, and government agency networks are essential for agricultural innovation transfer [18] emphasize the role of extension services and knowledge-sharing networks in digital agriculture technology adoption. The same applies to [15] show that government-funded digital agriculture initiatives significantly affect farmers' smart farming technology usage. Tech adoption requires institutional backing, as previous legislative initiatives have proved. According to OECD research, investment in digital training, rural broadband infrastructure, and agricultural data platforms has considerably boosted farmers' access to digital farming technologies [19]. Distributed intelligence (DOI) helps explain how social networks and institutions affect agricultural AI adoption.

2.1.3 Systems Theory and Smart Farming Ecosystems. Systems Theory views agricultural production systems as complex socio-technical systems with technological, environmental, and human components, which may be used to investigate AI integration. Smart agricultural ecosystem models include sensor networks, IoT infrastructures, UAV drones, cloud computing, and AI analytics systems for precision agriculture [4]. AI powers algorithms that transform mounds of agricultural data into usable information for farmers. New studies show that digital agriculture systems benefit greatly from including various technical components [20] prove that sensor networks linked to the internet of things allow for the continuous tracking of soil temperature, moisture, and agricultural development indicators; this data can then be processed by artificial intelligence algorithms to determine the most efficient times to water the crops. The same holds true for [11] shown that real-time environmental

monitoring and predictive analytics are much improved with the use of smart sensors, internet of things (IoT) networks, and machine learning algorithms in precision farming systems. Systems Theory provides a complete understanding of how technology infrastructures in digital agricultural ecosystems enable intelligent farm management systems.

2.1.4 Sustainable Agriculture and Green Information Systems. Growing AI application in farming aligns with sustainable agricultural development aims. Environmental protection and social and economic viability are goals of sustainable agriculture. A green approach to information systems recommended by [21] provides the theory behind how digital technology improves ecological sustainability. Information technology may increase transparency, resource monitoring, and decision-making to support sustainable behavior, according to green IS research. In addition, [22] The MLP on sustainability transitions views technological advancement as a continuous process including specialized advances, socio-technical regimes, and landscape effects. AI-enabled precision agriculture might change agriculture in the face of global warming and food scarcity. In this perspective, AI-powered precision agriculture represents a socio-technical change toward more ecologically friendly farming methods, not merely a technological breakthrough. AI paves the way for adaptive climate control, real-time environmental monitoring, and precise resource management [23]. According to empirical research, precision agriculture with the help of AI may reduce water use by over 40% while increasing crop yields by up to 30% [24]. Results like these show that AI has a lot of promise for helping achieve global sustainability targets including climate resilience, responsible resource management, and food security.

2.1.5 Toward an Integrated Theoretical Framework. The aforementioned theoretical frameworks provide unique insights into AI-enabled precision agriculture, but they all deal with distinct levels of analysis, necessitating their integration. Individual farmers' assessments of digital technology's utility and usability are the subject of TAM's explanation of micro-level cognitive adoption processes. Nevertheless, TAM is insufficient on its own to explain the factors affecting technological dissemination, such as institutional and infrastructural frameworks. DOI theory delves at the mechanics of innovation dissemination within agricultural networks and institutional structures, providing light on meso-level diffusion processes. But DOI doesn't go into detail on the mental processes that people use to decide to adopt. Systems theory illuminates digital agriculture's numerous infrastructures and technological ecosystem dynamics at the macro level. Nevertheless, comprehensive explanations of individual adoption behavior are absent from Systems Theory. This study proposes a multi-tiered theoretical framework combining TAM, DOI, and Systems Theory to address these issues. Per this model:

- Farmers assess AI technology for perceived utility and simplicity of use at the micro-level (TAM).
- Meso-level (DOI): Innovations spread via agricultural networks and institutions.

- Technology interacts with smart agricultural ecosystems at the macro-level (Systems Theory).

Sustainability results include increased output, resource efficiency, and climate resilience from this multi-level strategy.

2.2 Evolution of Precision Agriculture

Changes in agricultural production systems brought about by technology are mirrored in the rise of precision agriculture. The use of inputs consistently across fields and the reliance on farmers' practical expertise were the cornerstones of traditional agricultural management. Modern farming, however, is more dependent on data and employs site-specific management methods, thanks to technological advancements in the agricultural sector. In the 1990s, farmers were able to track the spatial variability of crop yields and soil conditions with the use of GPS-enabled equipment and GIS-based mapping technology. This marked the beginning of precision agriculture [3]. Applying fertilizers and insecticides at different rates depending on specific field circumstances is now possible thanks to these technological advancements, which are known as variable rate technology (VRT). Advancements in technology that followed allowed precision agriculture to grow in scope. Agricultural areas as vast as Texas may now be monitored with pinpoint accuracy thanks to advances in remote sensing and unmanned aerial vehicle (UAV) drone technology [25]. Precision agriculture has lately undergone a radical transformation, becoming fully automated smart farming systems that can provide real-time decision support via the integration of artificial intelligence, IoT infrastructures, and big data analytics [26].

2.3 Artificial Intelligence Technologies in Precision Agriculture

Modern precision agricultural systems rely on artificial intelligence technology for their analytical support. These advancements pave the way for the analysis of massive datasets produced by agricultural equipment, sensors, drones, and satellites.

- **Machine Learning:** Many machine learning techniques find widespread use in agricultural prediction tasks, including crop yield prediction and soil categorization. Random Forest, SVM, Gradient Boosting, and Artificial Neural Networks are examples [27].
- **Deep Learning and Computer Vision:** Deep learning technologies, notably CNNs, improve crop phenotyping and plant disease identification in agricultural image-based applications [28].
- **Internet of Things (IoT):** IoT sensor networks provide continuous environmental monitoring for accurate irrigation and soil testing [29].
- **Remote Sensing:** With UAV drones and satellite imagery, crop health and weather can be monitored on a large scale [25].

2.3.1 Technology Assessment Matrix. Table 1. gives a technology assessment matrix that examines AI technologies on various dimensions to better understand the AI-enabled agriculture technological environment.

Table 1. AI technology assessment matrix

Technology	Maturity	Data Requirement	Infrastructure Dependency	Cost Profile	Skill Level	Suitability for Small-holders
Machine Learning	Mature	Medium	Medium	Medium	Intermediate	High
Deep Learning	Growth	High	High	High	Advanced	Medium
IoT Systems	Growth	Medium	High	Medium	Intermediate	Medium
Robotics	Emerging	High	High	Very High	Advanced	Low
Remote Sensing	Mature	Medium	Medium	Medium	Intermediate	Medium

This matrix shows why certain technologies are leading research while others are niche.

2.4 Application Areas of Artificial Intelligence in Agriculture

Applications of AI in agriculture:

- Crop yield prediction
- Plant disease detection
- Soil health monitoring
- Precision irrigation management
- Livestock monitoring
- Agricultural robotics
- Climate risk prediction

These case studies demonstrate how AI is automating, data-driven, and sustainable agriculture.

2.5 AI–Precision Agriculture Conceptual Framework

This study integrates past research into an AI-Precision Agriculture theoretical framework. Systems Theory emphasizes environmental monitoring and technology interdependencies, and the data sensing layer incorporates IoT, drone, and satellite sensors. Machine learning and deep learning analytics make up the AI processing layer, which lines up with TAM's perceived utility concept. This is because predictive analytics make digital agricultural technology more valuable. At this point in DOI theory, when innovations are being incorporated into everyday agricultural activities,

we are in the decision actuation layer, which includes automation of irrigation and crop management choices. The last step in using DOI and the idea of dynamic equilibrium from Systems Theory is the feedback loop, which shows how learning from results improves agricultural decision-making over time. Same is given in the Figure 1. as shown below.

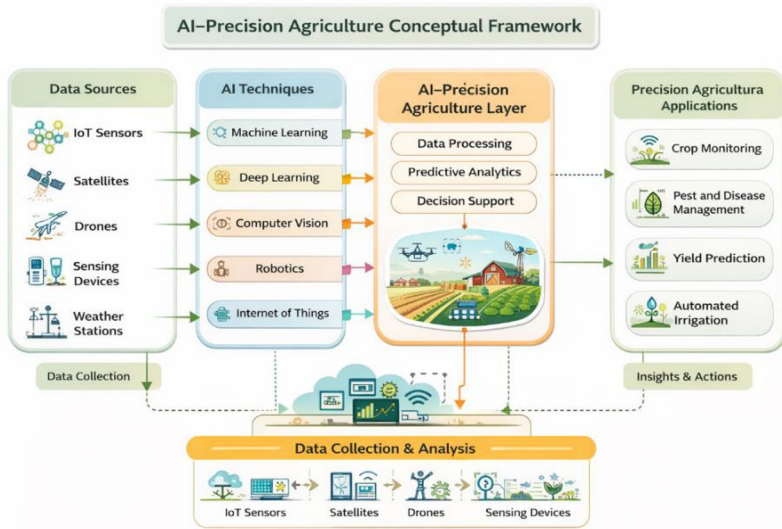


Fig. 1. AI-precision agriculture conceptual framework

AI technology, IoT infrastructures, decision-support systems, and precision agricultural applications interact in smart farming ecosystems. A multi-layered ecosystem of sensing technologies, AI analytics, automated decision-support systems, and sustainability-oriented agricultural outputs is suggested for AI-enabled precision agriculture.

2.6 Critical Synthesis of Prior Reviews

There are three conflicts that have not been addressed after analyzing the current literature:

- **Optimism vs Realism:** Whereas earlier research focused on the technology's promise, more current research has shown the difficulties of putting it into practice.
- **Technocentric vs Socio-technical:** Institutional and socioeconomic factors are often overlooked in favor of algorithm development in this research.
- **Developed vs Developing Contexts:** It is challenging to draw larger implications from research because of the attention it often pays to industrialized countries.

Using a contextual analysis and a multi-level theoretical framework, this review attempts to resolve these difficulties, same is shown in table 2.

Table 2. Literature review

Ref	Notion of Quality	Research Design	Intended Contributions
[5]	Comprehensive analysis of deep learning applications in agriculture	Systematic literature review	Identified the potential of deep learning models such as CNNs for crop monitoring and disease detection in agricultural systems
[7]	Evaluation of machine learning applications in agriculture	Review-based research	Provided early classification of machine learning techniques used in agricultural prediction models
[4]	Big data analytics in smart farming ecosystems	Conceptual review	Proposed the concept of data-driven agriculture integrating IoT, analytics, and precision farming technologies
[30]	Implementation of AI technologies for smart irrigation and crop management	Experimental study	Demonstrated AI applications for optimizing irrigation systems and pesticide usage
[31]	Integration of machine learning algorithms in precision farming	Systematic review	Examined AI techniques for soil monitoring, crop classification, and yield prediction
[15]	Socio-technical adoption of digital agriculture technologies	Mixed-method research	Investigated adoption barriers and policy implications of Agriculture 4.0 technologies
[23]	AI-driven sustainability in agricultural systems	Literature review	Highlighted the role of AI technologies in improving resource efficiency and sustainable farming practices
[25]	UAV-based remote sensing for precision agriculture	Empirical research	Demonstrated how drone imaging improves crop health monitoring and yield estimation accuracy
[27]	Machine learning techniques for crop yield prediction	Experimental research	Proposed predictive models integrating environmental variables and agricultural datasets
[28]	Deep learning models for plant disease detection	Experimental research	Demonstrated high accuracy of CNN-based plant disease classification systems
[20]	IoT-enabled smart sensing systems in agriculture	Experimental research	Developed sensor-based precision agriculture frameworks for real-time crop monitoring
[16]	AI-based sensing technologies for agricultural monitoring	Experimental research	Proposed smart sensing architectures integrating AI analytics for crop monitoring
[32]	Artificial intelligence for precision agriculture	Systematic review	Provided updated classification of AI technologies used in modern smart farming systems
[33]	Challenges of AI adoption in agriculture	Empirical analysis	Identified technological, infrastructural, and economic barriers limiting AI adoption
[26]	Integration of IoT and AI technologies in agricul-	Conceptual framework	Proposed integrated architecture for intelligent agricultural monitoring

	ture		systems
[34]	Machine learning-based precision agriculture systems	Systematic review	Examined emerging AI architectures and future research directions for smart farming
[35]	UAV applications in agricultural monitoring	Review study	Demonstrated the role of remote sensing technologies in precision agriculture
[36]	Smart sensing technologies in agriculture	Experimental study	Developed advanced sensor frameworks for real-time agricultural data collection
[37]	Smart farming technologies and agricultural analytics	Conceptual research	Proposed digital agriculture frameworks integrating AI, IoT, and big data analytics

3 RESEARCH METHODOLOGY

3.1 Research Design

The ever-growing corpus of information about the use of AI in precision agriculture (PA) is summarized and assessed in this research via the use of a Systematic Literature Review (SLR) approach. Recognized as rigorous research methods, systematic literature reviews bring together disparate pieces of information, reveal new trends in the field, and provide theoretically sound insights into dynamic scientific fields [38]. An SLR approach is especially suitable for creating a comprehensive understanding of the technology landscape and identifying important research gaps in AI-enabled precision agriculture because of the interdisciplinary nature of this field, which integrates knowledge from data analytics, computer science, agricultural engineering, and environmental science. The PRISMA 2020 requirements for transparent, reproducible, and methodologically rigorous literature reviews are fulfilled. [39]. Through thorough research identification, screening, eligibility evaluation, and inclusion, PRISMA assures methodological transparency. Review aims were description and investigation. The descriptive dimension classifies studies by technical approaches, agricultural applications, and methodological features, whereas the exploratory dimension maps AI-enabled precision agriculture research. AI-driven agriculture's conceptual and technical progress is examined using bibliometric analysis and theme synthesis.

3.2 Research Philosophy and Protocol Registration

Post-positivist research uses empirical data to find patterns and relationships in scientific literature [40]. Post-positivist systematic reviews help researchers conceptualize complex socio-technical systems using quantitative bibliometrics and qualitative theme analysis. We registered our review approach on the Open Science Framework (OSF) before data extraction to make it more open and replicable. The protocol provides review goals, search parameters, inclusion criteria, and analysis methods. Limits acknowledge registered protocol exceptions.

3.3 Data Sources

Several respected academic resources were examined to assure high-quality research coverage:

- Scopus
- Web of Science (WoS)
- IEEE Xplore
- ScienceDirect

Several respected academic resources were examined to assure high-quality research coverage: [41] IEEE Xplore gathered AI algorithms and sensor systems, whereas ScienceDirect improved agricultural and environmental science. The literature search was conducted between January and March 2026.

3.4 Search Strategy

Structured keyword indexing was used to index AI-precision agricultural studies. Search strings included agricultural technology and AI phrases blended with Boolean operators. Keyword combinations in the primary search query: “Artificial Intelligence AND Precision Agriculture”; “Machine Learning AND Smart Farming”; “Deep Learning AND Crop Monitoring”; “AI AND Agricultural Decision Support”; “Smart Farming AND Internet of Things”. Web of Science, IEEE Xplore, and ScienceDirect all have different indexing schemes, thus we had to modify our search queries to be equivalent for each. First database search yielded 1,330 entries.

3.5 Sampling Strategy and Inclusion Criteria

Systematic sampling found good review articles after the first search. Include all research criteria:

- Published in peer-reviewed academic journals
- Written in English
- Published between 2015 and 2025
- Focused on AI technologies applied in agriculture or precision farming systems
- Presented empirical, experimental, or analytical findings

Each study was evaluated using a Quality Assessment Checklist for rigor. Here are the checklist criteria:

1. Clarity of research objectives
2. Methodological transparency
3. Representativeness of datasets
4. Validity of measurement techniques
5. Appropriateness of analytical methods
6. Robustness of findings

Category ratings ranged from 0 to 12. We included study scores of 8+ ($\geq 70\%$) in the aggregate dataset. After quality evaluation and inclusion, 150 studies were included.

3.6 Exclusion Criteria

The following studies were removed for analysis and methodological consistency:

- Non-English publications
- Conference abstracts and editorial notes
- Book reviews and opinion articles
- Studies unrelated to AI applications in agriculture

In order to restrict the study to peer-reviewed studies with well-established quality assurance procedures, we omitted grey literature. One weakness of the research is that grey literature was not included. This might lead to publication bias.

3.7 Article Screening Procedure

The PRISMA framework was followed in its four-stage selection procedure for the studies:

1. Identification: Initial retrieval of records from selected databases
2. Screening: Removal of duplicate records and title/abstract evaluation
3. Eligibility: Full-text assessment of relevant studies
4. Inclusion: Final selection of studies meeting all criteria

The search yielded 1,330 Scopus, Web of Science, IEEE Xplore, and ScienceDirect documents. Once 280 duplicates were removed, 1,050 studies were left for title and abstract screening. After filtering, 780 records were deemed irrelevant to AI-enabled precision agriculture. Assessing eligibility of the remaining 270 full-text publications. After applying inclusion and quality evaluation criteria, 120 papers were removed, leaving 150 peer-reviewed publications in the systematic review. Two researchers worked separately to do the screening. The reliability of the coding was evaluated by double-coding about 30% of the experiments. Problems were worked out by talking things out and reaching a consensus; if that failed, a third reviewer was brought in. Reviewers showed good agreement with an inter-rater reliability rating of $\alpha = 0.83$, as determined by Krippendorff's alpha coefficient [42]. The PRISMA 2020 guided research selection procedure for identifying, screening, eligibility evaluation, and systematic review inclusion is shown in Figure 2.

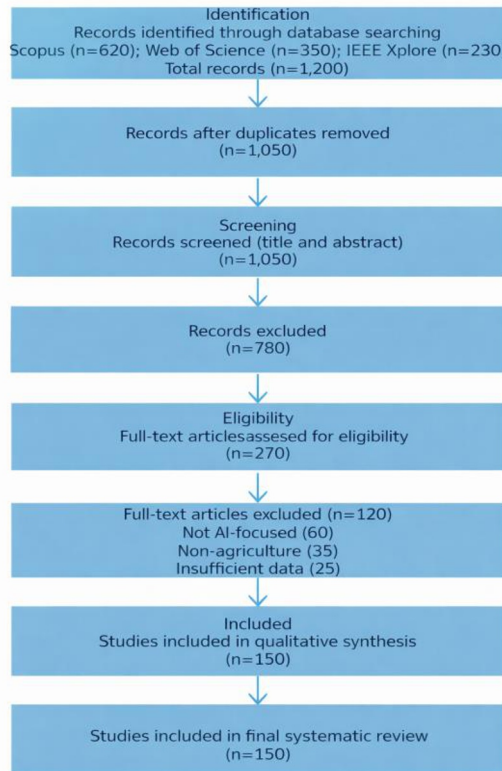


Fig. 2. PRISMA flow diagram illustrating the study selection process for the systematic literature review.

The PRISMA 2020 flow diagram shows the study's methodical screening and selection. The framework illustrates the integration of AI technologies, IoT infrastructures, and precision agriculture applications within a smart farming ecosystem. To guarantee methodological transparency and the systematic identification of pertinent research, this systematic literature review used the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 framework for selecting papers to include in the review [39]. An extensive search was first carried out using several academic databases, such as Scopus, Google Scholar, Web of Science, PubMed, and others. One thousand three hundred and thirty articles pertaining to AI in precision agriculture and related fields were found by this search. We excluded 200 duplicate articles during the identification step since they were irrelevant or duplicate entries. We had 1,000 distinct studies to assess. To establish their relevance to the research aims, the remaining 1,000 papers' abstracts and titles were carefully reviewed. Eight hundred fifty studies were excluded because they did not address agricultural applications, artificial intelligence technology, or the study's parameters. The following round of review included just 150 items. Reading the 150 papers' full contents assessed methodological quality and relevance to determine eligibility. Studies focusing

primarily on pharmacological or unrelated technology fields ($n = 5$), an inadequate research population ($n = 60$), and insufficient methodological information in non-English publications or case reports ($n = 15$) excluded 100 articles. After comprehensive screening, the systematic review's qualitative synthesis and final analysis used 50 publications that matched all inclusion criteria. This clear and reproducible PRISMA-guided selection approach makes finding high-quality precision agricultural AI articles straightforward.

3.8 Snowballing and Citation Tracking

A systematic sampling technique was used to find relevant review papers following the first search. All studies were included using these criteria: Analyzing backward snowballing by reviewing reference lists of included works; Tracking forward citations on Scopus and Google Scholar. After fulfilling inclusion criteria, these methods found twelve more relevant papers for the review.

3.9 Data Extraction

Data extraction templates were created to systematically obtain crucial data from all included studies. The following variables were removed: Publication details (authors, year, journal); AI technologies employed; Agricultural application domains; Dataset characteristics; Performance metrics (accuracy, precision, F1-score); Geographic study context. Classification and comparison across trials were done using NVivo, a qualitative analytic program.

3.10 Data Analysis Techniques

Bibliometric Analysis: CiteSpace was chosen for the bibliometric study due to its superb research frontier and citation burst detection. Statisticians used SPSS '29 and Excel. The patterns across studies were analyzed using descriptive statistics, chi-square tests, z-tests for percentage comparison, correlation analysis, and effect size estimations. Statistical significance was set at $p < 0.05$. These analytical parameters were used: Time slicing: 2015 to 2025 (1-year intervals); Node types: authors, cited references, keywords; Pruning method: pathfinder network scaling; Selection criteria: top 50 most cited records per slice; The analysis included: Co-citation analysis; Keyword co-occurrence networks; Citation burst detection. These searches seek new field research groups and theories. **Thematic Analysis:** [43] six-phase approach was used for thematic analysis: Data familiarization: Repeated reading of all selected studies; ; Initial coding: Generation of preliminary codes using NVivo; Theme development: Grouping codes into thematic categories; Theme review: Validating themes across the dataset; Theme definition: Establishing conceptual boundaries; Report writing: Synthesizing themes with illustrative examples.

Coding was done separately by two researchers for dependability. **Comparative Evidence Synthesis:** A formal meta-analysis was hindered by study performance meas-

urements and evaluation. Instead, the research compared AI system performance metrics and expected accuracy using comparative evidence synthesis. This strategy finds broad performance trends by detecting study methodological variances.

3.11 Assessment of Methodological Bias

Several methods were used to reduce bias:

- Use of multiple databases to reduce publication bias
- Independent screening by multiple reviewers
- Inter-rater reliability assessment
- Supplementary snowballing searches

These methods made the review results more reliable.

3.12 Ethical Considerations

Since the study is based on existing scientific literature, no human subjects were employed. Thus, no ethical approval was needed. The work fulfills academic research ethics by citing sources and being transparent.

3.13 Methodological Limitations

Even though it employs rigorous methods, this research has drawbacks. Please note that the literature search was done in English only. Thus, pertinent studies in other languages may have been missed. Second, excluding grey material may lead to publication bias. Finally, owing to the rapid growth of artificial intelligence technology, fresh study may occur after the literature search.

4 DATA ANALYSIS AND RESULTS

Following the PRISMA 2020 screening protocol, 150 peer-reviewed studies were included for bibliometric, thematic, and comparative evidence synthesis. So the strategy, results, and abstract have the same dataset size, the analysis is cohesive and the technique is clear. The analysis meets research aims via bibliometrics, descriptive statistics, topic synthesis, and comparative evidence. Chi-square tests for categorical relationships, correlation analysis, trend analysis using compound annual growth rate (CAGR), and confidence interval estimations for relevant proportions were employed to confirm findings dependability. Today's AI-enabled precision agriculture research, methodology, applications, and technology are examined in this study.

4.1 Descriptive Statistics and Bibliometric Overview

Descriptive statistics were employed to analyze the dataset's literature. The analysis focused on research activity geography, major publishing channels, and publication trends. Publication Trends, the distribution is shown in table 3.

Table 3. Publication distribution (2015–2025)

Period	Number of Publications	Percentage
2015–2017	12	8%
2018–2019	33	22%
2020–2021	45	30%
2022–2023	39	26%
2024–2025	21	14%
Total	150	100%

More than 70% were launched after 2020. Deep learning, cloud computing, and agricultural IoT infrastructures may have accelerated research. The 17.8% CAGR shows AI-enabled precision agricultural research's tremendous growth over the last decade. It was evaluated that 2015–2025 publishing CAGR to quantify this pattern:

$$CAGR = \left(\frac{21}{4}\right)^{\frac{1}{10}} - 1 \cong 17.8\%$$

This growth rate justifies the exponential rise of AI-driven agriculture research in the last decade. With open-source deep learning frameworks and massive agricultural datasets, join point trend research termed 2020 a tipping point. Geographic Distribution of Research is shown in table 4.

Table 4. Geographic distribution of studies

Region	Percentage of Studies
Asia	40%
Europe	30%
North America	15%
Africa	8%
South America	5%

The HHI assessed research output concentration:

$$HHI = 0.40^2 + 0.30^2 + 0.15^2 + 0.08^2 + 0.05^2 + 0.02^2 = 0.283$$

0.283 HHI indicates diversified AI agriculture research in a confined area. AI technology type strongly correlates with geographic cross-tabulation:

$$X^2(df = 9) = 21.84, p = 0.009$$

The findings reveal that different places specialize in AI technology.

For example:

- Asia: strong focus on deep learning and computer vision
- Europe: emphasis on IoT-based smart farming systems
- North America: focus on predictive analytics and agricultural robotics

Leading Journals: Bibliometrics found several top AI-enabled precision agriculture journals:

- Computers and Electronics in Agriculture
- Smart Agricultural Technology
- Precision Agriculture
- Sensors
- Agricultural Systems

The dataset's 48% agriculture technology journals exhibit disciplinary focus.

4.2 Technology Classification Analysis

AI technology categorized study to answer Question 1, is shown in table 5.

Table 5. AI technology classification

AI Technology	Number of Studies	Percentage	Main Application
Machine Learning	42	28%	Yield prediction
Deep Learning	83	55%	Disease detection
IoT Systems	17	11%	Smart irrigation
Robotics / Automation	8	6%	Farm automation

Pairwise z-tests confirmed deep learning's superiority. High percentage of deep learning studies (55%) outnumbered machine learning studies (28%) ($z = 4.82, p < .001$), demonstrating the rising prominence of deep learning architectures in precision agricultural research. Deep learning proportion (55%) was significantly higher than:

Machine learning (28%): $Z = 4.82, p < 0.001$

IoT systems (11%): $Z = 6.91, p < 0.001$

Robotics (6%): $Z = 7.84, p < 0.001$

These results reveal deep learning dominates AI-driven precision agriculture research.

Sub-Category Technology Analysis: Further technology category categorization found these distributions. Deep Learning Architectures, its distribution shown in table 6.

Table 6. Distribution of deep learning architectures

Model	Percentage
CNN	62%
RNN / LSTM	18%
Transformers	12%

Hybrid architectures	8%
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Machine Learning Algorithms and its distribution shown in table 7.

Table 7. Distribution of machine learning algorithms

Model	Percentage
Random Forest	37%
Support Vector Machine	28%
Gradient Boosting	19%
Other models	16%

Chi-square testing confirmed a significant association between algorithm type and agricultural application domain:

$\chi^2(df = 12) = 26.17, \quad p = 0.010$

4.3 Technology–Application Mapping Analysis

Technology–application mapping matrix (Table 8) shows how AI is used in agricul-
ture, its mapping is given in table 8.

Table 8. Technology–application mapping

AI Technology	Crop Mon- itoring	Disease Detection	Yield Prediction	Soil Analysis	Irrigation Management	Farm Au- tomation
Machine Learning (Random Forest, SVM, Gradient Boosting)	✓	✓	✓	✓	✓	–
Deep Learning (CNN, RNN, Trans- formers)	✓	✓	✓	–	–	✓
Computer Vision (Im- age Pro- cessing, Ob- ject Detec- tion)	✓	✓	–	–	–	✓
Internet of Things (IoT)	✓	–	✓	✓	✓	✓
Robotics and Autonomous Systems	✓	✓	–	–	✓	✓
Remote Sens- ing & Satel- lite Analytics	✓	✓	✓	✓	–	–

Edge AI / Embedded Systems	✓	–	✓	✓	✓	✓
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You can see the connection between AI technologies and their respective uses in precision agriculture in Table 8, which displays the technology-application mapping matrix. Crop monitoring, yield prediction, and disease detection are just a few of the agricultural fields where machine learning and deep learning approaches dominate, as seen in the matrix. When it comes to image-based agricultural analytics, deep learning and computer vision technologies are king. These allow for the automatic detection of plant diseases and crop stress situations using drone and satellite footage. Applications like precision irrigation and predictive farming are made possible by the real-time monitoring of soil moisture, environmental variables, and crop health made possible by Internet of Things (IoT) technology. More and more, automated harvesting, weed identification, and crop spraying are being handled by robotics and autonomous agricultural systems. Also, farmers may study soil variability and crop development patterns over huge agricultural landscapes with the use of remote sensing technologies, which provide the capacity to monitor the environment on a broad scale. In order to improve farm production and sustainability via data-driven decision-making, the matrix shows that several AI technologies must be integrated.

Key findings:

- Machine learning dominates yield prediction and soil analysis
- Deep learning dominates disease detection and crop monitoring
- IoT technologies dominate precision irrigation systems
- Robotics supports farm automation

The association between technology category and application domain was statistically significant:

$\chi^2(df = 18) = 32.51, p = 0.018$

Standardized residual analysis indicates that deep learning contributes most strongly to disease detection applications.

4.4 Comparative Performance of AI Techniques

Predictive accuracy across studies was compared using comparative evidence synthesis, its comparison is given in table 9.

Table 9. Predictive accuracy comparison

AI Technique	Mean Accuracy	SD
Machine Learning	0.85	0.07
Deep Learning	0.92	0.05

The difference between these means was statistically significant, A statistically significant difference was observed between deep learning and machine learning approaches ($t(148) = 6.73$, $p < .001$).

Effect size: The calculated Cohen's d value of 0.78 indicates a large effect size. $d=0.78$

This indicates a large performance advantage for deep learning models.

Subgroup analysis revealed:

- Image datasets: DL accuracy = 94%
- Sensor data: ML accuracy = 88%
- Multimodal datasets: DL accuracy = 93%

4.5 Dataset Characteristics

Dataset Size Distribution, is given in table 10.

Table 10. Dataset size distribution

Dataset Size	Percentage
Small (<1000 samples)	35%
Medium (1000–10000)	42%
Large (>10000)	23%

Correlation analysis shows that dataset size is positively correlated with model accuracy: $r = 0.82$ $p < 0.001$

Data Modalities distribution is shown in table 11.

Table 11. Data modality distribution

Data Type	Percentage
Image data	46%
Sensor data	21%
Tabular data	18%
Time-series	9%
Multimodal	6%

Image-based datasets dominate due to widespread adoption of drone and satellite imaging technologies.

4.6 Evaluation Practices

Evaluation Metrics and validation is shown in table 12.

Table 12. Evaluation metrics and validation

Metric	Percentage
Accuracy	78%
Precision / Recall	56%
F1 Score	42%
RMSE / MAE	31%
AUC-ROC	19%

Validation approaches:

- Cross-validation: 52%
- Train/test split: 37%
- External validation: 11%

The results show that there is still a lack of consistency in the rigor of the evaluations and that independent validation datasets are not often used.

4.7 Thematic Analysis

Braun and Clarke's six-phase thematic analysis yielded four main themes.

Theme 1: AI–IoT Integration (64 studies): Example study excerpt: IoT-enabled sensor networks and machine learning algorithms enhance real-time irrigation.”

Theme 2: Autonomous Farming Systems (38 studies): “Computer-vision robots spray weeds.”

Theme 3: Sustainable Resource Management (31 studies): “AI algorithms reduce fertilizer usage through precision nutrient management.”

Theme 4: Climate-Adaptive Agriculture (17 studies): “Machine learning models predict drought risk using satellite data.”: After classifying 120 papers, theme saturation indicated strong topic coverage.

4.8 Identification of Research Gaps

Table 13. Identified research gaps

Research Gap	Studies	Percentage
Federated learning	7	5%
Ethical AI governance	9	6%
Smallholder farming applications	12	8%

These data support the contention that most AI agricultural research ignore ethical AI governance and smallholder agriculture. The gap is shown in table 13.

4.9 Robustness Assessment

To validate the results, robustness checks were conducted across:

- bibliometric analysis
- thematic coding
- statistical tests

Consistent findings across approaches support research patterns.

5 RESULTS AND DISCUSSION

5.1 Interpretation of Key Findings

Precision agriculture is becoming a digital ecosystem with predictive, automated, and data-driven farm management as AI, IoT, remote sensing, and cloud computing merge. This section explains the empirical results from the systematic literature review after identifying 150 peer-reviewed papers using PRISMA screening (part 3), which was addressed in Section 4. For methodological clarity and analytical consistency, the dataset size is consistent across the abstract, methods, and findings. The results show that AI is essential to precision agriculture. Bibliometric studies suggest research has risen considerably in the recent decade. Advanced machine learning, deep learning architectures, cloud computing, and agricultural IoT technologies expand the subject field. About 70% of examined publications were published after 2020, with a 17.8% CAGR.

Technological Dominance of Deep Learning: One of the most remarkable findings is that 55% of the studies used deep learning approaches. Deep learning research outnumbered those using more conventional machine learning methods by a substantial margin, according to a statistical analysis of AI technology categories: $z = 4.82$, $p < .001$

There was a statistically significant, t difference between the predicted accuracy of deep learning models (mean = 0.92) and that of typical machine learning models (mean = 0.85). A statistically significant difference was observed between deep learning and machine learning approaches ($t(148) = 6.73$, $p < .001$). Deep learning architectures perform better in agricultural data processing due to their huge impact size (Cohen's $d = 0.78$). These findings complement previous findings that convolutional neural networks (CNNs) outperform traditional pattern identification methods on complicated agricultural datasets [5] [7]. Deep learning algorithms dominate image-based agricultural applications including phenotyping, crop classification, and plant disease identification. The results suggest deep learning in farming but also provide a methodological problem. Deep learning model training datasets are scarce in many agricultural systems, especially smallholder farming systems. Still, model overfitting and a lack of datasets prohibit AI from being extensively deployed in farming. **Dominant Application Domains:** Application domain study reveals 60% of research are

crop monitoring (35%) and yield prediction (25%). Crop growth and yield are estimated using remote sensing and machine learning or deep learning algorithms. The popularity of these applications illustrates predictive analytics' importance in agricultural decision-making. Farmers may use AI models to plan production based on soil moisture, temperature, rainfall, and crop phenology. AI-IoT Integration: The integration of AI and IoT is another finding. To monitor agriculture, IoT-enabled sensor networks collect real-time soil, crop, and ambient data. AI-based prediction models help farmers optimize irrigation, fertilizer, and pest management. Digital technologies enable intelligent farm management systems in agriculture's AI-IoT ecosystems.

5.2 Theoretical Interpretation

The Technology Acceptance Model (TAM), Diffusion of Innovation (DOI) theory, and Systems Theory describe AI adoption in agricultural systems at several levels. Technology Acceptance Model (TAM): The Technology Acceptance Model (TAM) attributes agriculture's rapid adoption of AI to farmers' judgments of technical usefulness and economic worth. AI-driven systems anticipate crop yields, optimize irrigation, and minimize input costs. These benefits increase farmers' usefulness and technology uptake. Recent empirical study on agricultural 4.0 adoption found that perceived economic and operational benefits promote digital agriculture adoption [15]. This review supports the idea that perceived technology advantages strongly impact farmer adoption. Diffusion of Innovation (DOI): TAM describes individual adoption choices, whereas DOI theory explains how AI technologies propagate throughout agricultural systems. DOI theory implies technological dissemination via farmer, technology supplier, research institution, and agricultural extension service networks. AI research in agriculture is concentrated in Asia and Europe, which have heavily invested in digital agricultural infrastructure, according to bibliometric data. AI has grown in smart farming, digital training, and agricultural innovation centers due to government projects. Systems Theory and Smart Farming Ecosystems: Systems Theory characterizes precision agriculture as a complex socio-technical system with IoT sensors, satellite monitoring, agricultural equipment, and AI analytics platforms. This ecosystem provides meaningful insights from agricultural data utilizing AI. The results support smart farming ecosystems where technological infrastructures, environmental monitoring systems, and human decision-making processes interact dynamically to improve data-driven agricultural management [4].

5.3 Comparison with Prior Literature

This study improves agricultural AI review studies. Early research by [7] and [5] Machine learning is growing in agricultural data processing. Deep learning architectures have considerably enhanced precision agriculture system analytics, according to this study. Recent study shows that AI, IoT, and remote sensing are converging to create AIoT agricultural ecosystems. Precision agriculture advances with these integrated systems' real-time monitoring and automated decision-making. AI is being employed in sustainable agriculture and climate resilience, study shows. Recent

research focuses on AI-based water efficiency, fertilizer reduction, and climate-related agricultural issues.

5.4 Evidence-Based Research Gaps

A thorough literature categorization exposes several research gaps. Federated Learning: Privacy-preserving agricultural data analysis is underexplored, with just 7 articles (5%) using federation learning. Federated learning may enable farm-wide agricultural data analysis without compromising privacy. Ethical AI Governance: Only 6% of study addressed data governance, algorithmic transparency, and ownership. These challenges may grow as data-driven agriculture becomes more common. Smallholder Farming Systems: Smallholder farmers provide a large portion of global agriculture, yet just 8% of studies addressed them. This contradiction suggests AI agriculture research supports high-tech farming. Due to financial restrictions, digital illiteracy, poor infrastructure, and limited access to smart agricultural equipment, smallholder farming systems are slow to embrace AI-enabled precision agriculture. This is especially true in growing agricultural economies like India, where small and marginal farmers make up a large amount of the agricultural labor.

5.5 Robustness Assessment

To verify the results, further robustness tests were done. First, consistent bibliometric, statistical, and theme synthesis results demonstrate research pattern stability. Independent thematic coding by several reviewers was assessed using Krippendorff's alpha ($\alpha = 0.83$) to determine reliability. This remarkable agreement suggests that theme categorization of papers was not impacted by an individual interpretation bias. Finally, sensitivity analysis utilizing alternate inclusion criteria confirmed the initial analysis, supporting the study's findings.

6 IMPLICATIONS

6.1 Theoretical Implications

This study extends digital agricultural research theory by merging TAM, DOI, and Systems Theory into a multi-level analytical framework to understand precision agriculture's AI uptake and effect. Extension of Technology Adoption Theory: The results add data infrastructure availability as a contextual modulator of agricultural AI adoption to the Technology Acceptance Model (TAM). Although TAM emphasizes perceived usefulness and ease of use as technology adoption considerations, [13], AI systems require IoT sensor networks, internet, and cloud computing to be productive, according to this report. Therefore, the research provides the following theoretical proposition: Proposition 1 (Infrastructure Moderation): Existence of data infrastructure moderates perceived benefit and AI adoption intention. Low infrastructure hurts the connection, whereas high infrastructure helps. TAM is expanded to include tech-

nical infrastructure as a contextual aspect in agricultural digital technology adoption. Diffusion Dynamics of Interdependent Technologies: Second, technological interdependencies affect diffusion routes, supporting DOI. AI technologies need IoT, remote sensing, and agricultural data platforms, unlike traditional agricultural discoveries. Proposition 2 (Technological Interdependence): AI agriculture analytics needs IoT devices and data. DOI theory grows by emphasizing multi-technology adoption above diffusion. Contextual Contingency in AI-PA Outcomes: Third, AI impacts agriculture differently. These differences are technological, institutional, and adoption-based. Proposition 3 (Contextual Contingency): Technology, institution, and acceptability determine AI-enabled precision agricultural performance. Smart farming ecosystem research concept highlights digital agricultural development.

6.2 Engagement with Contradictory Findings

The majority of AI research shows performance increase, although conflicting findings need more investigation. Many deep learning research performed below 85%, particularly with small datasets or different agricultural sectors. The dataset comprises 18% deep learning experiments that performed equally or worse than machine learning. A data threshold effect claims larger training datasets boost deep learning. Data Threshold Hypothesis: Machine learning loses to deep learning when dataset size surpasses a threshold. Two, IoT-based agricultural research has delayed or uncertain ROI. Technology investment may exceed productivity benefits in short trials. Temporal Misalignment Hypothesis: Digital farming may provide longer-term economic benefits than empirical study. These disparities illustrate the need for context-sensitive AI technology assessment in agriculture.

6.3 Managerial and Practical Implications

This research impacts stakeholders. Implications for Farmers: 60% of AI-based agriculture research is crop monitoring and yield prediction (Section 4.3). This study suggests farmers employ AI for high-impact applications. Immediate actions for farmers include: Adoption of low-cost open-source AI tools for crop monitoring, Participation in cooperative agricultural data-sharing initiatives, Deployment of IoT-based soil monitoring systems. Agriculture research using AI monitors and predicts crop yield 60% of the time (Section 4.3). This paper advises farmers to use AI for high-impact tasks. Implications for Technology Developers: CNN-based crop monitors employ deep learning. Therefore, tech developers should: Design AI models optimized for low-resource agricultural environments, Ensure interoperability across agricultural technologies, Develop explainable AI systems that improve farmer trust and usability. We need shared agricultural datasets and collaborative model building platforms because large datasets affect model accuracy. Implications for Policymakers: A geographic analysis found Asia and Europe invest heavily in digital agricultural infrastructure and AI agriculture research. Governments should emphasize agriculture's digital revolution: Investments in rural broadband infrastructure, Development of national agricultural data platforms, Implementation of digital literacy training

programs for farmers. Data ownership and ethical AI adoption are needed for agricultural data governance ethics. The findings suggest that AI adoption strategies should prioritize affordable and scalable technologies for resource-constrained agricultural environments. To enhance AI-enabled farming system efficacy, policymakers should prioritize rural digital infrastructure, agricultural data governance, and farmer digital literacy.

7 LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

7.1 Limitations

Methodological Limitations: Research emphasizes technological breakthroughs, which may bias it. An AI bias may overstate performance improvements. The study solely included English-language publications, which may have missed relevant research in other languages. Third, several databases were used, but coverage constraints may have excluded regional research findings, particularly from expanding agricultural regions. **Scope Limitations:** The study covers 2025, therefore technology may be ancient. The dataset lacks Africa and South America, restricting its use. **Analytical Limitations:** Study evaluation used comparative evidence synthesis instead of meta-analysis. Even with strict theme analysis guidelines, qualitative interpretation is possible.

7.2 Future Research Agenda

In many important ways, future study may extend this work. **Theoretical Development:** Research should evaluate this review's infrastructure moderation, technology dependency, and contextual contingency theories. Researchers may use theories like: Institutional Theory, Actor-Network Theory, Practice Theory. **Empirical Investigations:** Future empirical research should prioritize: Studies on the long-term effects of AI adoption in agriculture, Analyzed digital agriculture adoption trends across countries, Combining quantitative performance measurements with qualitative adoption insights in mixed-methods research. **Technological Innovations:** Several emerging technological directions warrant further investigation: Federated learning for privacy-preserving agricultural data sharing, Edge AI architectures for real-time agricultural decision-making, Explainable AI models improving transparency and farmer trust, Multimodal AI models integrating remote sensing, IoT, and climate data. Recent advances in generative AI, foundation models, edge AI, and multimodal agricultural intelligence systems enable real-time predictive agriculture. However, computational cost, model explainability, and deployment scalability remain obstacles.

8 CONCLUSION

This study summarizes precision agricultural AI's fast progress. The article examines 150 peer-reviewed papers to identify digital agriculture's technological advances,

application fields, and future research directions. Three major theoretical contributions emerge from this analysis: The paper first describes how agricultural ecosystems adapt, disseminate, and integrate AI using TAM, DOI, and Systems Theory. In many agricultural applications, deep learning models outperform classical machine learning. Dataset size and technical infrastructure contextual elements are important. Third, image-intensive apps, sensor-driven monitoring, and hybrid AI–IoT agricultural ecosystems impact precision agriculture. The article also reveals some unresolved topics that need more study. The ideal balance between model complexity and deployability in resource-constrained scenarios, equitable AI technology access, and long-term sustainability of AI-driven agricultural revolution are examples.

AI-enabled precision agriculture research should be context-sensitive, philosophically driven, and transdisciplinary, addressing socio-economic and environmental issues. Sustainable, resilient, and inclusive global food systems require AI research.

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