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Scoping Review of AI-Enabled Predictive Analytics and Decision Support in Agricultural Education

Current Trends, Tools, and Pedagogical Implications

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ABSTRACT

Artificial Intelligence (AI) and predictive analytics are increasingly reshaping contemporary agricultural systems by enabling data-driven decision support, early pest and disease detection, and optimized crop management. As these technologies become embedded in agricultural practice, agricultural education faces growing pressure to prepare learners with analytical reasoning and decision-making competencies aligned with AI-enabled environments. This scoping review maps peer-reviewed literature published between 2020 and 2025 on AI-enabled predictive analytics, crop advisory systems, and pest and disease detection technologies, with a specific focus on their educational implications. Following PRISMA-ScR guidelines, 18 studies were systematically identified and synthesized through thematic analysis. The results indicate rapid growth in technically oriented AI applications for precision agriculture, contrasted with limited empirical research on curriculum integration and competency-based learning outcomes. While project-based learning, simulations, and decision support tools are frequently proposed as pedagogical strategies, explicit assessment of learners' analytical and decision-making competencies remains scarce. This review highlights critical gaps between AI innovation and educational research, and underscores the need for interdisciplinary approaches, curriculum redesign, and competency frameworks that support responsible and effective AI use in agricultural education.

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Introduction

Artificial Intelligence (AI) has increasingly become a central driver of transformation in contemporary agricultural systems. Advances in machine learning, predictive analytics, computer vision, and Internet of Things (IoT) technologies have enabled the development of intelligent systems capable of forecasting crop yields, detecting pests and diseases at early stages, optimizing irrigation and fertilization, and supporting strategic farm-level decision making. Between 2020 and 2025, research on AI-enabled precision agriculture has expanded rapidly, reflecting global concerns over food security, climate change, resource efficiency, and the sustainability of agroecosystems [1], [2]. These developments position AI not merely as a technological innovation but as a cognitive tool that reshapes how agricultural knowledge is produced, interpreted, and applied.

Recent reviews demonstrate that predictive analytics models—ranging from traditional regression-based approaches to deep learning architectures—have achieved promising performance in yield prediction, soil and nutrient forecasting, and climate risk assessment [3], [4]. Similarly, computer vision techniques using Convolutional Neural Networks (CNNs), YOLO-based detectors, and hybrid deep learning models have shown high accuracy in identifying crop diseases and pest infestations using leaf images, UAV imagery, and multispectral data [5], [6]. Collectively, this body of work confirms the technical maturity and applicability of AI in precision agriculture. However, the dominant focus of existing studies remains on algorithmic performance, system accuracy, and deployment efficiency, with comparatively limited attention to the human and educational dimensions of AI adoption.

As AI-driven decision support systems become embedded in routine agricultural practice, the role of agricultural education is undergoing a fundamental shift. Future agronomists, extension officers, and farm managers are no longer required only to possess domain-specific agronomic knowledge, but also to develop competencies in data interpretation, analytical reasoning, and evidence-based decision making supported by AI outputs [7]. The effectiveness of AI in agriculture therefore depends not only on technical robustness, but also on users' capacity

to critically engage with model predictions, understand uncertainty and bias, and contextualize recommendations within local ecological and socio-economic conditions.

Despite this urgency, the integration of AI and predictive analytics into agricultural education remains fragmented. Existing educational studies tend to discuss digital tools or smart farming technologies in general terms, without systematically mapping how specific AI applications—such as yield prediction models, crop advisory systems, or pest detection technologies—are translated into curricula, learning activities, and competency development frameworks [8]. Moreover, there is a lack of consolidated evidence regarding how exposure to AI-enabled systems influences learners' analytical skills, decision-making processes, and readiness for data-driven agricultural practice.

In this context, a scoping review is particularly appropriate. Unlike systematic reviews that aim to answer narrowly defined effectiveness questions, scoping reviews are designed to map the breadth, characteristics, and conceptual boundaries of an emerging research field [9]. Given the interdisciplinary nature of AI in agriculture—spanning computer science, agronomy, and education—a scoping review allows for the identification of dominant research trends, key technological applications, educational strategies, and gaps that warrant further empirical investigation.

Accordingly, this study aims to map and synthesize literature published between 2020 and 2025 on AI-enabled predictive analytics and decision support systems in agriculture, with a specific focus on their implications for agricultural education. The review is guided by the following research questions:

1. What types of AI-enabled predictive analytics and decision support tools are most frequently applied in contemporary agricultural research?
2. How are these AI technologies linked to curriculum design, learning strategies, or educational interventions in agricultural education?
3. What forms of analytical reasoning and decision-making competencies are reported or implied in studies integrating AI into agricultural learning contexts?

By addressing these questions, this scoping review seeks to contribute a structured evidence base that informs curriculum development, pedagogical innovation, and future research on AI literacy and decision-making competence in agricultural education.

Materials and Methods

A. Review Design

This study adopted a scoping review methodology in accordance with the principles outlined in the Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension

for Scoping Reviews (PRISMA-ScR) [9]. The scoping review approach was selected to systematically map the range of AI-enabled predictive analytics applications in agriculture and to examine how these technologies intersect with educational practices and competency development, without restricting inclusion to a single study design or outcome measure.

B. Search Strategy

A comprehensive literature search was conducted across four major academic databases: Scopus, IEEE Xplore, ScienceDirect, and Google Scholar. These databases were selected to capture interdisciplinary research spanning agricultural science, artificial intelligence, and educational technology. The search was limited to publications released between January 2020 and December 2025 to reflect recent developments in AI and predictive analytics.

Search strings were constructed using combinations of keywords and Boolean operators, including: "artificial intelligence" OR "machine learning" OR "predictive analytics" AND "agriculture" OR "precision agriculture" AND "education" OR "learning" OR "curriculum" OR "decision support" OR "crop advisory" OR "pest detection". Title, abstract, and keyword fields were primarily used to ensure relevance.

C. Inclusion and Exclusion Criteria

Studies were included if they met the following criteria:

1. Peer-reviewed journal articles or high-quality conference proceedings;
2. Focused on AI-enabled predictive analytics, decision support systems, crop advisory tools, or pest and disease detection in agricultural contexts;
3. Provided empirical findings, conceptual frameworks, or systematic syntheses with explicit or implicit relevance to education, training, or competency development;
4. Published in English between 2020 and 2025.

Studies were excluded if they were purely technical without reference to learning, human decision making, or educational implications, or if they consisted of editorials, opinion pieces, or non-peer-reviewed reports.

D. Study Selection and Screening

All identified records were exported to a reference management system, and duplicates were removed. The initial database search yielded 312 records across Scopus, IEEE Xplore, ScienceDirect, and Google Scholar. After the removal of 64 duplicate records, 248 unique records remained for title and abstract screening. Based on relevance to AI-enabled predictive analytics, decision support systems, and educational implications in agriculture, 198 records were excluded.

Subsequently, 50 full-text articles were assessed for eligibility. Of these, 32 articles were excluded due to a lack of explicit or implicit educational relevance, insufficient methodological

rigor, or a purely technical focus without human or learning dimensions. A total of 18 studies met all inclusion criteria and were included in the final scoping review synthesis.

The study identification, screening, and inclusion process followed the PRISMA-ScR guidelines, ensuring transparency and reproducibility of the review process.

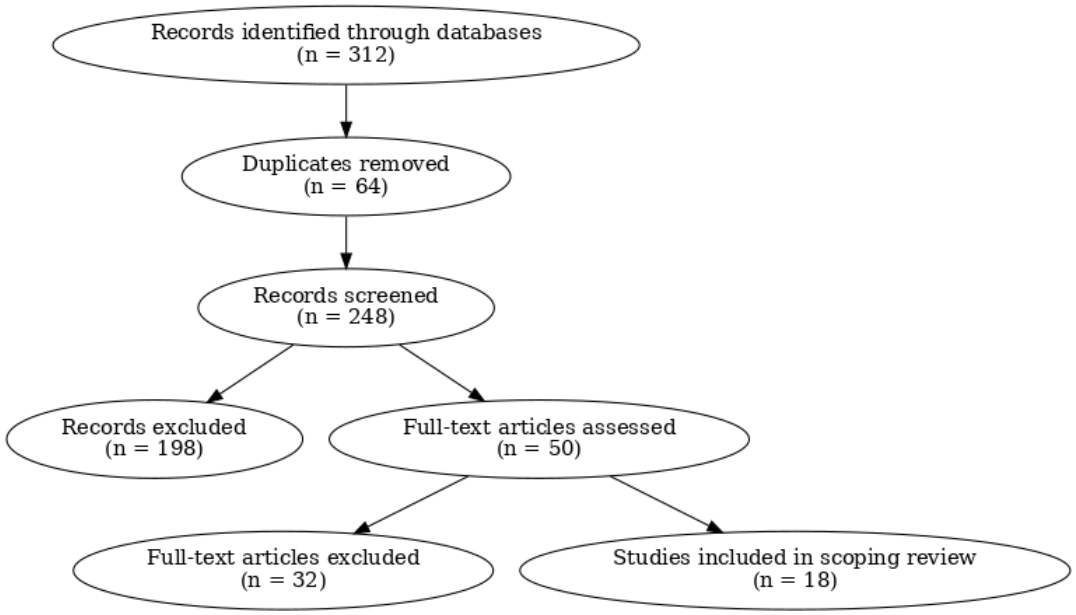


Fig. 1. PRISMA-ScR flow diagram

E. Data Charting and Synthesis

For each included study, key data were charted using a standardized extraction form. Extracted information included author(s), publication year, country or region, AI application domain (e.g., predictive analytics, crop advisory systems, pest detection), research methodology, and reported or inferred educational implications. The charted data were synthesized using descriptive and thematic analysis to identify dominant trends, recurring educational strategies, and gaps in the literature.

The results of this synthesis informed the development of thematic categories that structure the Results and Discussion sections, including AI in precision agriculture, AI-based crop advisory systems, pest and disease detection technologies, and analytical and decision-making competencies in agricultural education.

Results

A. Overview of Included Studies

Following the screening and eligibility assessment, the included studies represent interdisciplinary research spanning agricultural science, artificial intelligence, and education. The literature demonstrates a clear concentration on three dominant AI application domains: (1) predictive analytics for precision agriculture, (2) AI-based crop advisory and decision support

systems, and (3) pest and disease detection using computer vision and sensor-driven analytics. Although most studies primarily emphasize technical performance, a subset explicitly or implicitly addresses educational integration, skill development, or competency formation relevant to agricultural learning contexts. Table 1 presents the characteristics of representative studies included in this scoping review, highlighting publication year, geographical context, AI focus, methodological approach, and educational implications.

Table 1. Characteristics of Included Studies (2020–2025)

Author(s) & Year	Country /Region	AI Application Focus	Research Method	Educational Implication	Ref. No.
Lengyel et al., 2024	Europe	AI integration in agricultural higher education	Conceptual review	Curriculum redesign for AI literacy	[6]
Krishna et al., 2025	India	Pest and disease detection (CNN-based)	Experimental	Computer vision learning modules	[5]
Wang et al., 2025	China	AI-enabled decision support systems	System modeling	Decision-making skill development	[3]
Kaushik, 2025	Global	AI in precision agriculture	Narrative review	Overview for instructional use	[1]
Pathak & Mahajan, 2025	India	Smart farming decision systems	Review	Case-based learning resources	[2]
Liakos et al., 2020	Global	Precision farming analytics	Descriptive synthesis	Introductory AI-agriculture teaching	[11]
Discover Food, 2025	Global	Yield and soil prediction	Review	Data interpretation exercises	[4]
Li et al., 2024	Global	Visual sensor-based pest detection	Experimental	Image-based diagnostic training	[7]

Note: The table summarizes representative studies. The full dataset includes additional Scopus-indexed publications aligned with the inclusion criteria.

B. AI-Enabled Predictive Analytics in Agricultural Learning

A substantial proportion of the reviewed studies focus on predictive analytics models for yield forecasting, soil nutrient dynamics, irrigation scheduling, and climate risk prediction. These models typically employ machine learning or deep learning techniques trained on multisource datasets, including weather data, satellite imagery, and IoT sensor readings. From an educational perspective, such studies provide valuable opportunities for experiential learning, enabling students to engage with real-world datasets and interpret model outputs in simulated or field-based learning environments. Several studies suggest that integrating predictive analytics into laboratory activities and project-based learning enhances learners' analytical reasoning by requiring them to assess prediction accuracy, uncertainty, and contextual relevance. However, explicit assessment of learning outcomes remains limited, indicating a gap between technical innovation and pedagogical evaluation.

C. AI-Based Crop Advisory and Decision Support Systems

AI-driven crop advisory systems translate predictive outputs into actionable recommendations related to crop selection, nutrient management, irrigation planning, and harvesting strategies. The reviewed literature indicates that these systems are increasingly designed as decision support tools rather than automated decision-makers, emphasizing the role of human judgment. In educational settings, crop advisory platforms are commonly introduced through case studies, simulations, and decision-making workshops that allow learners to explore trade-offs between productivity, sustainability, and risk. Despite their pedagogical potential, few studies systematically examine how engagement with AI advisory systems influences students' decision-making competence. Most educational implications are inferred rather than empirically measured, underscoring the need for more rigorous educational research designs.

D. Pest and Disease Detection Technologies

Pest and disease detection represents one of the most mature application areas of AI in agriculture. The reviewed studies report high accuracy in detecting plant diseases and pest infestations using CNN-based image classification, UAV imagery, and hybrid sensor-vision approaches. These technologies are frequently proposed as instructional tools in agricultural programs, particularly within courses on crop protection, digital agriculture, and applied machine learning. Educationally, pest detection systems support the development of data literacy and diagnostic reasoning by exposing learners to noisy, real-world image datasets. Advanced approaches, such as explainable AI and few-shot learning models, further contribute to learners' understanding of model transparency and adaptability, although their adoption in formal curricula remains limited.

E. Synthesis of Educational Implications

Across the reviewed literature, educational implications are most commonly framed around enhancing analytical reasoning, data interpretation, and evidence-based decision making. However, the synthesis reveals that these competencies are often treated as secondary outcomes rather than primary research objectives. As a result, there is limited empirical evidence linking AI-based learning activities to measurable improvements in student competencies, highlighting a critical gap for future research.

Discussion

The discussion is organized around three interrelated themes: the dominance of technically oriented AI research, emerging patterns of educational integration, and the implications for analytical and decision-making competency development in agricultural education.

A. Technical Dominance and Educational Gaps in AI–Agriculture Research

Across the reviewed studies, AI applications in agriculture are predominantly framed through a technical lens, emphasizing model accuracy, algorithmic efficiency, and system performance. Reviews and empirical studies consistently report strong performance of machine learning and deep learning models for yield forecasting, soil and nutrient modeling, and climate risk assessment, particularly within precision agriculture contexts [1], [3], [10], [11], [16]. Similarly, pest and disease detection research prioritizes classification accuracy and real-time detection using CNN-based architectures, UAV imagery, and hybrid sensor–vision approaches [5], [7], [15], [17]. While these contributions are essential for advancing smart and sustainable agriculture, they reveal a persistent gap between technological innovation and educational application. Only a limited subset of studies explicitly addresses how AI systems are embedded into formal agricultural education or professional training programs [6], [18]. In many cases, educational relevance is implied rather than empirically examined, suggesting that learners are assumed to benefit indirectly from technological exposure without systematic evaluation of learning processes or outcomes.

B. Patterns of Educational Integration and Pedagogical Approaches

Despite the overall technical emphasis, the reviewed literature reveals recurring patterns of educational integration. AI-enabled predictive analytics and big data infrastructures are most commonly incorporated into learning environments through project-based laboratories, simulation exercises, and case studies using real or realistic agricultural datasets [4], [12], [13]. These pedagogical approaches align with experiential learning principles, which emphasize active engagement, reflection, and contextual problem solving as foundations for higher-order cognitive development. Crop advisory and decision support systems demonstrate particularly strong potential for fostering decision-making competencies. Several studies emphasize that AI-based systems are increasingly designed to support, rather than replace, human judgment by presenting alternative scenarios, uncertainty indicators, and trade-off analyses [3], [14]. When integrated into instructional contexts, such systems function as cognitive scaffolds that enable learners to practice evidence-based reasoning and context-sensitive decision making. However, the review indicates that empirical studies directly measuring the impact of these tools on student decision quality, reasoning strategies, or long-term competence development remain scarce [9].

C. Pest and Disease Detection as a Vehicle for Analytical Skill Development

Pest and disease detection technologies represent one of the most mature and pedagogically promising application areas of AI in agriculture. Image-based AI systems require learners to engage with complex, noisy, and often incomplete datasets, thereby supporting the development

of analytical reasoning and diagnostic skills [5], [7], [17]. Learning activities involving model training, validation, and error analysis can help students critically evaluate model limitations, bias, and uncertainty, which are essential components of responsible AI use. Emerging approaches such as explainable artificial intelligence (XAI) and few-shot learning further enhance educational relevance by emphasizing model transparency, interpretability, and adaptability [8], [17]. These features are closely aligned with contemporary calls for ethical and trustworthy AI education, although their systematic integration into agricultural curricula remains limited [18]. The absence of curriculum frameworks explicitly linking advanced AI techniques to learning outcomes represents a missed opportunity for deeper competency development.

D. Implications for Analytical and Decision-Making Competencies

A central finding of this scoping review is that analytical reasoning and decision-making competencies are widely acknowledged as critical outcomes of AI integration in agriculture, yet they are rarely operationalized or assessed in educational research. Many studies assert that AI tools enhance data literacy and decision quality, but few provide explicit competency models, assessment instruments, or longitudinal evidence of learning impact [6], [9], [18]. As a result, the educational effectiveness of AI-enabled learning environments remains difficult to compare across institutional and cultural contexts. To address this limitation, future research should move beyond descriptive accounts of AI-enhanced instructional settings and adopt mixed-methods or longitudinal designs capable of capturing changes in learners' reasoning processes, confidence, and decision performance over time [9], [18]. Aligning AI applications with clearly articulated learning outcomes and assessment strategies will be critical for translating technological advances into meaningful educational transformation.

E. Synthesis and Research Directions

Taken together, the findings suggest that AI-enabled predictive analytics, crop advisory platforms, and pest detection systems offer substantial pedagogical potential for agricultural education, particularly in developing analytical reasoning and decision-making competencies. However, realizing this potential requires stronger alignment between technological design, curriculum development, and educational research. Interdisciplinary collaboration among agricultural scientists, AI developers, and education researchers is essential to ensure that AI tools are not only technically robust but also pedagogically effective and ethically grounded [12], [13], [18]. This scoping review, therefore, underscores the need for future studies that explicitly position education as a primary research focus, supported by theoretical frameworks, empirical evaluation, and competency-based assessment. Such efforts are necessary to bridge the gap between AI innovation and human capacity building in the context of data-driven and sustainable agricultural systems.

Conclusion

This scoping review examined recent literature on AI-enabled predictive analytics and decision support systems in agriculture, with particular attention to their implications for agricultural education. The findings demonstrate that while AI applications for yield prediction, crop advisory, and pest and disease detection have reached a high level of technical maturity, their integration into educational frameworks remains limited and uneven. Most studies prioritize system performance and accuracy, with educational value often inferred rather than empirically evaluated.

The review further reveals that AI-based learning environments hold strong potential for developing analytical reasoning and decision-making competencies when embedded within experiential pedagogies such as project-based learning, simulations, and case-based instruction. However, the absence of clearly defined competency frameworks and assessment strategies constrains the ability to evaluate educational impact and transferability across contexts.

To bridge the gap between technological innovation and human capacity building, future research should foreground educational objectives, adopt interdisciplinary designs, and employ rigorous methods to assess learning outcomes associated with AI use. Curriculum designers and policymakers are encouraged to integrate AI literacy, ethical considerations, and decision-making skills into agricultural education programs to ensure that graduates are equipped to navigate data-driven and sustainable agricultural systems.

Conflict of Interest

The authors declare no conflict of interest.

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