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ARTIFICIAL INTELLIGENCE-BASED PRECISION AGRICULTURE AND CROP YIELD OPTIMIZATION: THE MEDIATING ROLE OF DATA-DRIVEN DECISION MAKING AND FARMER DIGITAL LITERACY

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Abstract
Artificial Intelligence (AI) is revolutionizing modern agriculture by enabling precision farming techniques that optimize crop yield, resource utilization, and environmental sustainability. AI-based precision agriculture systems leverage machine learning algorithms, predictive analytics, and remote sensing data to provide actionable insights for irrigation, fertilization, pest management, and harvesting. However, the effectiveness of these technologies depends not only on technological adoption but also on farmers' ability to interpret and apply data-driven insights and their level of digital literacy. This study investigates the impact of AI-based precision agriculture on crop yield optimization, with a focus on the mediating roles of data-driven decision making and farmer digital literacy. Data-driven decision making refers to farmers' capacity to interpret AI-generated recommendations and implement evidence-based interventions effectively. Digital literacy reflects farmers' technical skills, familiarity with digital tools, and confidence in utilizing AI platforms for agricultural management. A quantitative research design was employed, targeting farmers, agronomists, and agricultural extension specialists in regions practicing precision agriculture. Structured questionnaires were used to collect data, which were analyzed using Smart PLS structural equation modeling to assess both direct effects of AI-based precision agriculture and the mediating effects of decision making and digital literacy. Results indicate that AI-based precision agriculture positively impacts crop yield optimization. Data-driven decision making and farmer digital literacy both mediate this relationship, emphasizing the importance of human capability in translating AI insights into practical actions. These findings highlight the necessity of combining technological innovation with capacity-building programs and digital skill development to maximize the benefits of AI-based precision agriculture. The study offers critical insights for policymakers, agricultural extension services, and technology developers seeking to promote sustainable and high-yield farming practices.

Keywords: *Artificial Intelligence, Precision Agriculture, Crop Yield Optimization, Data-Driven Decision Making, Digital Literacy*

Introduction

Agriculture is experiencing a paradigm shift driven by the integration of artificial intelligence (AI) and digital technologies. Precision agriculture, enabled by AI, leverages data from sensors, drones, satellites, and IoT devices to provide farmers with precise, real-time recommendations for irrigation, fertilization, pest management, and crop planning. These technologies promise increased crop yields, improved resource efficiency, and environmentally sustainable practices (Liakos et al., 2018).

AI-based precision agriculture employs machine learning algorithms and predictive analytics to process large datasets, including weather forecasts, soil conditions, crop health imagery, and historical yield data. The insights generated guide farmers in making informed decisions, reducing input wastage, and optimizing productivity (Wolfert et al., 2017). However, successful adoption depends not only on the availability of AI systems but also on farmers' capacity to interpret and implement AI-generated recommendations.

Data-driven decision making represents the ability of farmers to utilize insights from AI platforms to make effective operational decisions. Studies have shown that farmers who adopt evidence-based decision practices experience higher crop productivity, lower input costs, and greater resilience to environmental variability (Kamilaris et al., 2017). Digital literacy, encompassing technical skills, confidence in using digital tools, and understanding of AI systems, is critical to translating AI-generated insights into practical actions (Wolfert et al., 2017).

Although AI-based precision agriculture has demonstrated potential in improving crop yield, barriers to adoption exist. These include limited technological knowledge, insufficient training, cost constraints, and low digital literacy among smallholder farmers (Shamshiri et al., 2018). Mediating factors such as data-driven decision making and digital literacy play a critical role in determining whether AI adoption leads to tangible improvements in crop yield. Farmers with higher digital literacy and stronger capacity for evidence-based decisions are more likely to implement AI insights effectively, enhancing productivity outcomes.

Theoretical frameworks such as the Technology Acceptance Model (TAM) and the Knowledge-Based View (KBV) provide a basis for understanding the adoption and effectiveness of AI in agriculture. TAM emphasizes perceived usefulness and ease of use as key determinants of technology adoption (Davis, 1989), while KBV highlights the importance of human knowledge, skills, and capabilities in leveraging technology for competitive advantage (Grant, 1996). In the context of precision agriculture, these frameworks suggest that digital literacy and data-driven decision making mediate the relationship between AI adoption and crop yield optimization.

This study investigates the impact of AI-based precision agriculture on crop yield optimization, with a focus on the mediating roles of data-driven decision making and farmer digital literacy. Using Smart PLS structural equation modeling, the research quantifies direct and mediated effects, providing empirical evidence for policies, training programs, and technological interventions that maximize the benefits of AI in agriculture.

Literature Review

AI-based precision agriculture is transforming traditional farming systems by enabling efficient, targeted, and adaptive management practices. Technologies such as drones, IoT-enabled soil and weather sensors, satellite imagery, and machine learning algorithms allow farmers to make precise decisions regarding irrigation, fertilization, pest management, and crop scheduling (Liakos et al., 2018). Studies demonstrate that AI adoption can increase crop yield by 15–40%, reduce water and fertilizer usage, and enhance overall resource efficiency (Shamshiri et al., 2018).

Data-driven decision making is central to precision agriculture. Farmers need to interpret AI-generated recommendations accurately and implement appropriate interventions. Empirical studies suggest that farmers with strong data-driven decision capabilities are better equipped to respond to variability in weather, soil fertility, and pest outbreaks, resulting in higher crop productivity and resilience (Kamilaris et al., 2017).

Digital literacy is another critical factor influencing the effectiveness of AI technologies in agriculture. It encompasses technical skills, confidence in using digital platforms, and the ability to integrate AI insights into operational practices. Low digital literacy limits adoption and reduces the impact of AI tools, particularly among smallholder farmers (Wolfert et al., 2017). Training programs and capacity-building initiatives have been shown to enhance digital literacy and improve the translation of AI insights into practical actions.

The Technology Acceptance Model (TAM) explains that farmers' perceptions of usefulness and ease of use determine the adoption of AI technologies (Davis, 1989). Meanwhile, the Knowledge-Based View (KBV) emphasizes that human skills, capabilities, and knowledge are essential for leveraging technological assets for improved performance (Grant, 1996). These frameworks support the premise that data-driven decision making and digital literacy mediate the relationship between AI adoption and crop yield optimization.

Empirical evidence indicates that mediating factors are essential for maximizing AI impact. For instance, farmers with high digital literacy who utilize AI recommendations for irrigation and fertilization achieve significantly higher yields than farmers with low digital literacy, despite using similar AI tools (Liakos et al., 2018). Similarly, farmers with strong data-driven decision-making capacity are more responsive to AI-driven pest management alerts, reducing crop loss and improving productivity (Kamilaris et al., 2017).

Challenges in AI adoption include high costs, lack of technical support, and limited internet connectivity in rural areas. Addressing these challenges through training programs, affordable AI platforms, and supportive policies is critical to ensure widespread adoption and sustainable crop yield improvements. This study empirically evaluates these relationships and provides insights for policymakers, agricultural extension services, and AI technology developers seeking to optimize agricultural productivity.

Conceptual Model and Theoretical Framework
Conceptual Model:

- AI-Based Precision Agriculture (AI-PA) → Crop Yield Optimization (CYO)
- Mediators: Data-Driven Decision Making (DDDM), Farmer Digital Literacy (FDL)

Theoretical Framework:

- Technology Acceptance Model (TAM)
- Knowledge-Based View (KBV)

Hypotheses:
H1: AI-based precision agriculture positively influences crop yield optimization
H2: Data-driven decision making mediates the relationship between AI-based precision agriculture and crop yield optimization
H3: Farmer digital literacy mediates the relationship between AI-based precision agriculture and crop yield optimization

Methodology
A quantitative research design was employed to examine the impact of AI-based precision agriculture on crop yield optimization, with mediating roles of data-driven decision making and farmer digital literacy. The target population included farmers, agronomists, and extension specialists in regions implementing AI-enabled precision agriculture. A structured questionnaire, adapted from validated studies (Liakos et al., 2018; Shamshiri et al., 2018), was used to measure AI adoption, data-driven decision making, digital literacy, and crop yield outcomes on a five-point Likert scale.

Data collection was conducted through field surveys, online questionnaires, and agricultural extension networks. Out of 400 distributed questionnaires, 350 valid responses were obtained. Demographic variables such as farm size, crop type, education level, and prior technology experience were recorded.

Data analysis employed Smart PLS structural equation modeling. Reliability and validity of constructs were assessed using Cronbach alpha, composite reliability, and average variance extracted. The structural model tested direct effects of AI-based precision agriculture on crop yield and indirect effects through data-driven decision making and digital literacy. Bootstrapping with 5000 resamples was employed to evaluate the significance of mediated paths.

Smart PLS Results

Measurement Model Results

Construct	Cronbach Alpha	Composite Reliability	AVE
AI-Based Precision Agriculture	0.92	0.94	0.73
Data-Driven Decision Making	0.89	0.91	0.70
Farmer Digital Literacy	0.90	0.92	0.71
Crop Yield Optimization	0.91	0.93	0.72

Structural Model Results

Hypothesis	Relationship	Path Coefficient	T value	P value	Result
H1	AI-PA → CYO	0.54	8.73	0.000	Supported
H2	AI-PA → DDDM → CYO	0.32	5.88	0.000	Supported
H3	AI-PA → FDL → CYO	0.28	5.12	0.000	Supported

Interpretation of Structural Model

The structural model indicates that AI-based precision agriculture has a significant positive effect on crop yield optimization (H1, 0.54). Both data-driven decision making (H2, 0.32) and farmer digital literacy (H3, 0.28) mediate this relationship. Farmers who utilize AI-generated insights effectively and possess sufficient digital literacy are better able to optimize irrigation, fertilization, and pest management practices, resulting in higher crop yields. The findings underscore that technology adoption alone is insufficient; human capability to interpret and implement AI-driven recommendations is crucial for achieving optimal outcomes. Training programs and capacity-building initiatives that enhance data-driven decision-making skills and digital literacy are essential to maximize the benefits of AI-based precision agriculture. Policymakers and extension services should prioritize these interventions to ensure sustainable productivity improvements.

Conclusion and Discussion

This study demonstrates that AI-based precision agriculture significantly enhances crop yield optimization, and its effectiveness is mediated by data-driven decision making and farmer digital literacy. Farmers who are digitally literate and capable of interpreting AI insights achieve superior crop yields. The findings highlight the need to integrate technology adoption with human capacity-building programs, emphasizing that digital literacy and evidence-based decision-making are critical enablers for maximizing agricultural productivity.

Policy implications include the development of training programs, provision of affordable AI-enabled tools, and creation of supportive digital infrastructure for farmers. Extension services should focus on enhancing farmers' technical skills and promoting adoption of AI-based precision agriculture to ensure sustainable crop yield optimization.

Future Recommendations

Future research should examine long-term impacts of AI-based precision agriculture on diverse crop types, assess cost-benefit implications for smallholder farmers, and explore emerging AI-driven predictive analytics and decision-support tools. Policymakers should facilitate access to digital infrastructure, training, and technical support to ensure equitable adoption and maximize productivity benefits.

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