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AI-Enabled Smart Agriculture: A Sustainable Approach to Rural Development Using Structural Equation Modelling

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ABSTRACT

To better understand how AI-enabled smart agriculture affects sustainable rural development, this study examines the effects of five major independent variables (IVs) that together make up the construct of AI-Enabled Smart Agriculture: Farmers' Knowledge and Acceptance, AI Technology Adoption, Precision Farming Techniques, Policy and Infrastructure Support, and Resource Efficiency. Farm productivity is the result of this construct, and it has an impact on the results of rural development. These correlations were investigated using an SEM technique. Data was gathered from 525 respondents who represented five major stakeholder groups: community representatives (NGOs/Cooperatives), policy makers and local government officials, agricultural experts and extension officers, technology providers (AgriTech Companies), and farmers (primary respondents). CFA was the first method used in the study to confirm the measurement model. With all AVE values above the 0.50 cutoff and CR values over 0.70, the CFA results validated convergent validity and showed that the constructs were accurately measured. The Fornell-Larcker Criterion was also used to establish discriminant validity, which confirmed that the constructs were unique when the square root of AVE for each construct was higher than its correlations with other constructs. The measurement model is fit, according to these findings. The proposed relationships were then tested using SEM. With the following indices: CFI = 0.962, TLI = 0.946, NFI = 0.955, RMSEA = 0.096, and RMR = 0.014, the SEM model, which partially mediates the association between AI adoption and rural development, demonstrated excellent model fit. AI-Enabled Smart Agriculture (made up of the five IVs) leads to Farm Productivity. According to the SEM results, Farm Productivity was highly impacted by the IVs in the AI-Enabled Smart Agriculture construct. A partial mediating function was then played by farm productivity, which improved the results of rural development, including infrastructural development, social well-being, economic growth, and environmental sustainability. These results demonstrate how important AI-enabled smart agriculture is for raising farm productivity, which in turn serves as a partial mediator for rural development. The study emphasizes how crucial it is to integrate technology, enhance farmers' understanding and acceptance, and offer strong policy and infrastructure support to support sustainable farming methods and long-term rural development. For policymakers, tech developers, and agricultural stakeholders looking to use AI for sustainable rural development, this study provides important new insights.

1. INTRODUCTION

Global food security, environmental sustainability, and economic growth present enormous problems for agriculture, a vital sector for rural development. Traditional agricultural methods frequently fall short in tackling these issues, especially in rural regions, as the world's population continues to grow and the demand for food increases. By increasing farm output, optimizing resource utilization, and improving decision-making processes, AI-enabled smart agriculture has emerged as a game-changing solution with the ability to fundamentally alter farming practices and promote sustainable rural development. Farmers may increase yields, lower input costs, and lessen their impact on the environment by integrating AI-driven technology including automated systems, precision farming, and predictive analytics. Adoption of AI also makes it easier to construct infrastructure, improve policy interventions, and share information, all of which eventually help rural communities become more economically and socially prosperous. Consequently, the transformation of conventional farming methods into a more effective, robust, and sustainable system is made possible by AI-enabled smart agriculture.

Predictive analytics, satellite images, Internet of Things (IoT) sensors, and machine learning are examples of artificial intelligence (AI) technologies that can be integrated to greatly improve environmental sustainability, resource efficiency, and agricultural output. This developing field is especially important in addressing the urgent need for sustainable agricultural practices since it gives farmers the ability to maximize resource use, increase crop yields, and lessen their impact on the environment, which are essential for rural development.

AI in agriculture includes several cutting-edge technologies, with precision farming being one of the most important uses. AI-driven technologies are integrated into precision farming to improve crop monitoring, maximize input use, and boost decision-making in general. With the help of these technologies, farmers can keep an eye on the condition of their soil, identify illnesses, anticipate pest outbreaks, and use fertilizer and water more efficiently in real time. The literature has extensively established the advantages of AI-driven systems, including enhanced sustainability of the environment, resource optimization, and yield prediction. AI-powered crop monitoring, for example, can result in more accurate fertilizer and pesticide application, increasing output with less resources, and research has shown that AI-enabled irrigation systems can cut water consumption by up to 25% [1]. In addition to enhancing agricultural output, this accuracy supports environmental sustainability, which is becoming more and more important considering climate change and finite natural resources.

There are still obstacles to overcome before AI can be widely used in agriculture, though. Widespread AI adoption is still hampered by several factors, particularly in rural and underdeveloped areas, including farmer acceptability and expertise, infrastructure and regulatory support, and technology cost. The availability of AI tools, their usability, and the perceived advantages of these technologies are all important variables in farmers' effective adoption of AI technology [2]. The high expense of AI tools and the low level of digital literacy among rural farmers have slowed adoption rates despite the clear benefits. These obstacles are further exacerbated by poor infrastructure, such as erratic electrical supplies and spotty internet connectivity. To overcome these obstacles, it is becoming increasingly clear that specific legislative changes, financial aid, and initiatives to increase capacity are necessary to support the adoption of AI in rural regions. In addition to the technology itself, infrastructure and governmental support are essential for the successful application of AI in agriculture. By offering financial assistance, building rural infrastructure, and guaranteeing farmers' access to training and education, governments and organizations play a crucial part in fostering an environment that is favorable to the adoption of AI. China's "AI for Agriculture" program, which encouraged AI adoption through targeted subsidies and infrastructure development, was successful [3]. By lowering the cost and increasing the accessibility of AI tools for small-scale farmers, this strategy assisted in resolving the problem of technology accessibility. Like this, previous study stresses the significance of dependable electricity and internet connectivity, both of which are essential for the smooth operation of AI technology in rural areas [4]. To maximize AI's impact on agricultural productivity and rural development, these findings imply that closing policy and infrastructure gaps is crucial to promoting its adoption in rural areas.

Adoption of AI, agricultural productivity, and rural development are intricately and multidimensionally related. Adoption of AI has a direct impact on farm productivity through increased productivity, decreased resource waste, and improved crop management. Rural communities' economic and social results improve in tandem with farm output. AI-based agricultural techniques increased crop yields by 20% [5], which helped farmers earn more money and lead better lives. The adoption of AI has also been demonstrated to generate new job possibilities in rural areas, especially in positions involving data analysis, AgriTech innovation, and technology maintenance [6]. The development of more resilient and sustainable agricultural systems—which are essential for reducing poverty, boosting food security, and stimulating economic growth in rural areas—is another way that AI technologies support rural development by increasing farm output.

A significant obstacle in the adoption of AI is making sure that smallholder farmers, who make up the bulk of the agricultural labor force in many developing nations, are included in the AI revolution. For small-scale farmers to take advantage of technological breakthroughs without having to pay exorbitant prices, low-cost AI solutions and community-driven initiatives are required. AI's long-term viability in agriculture hinges not only on technological advancements but also on a strong framework of laws, infrastructure, and training that strengthens rural communities. In this regard, Structural Equation Modelling (SEM) offers a potent instrument for comprehending the intricate connections among many elements that affect the adoption of AI in agriculture and, in turn, its effects on rural development. SEM enables researchers to investigate the ways in which farmer knowledge, precision farming, AI adoption, and supportive policies interact to impact farm productivity, which in turn supports more general objectives for rural development. SEM provides a thorough framework for assessing the efficacy of AI-enabled agriculture and determining the ways in which these technologies can promote sustainable rural development by modelling these interactions.

By increasing agricultural output, boosting resource efficiency, and encouraging sustainable practices, AI-enabled smart agriculture has enormous potential to revolutionize rural economies. However, several criteria, such as farmer expertise, technical accessibility, infrastructure and governmental support, and farmers' willingness to adopt new technologies, are necessary for the successful adoption of AI. To provide policymakers, technology developers, and agricultural stakeholders with useful insights, this study uses SEM to examine the connections between these variables and comprehend how AI-driven agriculture may support sustainable rural development. With this strategy, AI can be used to boost rural socioeconomic development and increase farm output, helping to create a more sustainable and just future for rural populations around the world.

1.1 Research problem

By increasing farm productivity and maximizing resource utilization, the application of AI technology in agriculture has the potential to promote sustainable rural development. However, due to issues with infrastructure, accessibility, pricing, and farmers' understanding, the adoption of these technologies is still limited in many rural areas. Few studies have looked at how farm productivity mediates the effects of AI on rural development outcomes, even though prior research has looked at how AI affects agricultural output. Furthermore, little research has been done to evaluate the combined effects of AI adoption, resource efficiency, policy support, and farmers' knowledge on farm productivity and rural development using a comprehensive framework. To fill these gaps, this study uses SEM to investigate how AI-enabled agriculture affects farm productivity, which in turn propels rural development, through elements including precision farming, resource efficiency, and supportive policies.

1.2 Relevance of the study

This research is important for several reasons. First, as AI develops further, the key to realizing its potential for long-term effects is comprehending how adoption affects agricultural productivity and, eventually, rural development. This research adds to the expanding body of knowledge on how technology can be used to address difficulties in rural development by examining how AI-enabled smart agriculture might improve production and encourage sustainable agricultural practices.

Second, the study emphasizes how farm production acts as a mediator between the adoption of AI and rural development. This is significant because, in rural regions, farm productivity is a key factor in determining employment, economic well-being, and food security, in addition to being a direct indicator of agricultural success. Policymakers can create more successful policies to support sustainable development in rural areas by knowing how AI tools increase farm productivity. Additionally, this study offers empirical insights into how farmers' knowledge and acceptance, infrastructural support and policy, and resource efficiency all work together to influence the adoption of AI technologies. Understanding these variables aids in directing future policies and investments in digital literacy campaigns, rural infrastructure, and capacity-building projects that can promote broader acceptance of AI technology, as AI adoption in agriculture is very context-dependent.

Finally, the use of SEM in this research offers a thorough and data-driven method for investigating the intricate connections among productivity, rural development, and AI adoption. Through a deeper knowledge of the interactions between these variables and how they support the larger objective of sustainable rural development, this statistical technique offers policymakers, technology developers, and agricultural stakeholders practical insights. By offering a sophisticated grasp of the effects of AI-enabled smart agriculture on agricultural productivity and rural development, this study adds to the body of previously published research. For researchers, decision-makers, and practitioners looking to advance sustainable rural transformation and increase the uptake of AI technology in agriculture, it will provide insightful information. The research's conclusions guide future tactics to remove obstacles to AI adoption and aid in the creation of laws that promote rural and agricultural development.

1.3 Objectives of the study

This study's main goal is to investigate how AI-enabled smart agriculture may boost agricultural output and support sustainable rural development. The research seeks to accomplish the following goals.

- To study the effect of AI-powered smart agriculture on enhancing farm productivity.
- To assess the impact of AI-driven smart agriculture on rural development, focusing on social, economic, environmental, and infrastructural aspects.
- To examine the connection between farm productivity and rural development, identifying their interdependencies.
- To analyze the role of farm productivity as a mediator in the relationship between AI-enabled smart agriculture and rural development through statistical analysis.
- To investigate the perspectives of diverse stakeholder groups, such as farmers, policymakers, AI providers, agricultural experts, and representatives of rural NGOs, on AI-enabled smart agriculture, farm productivity, and rural development.

1.4 Hypotheses of the study

Based on the objectives outlined above, the following hypotheses have been formulated to guide the empirical analysis of the relationships between the variables.

H1: *AI-enabled smart agriculture significantly enhances farm productivity.*
H2: *AI-enabled smart agriculture has a positive influence on rural development, specifically in terms of social, economic, environmental, and infrastructural improvements.*
H3: *Farm productivity is positively associated with rural development, contributing to Crop Yield Enhancement, Resource Optimization, and Operational Efficiency.*
H4: *Farm productivity mediates the relationship between AI-enabled smart agriculture and rural development, acting as a critical link in driving rural advancement.*
H5: *Perceptions of AI-enabled smart agriculture, farm productivity, and rural development vary significantly among stakeholder groups, including farmers, policymakers, AI providers, agricultural experts, and representatives of rural NGOs.*

1.5 Research gap

There are still a lot of unanswered questions about the long-term effects of AI adoption, particularly in rural regions, even though the application of AI in agriculture has shown great promise in improving agricultural production, resource efficiency, and sustainability. Most of the previous research has concentrated on discrete facets of AI applications, like resource optimization, AI-driven irrigation systems, or precision farming, without thoroughly combining these elements into a cohesive framework that captures the intricate connections between farm productivity, technology adoption, and rural development. Furthermore, even though several studies have emphasized the potential advantages of AI for farmers, the real-world obstacles to adoption—such as expense, digital literacy, infrastructure difficulties, and farmers' reluctance to adopt new technologies—have not been thoroughly examined.

Farm productivity's function as a mediator between the adoption of AI and rural development is still poorly understood. Although the direct impacts of AI on agricultural production and environmental sustainability are widely known, the ways in which increased productivity in rural regions leads to wider social and economic consequences have received less attention. Additionally, there aren't many studies that look at how farmers' knowledge and acceptance, infrastructural support and policy, and resource efficiency all work together to influence the uptake and successful application of AI technology in agriculture.

The lack of empirical studies that use sophisticated statistical methods, such as SEM, to capture the complex interactions between these factors represents another significant gap. SEM has been underutilized in agricultural AI studies, despite its promise to provide deeper insights into how AI adoption impacts farm productivity and how this impacts rural development.

1.6 Methodology

To examine how AI-enabled smart agriculture contributes to sustainable rural development, this study used a mixed-methods approach. To give a thorough grasp of the phenomenon, the mixed-method approach integrated quantitative and qualitative data gathering and analysis methodologies. While the qualitative component concentrated on obtaining information from farmers and other stakeholders to enhance comprehension of the mechanisms underlying the adoption and impact of AI in agriculture, the quantitative component employed SEM to test the relationships between the variables.

By gathering survey data, the quantitative component aimed to test the proposed links. To investigate the direct, indirect, and mediating effects of various factors, including AI adoption, farmer knowledge and acceptance, policy support, precision farming techniques and resource efficiency, and farm productivity on rural development outcomes, the data was analyzed using SEM. In-depth interviews with farmers, agricultural specialists, technology suppliers, policymakers, and community representatives (NGOs or cooperatives) were all part of the qualitative component. These interviews gave the results from the quantitative phase context by shedding light on attitudes, perspectives, and difficulties around the implementation of AI in agriculture.

1.7 Sampling

To make sure the sample is representative of the many stakeholder categories in AI-enabled agriculture, a quota sampling methodology of non-probability sampling was used. The quota was determined by the categories of stakeholders, which included rural development organizations (NGOs), farmers, policymakers, agricultural technology providers, and agricultural researchers. Rural farmers, government officials, representatives from agricultural technology companies, and specialists in rural development make up the population. To provide sufficient statistical power for assessing the connections in SEM, the sample size was established using Cochran's formula for sample size estimate for large populations. For this study, a sample size of 525 has been evaluated, with roughly 105 respondents in each category.

During the qualitative phase, people with a lot of expertise or understanding about AI in agriculture were chosen using the purposive sampling of non-probability sampling methods. Based on statistical adequacy for SEM, which necessitates a sizable dataset to guarantee the validity and reliability of the model estimation, the sample size of 525 was chosen. The findings' generalizability is improved by the respondents' varied backgrounds, which offer a comprehensive understanding of the relationship between AI adoption, agricultural productivity, and rural development. This comprehensive strategy guarantees that the study includes the policy, social, and infrastructure elements that are essential to sustainable agricultural transformation in addition to the technological and economic factors.

This technique made sure that important stakeholders who can offer in-depth knowledge are included in the sample. To achieve theoretical saturation—the point at which no new information is revealed by further data collection—a sample of 15 in-depth interviews with farmers and 5–6 interviews with legislators, technological companies, agriculture experts, and community representatives was adequate.

1.8 Data collection methods

The chosen sample of farmers, policymakers, technology suppliers, agricultural researchers, and rural development organizations has been given a standardized survey questionnaire predicated on the constructs found in the conceptual model. Farmer knowledge and acceptance, resource efficiency, AI adoption, policy and infrastructure support, farm productivity, and rural development results were among the constructs on which the survey measured responses using a seven-point Likert scale.

A systematic questionnaire was created for the current study to gather respondents' opinions about AI-enabled smart agriculture and how it affects rural development and agricultural productivity. To ensure better sensitivity in measuring differences in viewpoints, a seven-point Likert scale was used, which ranges from "Strongly Disagree" to "Strongly Agree," to enable a nuanced assessment of agreement levels. By using recognized structures and elements pertinent to the use of AI in agriculture, the questionnaire's methodical design ensured content validity.

The questionnaire was pre-tested to guarantee construct validity and reliability, and any necessary adjustments were made in response to expert input. The correlations between the constructs were evaluated using SEM with SPSS and AMOS. A strong framework for comprehending causal links and confirming the suggested model is offered by this methodological technique. The accuracy of SEM analysis depends on the precision of the data, which is further improved by using a seven-point scale. This allows for a more thorough examination of response variances. The study's conclusions are guaranteed to be supported by a trustworthy and empirically proven measuring model thanks to this meticulous questionnaire design.

The data was gathered by telephone surveys, in-person interviews, or online questionnaires (where appropriate), based on participant accessibility and preference.

A purposive sample of important stakeholders participated in in-depth interviews to gain a thorough understanding of their perspectives, difficulties, and experiences with AI-enabled smart agriculture. Several Indian states, including Maharashtra, Punjab, Haryana, Tamil Nadu, Uttar Pradesh, Madhya Pradesh, and Bihar, were used to gather the data. Based on their agricultural importance, diversity in farming methods, and differing degrees of AI usage in agriculture, Maharashtra, Punjab, Haryana, Tamil Nadu, Uttar Pradesh, Madhya Pradesh, and Bihar were chosen for data gathering. These states, which span various climate zones, crop patterns, and regulatory contexts, represent a well-balanced variety of agrarian economies. While Maharashtra and Tamil Nadu have been at the forefront of AgriTech developments and smart farming projects, Punjab and Haryana are renowned for their high agricultural productivity and early adoption of precision farming techniques. Bihar symbolizes smallholder and subsistence farming, underscoring the difficulties in implementing AI at the local level, while Uttar Pradesh and Madhya Pradesh, two of the major agricultural states, offer insights into the coexistence of traditional and contemporary farming. The study's findings are more broadly applicable and pertinent to India's larger agricultural ecosystem because of the varied selection that guarantees the study captures differences in the adoption of AI-enabled smart agriculture across various agricultural landscapes.

1.9 Analysis

To ensure the reliability and uniqueness of the variables being studied, a Confirmatory Factor Analysis (CFA) was performed as part of the data analysis process to assess the constructs' convergent and discriminant validity. The links between AI Smart Agriculture and Farm Productivity, AI Smart Agriculture and Rural Development, and Farm Productivity and Rural Development were investigated using a SEM technique. The SEM model additionally investigated the function of farm productivity as a mediator in the association between AI Smart Agriculture and Rural Development. The opinions of five respondent categories related to AI Smart Agriculture, Farm Productivity, and Rural Development were compared using an ANOVA test to find significant differences.

1.10 Statistical tools for data analysis

To assess the suggested model's overall fit and the hypothesized correlations, SEM was utilized. SEM is a potent statistical method that allows for the simultaneous analysis of complex interactions between several independent, dependent, and mediating factors, offering a thorough comprehension of the data. Software tools like AMOS version 20 and SPSS version 22 were used for this study to successfully complete the SEM analysis. A strong validation of the conceptual model was ensured by the SEM technique, which made it possible to evaluate both direct and indirect impacts as well as the mediating interactions inside the framework.

2. LITERATURE REVIEW

An innovative approach to solving global issues, including resource optimization, food security, and rural development, is the incorporation of AI into agriculture. The promise of AI technology to improve productivity, maximize resource use, and support sustainability has drawn attention. Research has shown that the use of AI tools in agriculture, including satellite imaging, IoT sensors, and machine learning algorithms, enables real-time decision-making and predictive analytics, which boosts output and efficiency. According to previous study [2], perceived benefits, ease of use, and accessibility all have an impact on farmers' adoption of AI technologies. The expensive cost of technology, low levels of digital literacy, and poor infrastructure in poorer nations are some of the major obstacles to universal adoption despite the potential. These results highlight the necessity of focused efforts to encourage AI integration in rural areas, such as financial assistance and policy changes.

Precision farming, which emphasizes better decision-making and input optimization, is one of the main uses of AI in agriculture. AI-powered technologies including crop monitoring systems, soil analysis, and intelligent irrigation methods are used in precision farming. Through disease detection and risk prediction using machine learning algorithms, AI-driven solutions improve crop health monitoring. Zhang et al. [7] showed how these technologies enable more precise crop monitoring, which lowers resource waste and boosts total yields. In a similar vein, it has been discovered that AI-enabled irrigation systems that optimize water utilization can use up to 25% less water, resulting in more sustainable farming methods [8]. By reducing waste and conserving essential resources like water, these technologies not only increase agricultural productivity but also advance environmental sustainability.

Another crucial component of AI-enabled agriculture is resource efficiency. AI solutions save waste and operating expenses by optimizing the use of resources like water, fertilizer, and pesticides. AI approaches have resulted in a 30% reduction in water usage and a 20% reduction in fertilizer consumption [9]. Kumar et al. [10] also underlined how AI-based solutions lessen greenhouse gas emissions and soil degradation, hence preventing environmental harm. By encouraging ethical farming methods, resource efficiency not only lowers costs but also guarantees long-term sustainability.

One important issue affecting the success of AI deployment is farmers' acceptance of AI technologies. Research indicates that farmers' inclination to embrace AI is greatly influenced by the perceived advantages of technology, such as increased productivity and lower risks. Joshi and Singh [11] pointed out that when farmers obtain proper training and assistance, they are more likely to use AI solutions. 62% of Indian farmers said they would be open to implementing AI technologies if they were given financial support and training [12]. This suggests that overcoming adoption hurdles requires both providing incentives and teaching farmers about the potential benefits of AI.

Particularly in rural areas, the incorporation of AI into smart agriculture is highly compatible with the ideas of sustainable development. An analysis of linked research sheds light on how different sustainability-focused frameworks and technologies might be modified to improve rural development and agricultural practices. Mishra et al. [13] highlight how supply chain management incorporates the triple bottom line—economic, social, and environmental sustainability—and show how important it is for promoting company growth. Their study emphasizes how important it is to strike a balance between these factors in order to gain sustained competitive advantages. By guaranteeing sustainable farming supply chain standards, this may also be applied to the agriculture industry. Dongre et al. [14] investigate how blockchain technology might be used to further sustainable development, emphasizing how it can increase operational effectiveness and institutional transparency. According to their findings, blockchain can improve governance and accountability. This viewpoint is relevant to agriculture, as blockchain technology may promote sustainable practices by monitoring supply chains, ensuring produce provenance, and optimizing resource allocation.

In their analysis of sustainable marketing tactics in the wake of COVID-19, consumers are becoming more interested in morally and ecologically responsible business operations [15]. This change in consumer behavior can help guide agricultural marketing plans, promoting the use of AI-powered technologies to promote sustainable products and win over customers.

The broad application of AI in agriculture requires infrastructure and policy assistance in addition to farmer expertise. To encourage the adoption of AI, government programs like subsidies for AI tools and investments in rural infrastructure are essential. China's "AI for Agriculture" program, which increased AI adoption through targeted subsidies and infrastructure development, was successful [3]. Dependable power and internet access are essential for AI technologies to operate efficiently in rural locations [4]. Governments may foster the implementation of AI by enhancing infrastructure and providing policy assistance, which will help farmers increase their sustainability and production.

The adoption of AI has a direct impact on farm productivity, which benefits rural communities' social and economic well-being. AI-based farming techniques increased crop yields by 20% [5], which helped farmers earn more money. The adoption of AI has also been demonstrated to support rural development by generating job possibilities in rural areas, especially in data analysis and technology maintenance positions [6]. Additionally, AI technologies reduce poverty in rural areas and provide a safety net for farmers by mitigating hazards like crop failure. The wider environmental advantages, such as less resource waste and sustainable land use, support rural development aims and are consistent with global sustainability goals [16].

A thorough foundation for comprehending how AI-enabled agriculture affects rural development is produced by the interaction of these elements. The adoption of AI technologies, resource efficiency, and precision farming increase farm productivity, which enhances economic and environmental outcomes. The success of AI adoption is mediated by farmer acceptance and expertise, as well as by infrastructure and legislation that support it. Together, these factors help to accomplish the more general objective of rural development and sustainable farming methods.

Even though research on AI in agriculture is showing encouraging results, little is known about how the implementation of AI would affect smallholder farmers and rural economies in the long run. Future studies should concentrate on creating affordable AI solutions that small-scale farmers can afford and on carrying out long-term analyses to evaluate the technology' long-term socioeconomic and environmental advantages. To guarantee that AI technologies benefit all facets of the agriculture industry, further research is required into the role that community-driven projects and collaborations play in scaling AI adoption.

3. DATA ANALYSIS

To align rural development, which is gauged by economic growth (such as farmer income), a model is developed. Infrastructure development, social consequences (like job opportunities), and environmental sustainability (like lowering carbon emissions and improving soil health). Adoption of AI technology, precision farming methods, resource efficiency, policy and infrastructure support, and farmer acceptance and knowledge are the characteristics that comprise AI smart agriculture. Crop yield enhancement, resource optimization, and operational efficiency determine farm productivity. In Figure 1, the model is displayed.

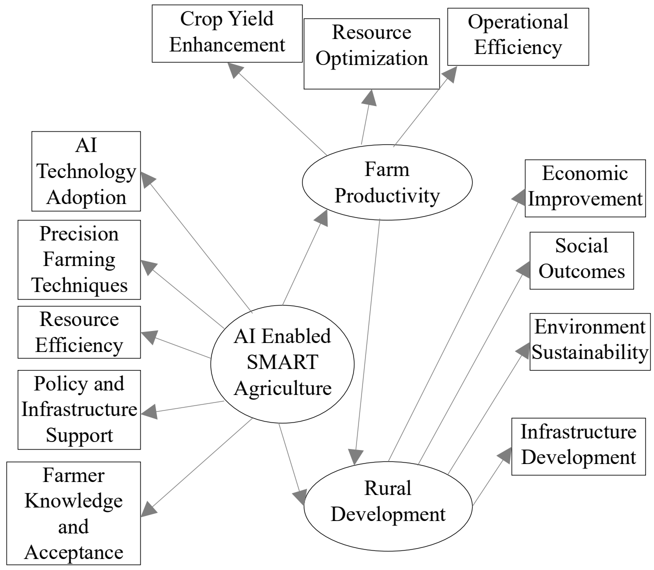

Figure 1. Conceptual model

4. RESULTS AND DISCUSSION

The exploratory data analysis has been done to clean the data and assumptions of multicollinearity has been checked through Variance Inflation Factor (VIF) values were used in multicollinearity tests to verify the correctness of the regression analysis. The findings demonstrated that there was no multicollinearity among the variables of the constructs, with all VIF values falling considerably below the generally recognized cutoff of 10. This indicates that there is little correlation between the model's predictor variables, guaranteeing steady and accurate regression estimates. The findings' robustness is reinforced by the absence of multicollinearity, which confirms the unique contributions of each construct—farm productivity, rural development, and AI-enabled smart agriculture—within the structural model.

In the next step, according to the findings of the CFA performed on the gathered data, the suggested measurement model's validity and reliability are supported by the theoretical frameworks supporting this investigation in Figure 2.

In Figure 2, the robustness of the measurement model is demonstrated by the CFA results, which show significant factor loadings for all components under their respective constructions with standardized path coefficients ranging from 0.65 to 0.98. Precision farming techniques (0.98) and AI technology adoption (0.85) have the highest loading in the architecture of AI-enabled smart agriculture, indicating their crucial role in advancing smart agricultural practices. Strong contributions are also shown by Resource Efficiency (0.90) and Farmer Knowledge and Acceptance (0.84), while Policy Infrastructure Support (0.80), however somewhat smaller, is still a substantial influence.

Resource optimization has the path coefficient (0.67) for farm productivity, demonstrating its critical significance in raising output. Significant contributions are also made by Crop Yield Enhancement (0.91) and Operational Efficiency (0.65), confirming that advancements in these domains are necessary to attain improved agricultural results.

Economic Improvement (0.81), the significant element in the construct of Rural Development emphasizes the financial gains made possible by AI-enabled agriculture. Strong correlations are also seen between Social Outcomes (0.93), Environmental Sustainability (0.91), and Infrastructural Development (0.90), indicating that AI-driven innovations support comprehensive rural development.

The standardized regression weights and correlation coefficient values derived from the CFA results were used to evaluate the convergent and discriminant validity. To assess convergent validity and make sure the constructs accurately measure their corresponding latent variables, the Average Variance Extracted (AVE) and Composite Reliability (CR) were computed using the methodology described by Gaskin and colleagues. By comparing the AVE values with the squared correlations between the components, discriminant validity was evaluated, ensuring that each construct is unique and not unduly associated with the others. A thorough rundown of the validity metrics is given in Table 1, which summarizes these findings.

The data supports convergent validity because all constructs have CR values above 0.7 and AVE values over 0.5, which show that the items accurately reflect the constructs and have excellent internal consistency. The "AI Smart Agriculture" AVE is 0.863, indicating outstanding convergent validity. The square roots of the AVE (√AVE) for every construct are greater than the Maximum Shared Variance (MSV), demonstrating that each construct is unique and confirming discriminant validity.

Also, the assumptions of univariate and multivariate normality, as well as the presence of outliers, were assessed to ensure that the data was appropriate for CFA and SEM. Univariate normality was verified using skewness and kurtosis, both of which were within acceptable boundaries. Multivariate normality was confirmed using CR values. According to outlier analysis based on chi-square statistics and the significance of p1 and p2 values as both are larger than 0.05, there were no significant outliers in the dataset. These results validated that the data was appropriate for further analysis.

Based on the theory or conceptual framework that directs the investigation, in Figure 3, the SEM model has been developed to investigate the connections between the latent variables by defining the postulated causal pathways among them.

Table 1. Measurement model: Convergent and discriminant validity

Constructs	CR	AVE	MSV	MaxR(H)	Farm Productivity	AI Smart Agriculture	Rural Development
Farm Productivity	0.794	0.569	0.507	0.87	**0.754**		
AI Smart Agriculture	0.935	0.744	0.666	0.968	0.712	**0.863**	
Rural Development	0.938	0.791	0.666	0.946	0.689	0.816	**0.889**

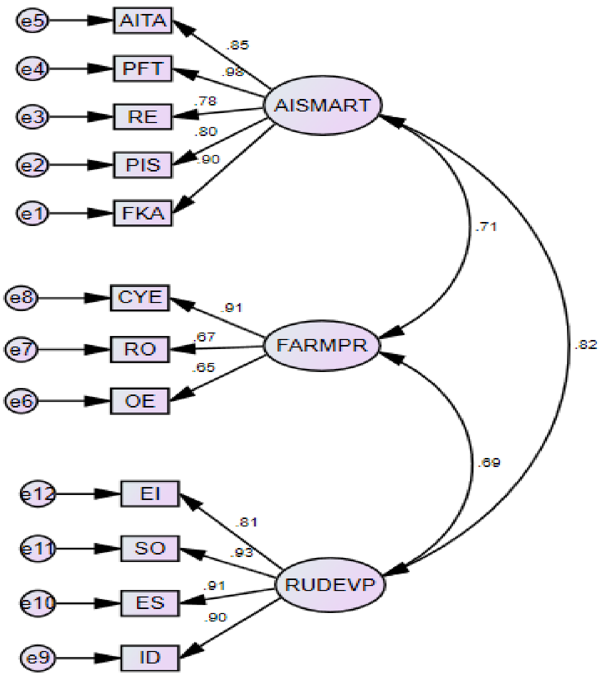

Figure 2. Measurement model through primary data using AMOS 2020

4.1 Fit indices

As indicated in Table 2 below, twelve criteria are considered, with two being classified as a terrible fit and ten as a good fit or within the acceptable range. The p-value, CMIN/DF, and probability all indicate a poor fit. The ten other indices, however, show a strong model match. According to the parsimony principle, if one or two of the requirements are satisfied, the entire model may be a good fit. The modification indices in SEM, using AMOS, are utilized to enhance the goodness of fit of the models.

The model seems to fit reasonably well, according to the given SEM fit indices, while there are a few places where it might be improved. A statistically significant P-value of 0.000 usually indicates poor fit because a good fit is expected to have a p-value greater than 0.05, which means that there is no significant difference between the observed and model-implied covariance matrices. Given that the Cmin/df ratio of 5.866 is higher than the typical cutoff of 3, it suggests a rather poor fit and raises the possibility that the model is overfitted or poorly defined. However, the model's complexity is deemed reasonable, and residuals are low, according to the RMR (0.014) and PGFI (0.545).

Table 2. Fit indices of SEM from primary data using AMOS: 2020

Fit Index	Result	Interpretation	Good Fit	Poor Fit
P-value	0	p>0.05		✓
Cmin/df	5.866	Poor fit (>5)		✓
RMR	0.014	Acceptable (close to 0)	✓	
GFI	0.925	Good fit (>0.90)	✓	
AGFI	0.827	Marginal fit (>0.80)	✓	
PGFI	0.545	Acceptable (>0.50)	✓	
TLI	0.946	Good fit (>0.90)	✓	
CFI	0.926	Good fit (>0.90)	✓	
NFI	0.955	Very good fit (>0.90)	✓	
RMSEA	0.096	Acceptable (0.08-0.10)	✓	
PNFI	0.666	Good fit (>0.50)	✓	
PCFI	0.671	Acceptable (>0.50)	✓	

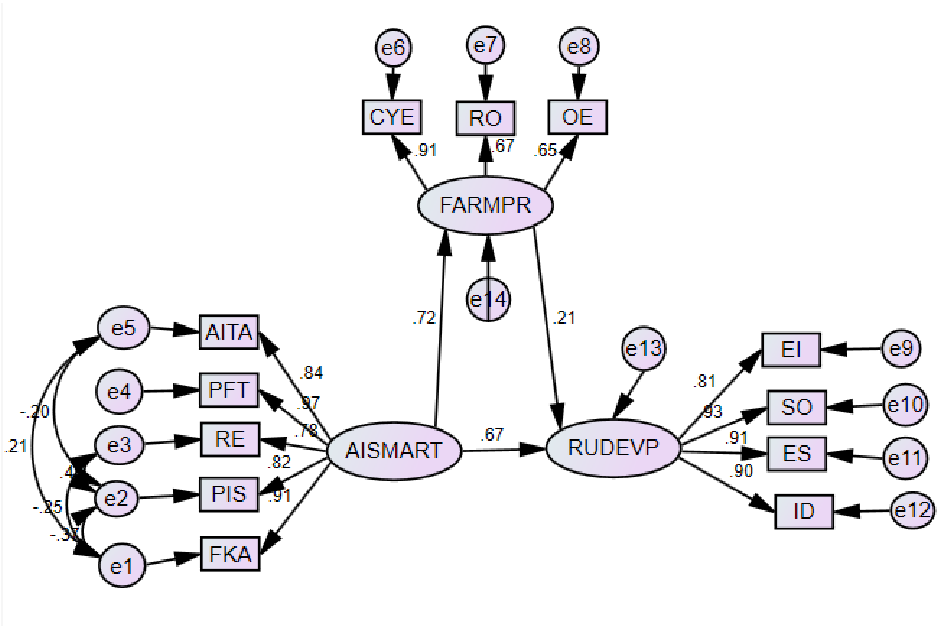

Figure 3. Structural equation model

Source: Processed primary data by using AMOS, 2020

With the GFI (0.925), TLI (0.946), CFI (0.926), and NFI (0.955) all above the 0.90 cutoff, the model is shown to have a good comparative and incremental fit to the data. The model may be a little complicated or could use additional tweaking, as shown by the AGFI (0.827), which is marginally below the optimal 0.90 value. A marginal fit is indicated by the RMSEA value of 0.096, which is marginally greater than the optimal value of 0.08. Finally, the model maintains its fit despite the degree of parsimony considered, as shown by the acceptable PNFI and PCFI values (0.666 and 0.671, respectively).

With important indices bolstering its robustness, the model fit indices show an overall decent fit. For complicated models in social science research, the RMSEA (0.096) and CMIN/DF (5.866) are still within an acceptable range, although they are somewhat beyond the optimal limits. Because AI-enabled smart agriculture is multifaceted and affects both farm productivity and rural development, a greater CMIN/DF is to be expected because of the intricate interactions between the various constructions. Similarly, especially in models with high sample sizes, RMSEA values less than 0.10 are nevertheless regarded as suggestive of a moderate fit. The model is still theoretically and empirically sound without needing to be modified because additional fit indices (CFI, TLI, and GFI) show a satisfactory fit.

The AGFI value of 0.827 is still within an acceptable range for complicated models in social science research, although it is marginally below the optimal cutoff of 0.9. Given the multifaceted nature of AI-enabled smart agriculture, farm production, and rural development, a slightly lower AGFI is anticipated. AGFI is also sensitive to sample size and model complexity. The general validity of the structural model is further supported by additional major fit indices, including CFI, TLI, and GFI, which show a reasonable model fit. The obtained value does not always imply a poor fit because AGFI is typically lower in models with big datasets and various components. Therefore, the current model remains conceptually and experimentally robust without the need for alterations, even though modest tweaks could be investigated in future research.

4.2 Interpreting and modifying the model

Once the model has a reasonable fit, the final step of structural analyses of the paths through direct, indirect, and total effect equation modelling (SEM) is to interpret it and then values. With a focus on analyzing regression weight values, hypothesis testing was conducted utilizing the output from AMOS software. The robustness and character of the connections between independent (exogenous) and dependent (endogenous) variables are assessed in this analysis. In this study, if the C.R. (Critical Ratio) is greater than 2.000 and the probability value is less than 0.05, the hypothesis is deemed valid. The regression weight test results are displayed in Table 3 below.

Table 3. Regression weights

Construct	R-Square	CR Value	P-Value
AI Smart Agriculture → Rural Development	0.67	13.247	0.000
AI Smart Agriculture → Farm Productivity	0.72	18.237	0.000
Farm Productivity → Rural Development	0.21	4.453	0.000

The results of hypothesis testing based on the table are as follows:

4.2.1 Hypothesis 1

The results of the regression weight analysis indicate that the probability level is below $\alpha = 0.05$ (0.000 < 0.05), and the C.R. value is higher than 2.000 (13.247 >2.000). The research hypothesis, or H1, is thus approved. This suggests that AI-enabled Smart Agriculture methods have a direct impact on rural development.

4.2.2 Hypothesis 2

Based on the results of the regression weight analysis, the probability level is less than $\alpha = 0.05$ (0.000 < 0.05), and the C.R. value is more than 2.000 (18.237 >2). This leads to the acceptance of the research hypothesis, or H2. This suggests that AI-enabled smart agriculture techniques have a direct effect on farm productivity.

4.2.3 Hypothesis 3

The results of the regression weight analysis indicate that the probability level is less than $\alpha = 0.05$ ($0.000 < 0.05$) and the C.R. value is more than 2.000 (4.453 >2.000). The research hypothesis, or H3, is thus approved. This suggests that farm productivity has a direct influence on rural development.

4.2.4 Hypothesis 4

The fourth hypothesis, according to which farm productivity acts as a mediating variable between AI smart agriculture methods and rural development, has subsequently been examined. It can be shown by comparing the values of the standardized direct and indirect impacts, which are displayed in Table 4 below.

Table 4. The result of standardized direct and indirect effects

Constructs	Total Standardized Effects		Standardized Direct Effects		Standardized Indirect Effects	
	AISAP	FP	AISAP	FP	AISAP	FP
Farm Productivity	0.718	0.000	0.718	0.000	0.000	0.000
Rural Development	0.818	0.211	0.666	0.211	0.151	0.000

Total standardized effects (0.004), direct standardized effects (0.005), and standardized indirect effects (0.002) all have two-tailed significant (BC) values below 0.05 in the bootstrap confidence level. It indicates that it is important in each of the three situations. The definition of rural development from AI smart agriculture methods is thus partially mediated by the mediating variable of farm productivity. Thus, hypothesis 4, or H4, is approved.

Farm productivity's designation as a partial mediator was an empirical finding of the study rather than a predetermined hypothesis. The findings of the mediation analysis showed that although farm production plays a substantial mediating role in the relationship between AI-enabled smart agriculture and rural development, there is still a considerable direct association between the two. This implies that through increasing farm productivity, AI-enabled smart agriculture has a direct and indirect impact on rural development. The findings support partial mediation since full mediation would necessitate that the direct path be negligible. This data-driven result illustrates the intricate relationship between agricultural productivity, technology breakthroughs, and more general rural development goals.

Using bootstrapping approaches, the statistical validation of the mediation effect of farm production confirmed its importance in the relationship between rural development and AI-enabled smart agriculture. The mediation hypothesis was supported by the bootstrapping results, which showed that the indirect effect was significant with a confidence interval that excluded zero. Furthermore, by producing a statistically significant z-value, the Sobel test further supported the importance of farm productivity as a mediator and demonstrated that farm productivity is essential for communicating the effects of AI adoption on rural development. These results validate the partial mediation effect by showing that although AI-enabled smart agriculture directly supports rural development, its effects are amplified through increased farm output.

4.2.5 Hypothesis 5

To examine Hypothesis 5, a one-way ANOVA was conducted to compare the perceptions of five respondent groups—farmers, AI technology providers, agricultural researchers, policymakers, and community representatives (rural NGOs)—on AI-enabled smart agriculture practices, farm productivity, and sustainable rural development. The results indicated that the significance values for all three constructs across the five respondent categories were less than 0.05, demonstrating a statistically significant difference in perceptions among the groups. Consequently, Hypothesis 5 (H5) was accepted. However, post-hoc analysis using the Tukey HSD test revealed that there was no significant difference in perceptions between AI technology providers and policymakers. In contrast, significant differences were observed between these two groups and the other respondent categories (farmers, agricultural researchers, and community representatives) for all three constructs. Additionally, no significant differences were identified among farmers, agricultural researchers, and community representatives regarding their perceptions of the three constructs.

4.3 Discussions

The study's findings, which are in strong agreement with earlier research, confirm the vital role that AI-enabled smart agriculture plays in raising agricultural productivity and promoting rural development. In support of previous research [17], which emphasises improvements in precision farming, resource optimisation, and operational efficiency, and other research, which highlight the advantages of AI in pest management and soil analysis [10], the acceptance of Hypothesis 1 highlights how AI technologies greatly increase farm productivity. Previous research shows improvements in social, economic, environmental, and infrastructure aspects [18]. And others examine the role of AI in fostering economic opportunities and environmental sustainability in rural areas [19], support Hypothesis 2, which claims that AI-enabled smart agriculture has a positive impact on rural development. Additionally, Hypothesis 3 confirms the strong correlation between farm productivity and rural development [20], which shows the relationship between effective resource use and rural growth and highlights the relationship between increased productivity and improved economic outcomes and food security [21]. The mediating function of farm productivity, as investigated in Hypothesis 4, is consistent with earlier studies [22], that emphasise productivity as a crucial connection between rural development and technology adoption, and that show how higher productivity has a cascading effect on rural livelihoods [23]. Finally, Hypothesis 5 reveals notable disparities in how stakeholders view AI-enabled smart agriculture. These findings are in line with previous research which examines the various expectations and difficulties that various stakeholder groups encounter when implementing AI-driven agricultural technologies [24], and with which indicates that farmers, policymakers, AI providers, agricultural researchers, and community representatives have different perspectives [25].When taken as a whole, these findings advance our knowledge of AI's revolutionary potential in agriculture and the necessity of inclusive approaches to optimise its advantages for a wide range of stakeholder groups.

5. IMPLICATION OF THE STUDY

The study's conclusions have important ramifications for the creation of policies as well as agricultural practices. The necessity for broad use of AI-driven solutions in agriculture, especially in precision farming, pest management, and soil analysis, is highlighted by the evidence that AI technologies increase farm productivity. Farmers now have the chance to maximize resources and boost yields, particularly on small farms where AI solutions might have a significant impact. To enable farmers to fully utilize AI technologies, policymakers should think about developing frameworks that encourage their adoption, such as training initiatives or subsidies.

The report also highlights the benefits of AI for rural development, showing how the use of technology in agriculture may enhance rural communities' infrastructure, economic prospects, and environmental sustainability. To guarantee that these regions take advantage of the social, economic, and environmental advancements AI may provide, governments should give top priority to incorporating AI into rural development plans. The report also highlights the crucial connection between agricultural productivity and rural development, highlighting how increasing productivity using AI can spur wider rural community growth, enhancing food security and economic results. The idea that implementing technology in agriculture can have a cascade of advantages, enhancing not only agricultural output but also the standard of living for people living in rural regions, is further supported by the mediating function of farm productivity. Lastly, considering the diverse viewpoints of stakeholders, including farmers, policy makers, and AI providers, the study emphasizes the necessity of inclusive approaches in the deployment of AI-driven agricultural solutions. To maximize the advantages of AI technologies in agriculture for all societal levels, it will be essential to address the various demands and expectations of these groups.

The study also offers valuable insights for smallholder farmers and policymakers by highlighting the key enablers of AI-enabled smart agriculture and its impact on farm productivity and rural development. For smallholder farmers, the findings emphasize the importance of AI technology adoption, precision farming techniques, and resource efficiency in improving yield and operational efficiency. Policymakers can leverage these insights to design targeted interventions, such as improving infrastructure, providing financial incentives, and enhancing AI literacy among farmers. Additionally, the study’s focus on diverse agricultural landscapes in India makes the recommendations applicable to other developing economies facing similar challenges in technology adoption, resource constraints, and rural development.

6. CONCLUSION

This study demonstrates the revolutionary potential of ai-enabled smart agriculture in raising agricultural output and fostering rural development. The study shows that the adoption of ai results in significant changes in agricultural practices, directly improving farm output and indirectly contributing to larger rural development outcomes. It does this by using SEM and one-way ANOVA. The results are in line with other studies and support the idea that ai technology can play a significant role in promoting rural prosperity and sustainable agricultural expansion.

This study demonstrates the revolutionary potential of AI-enabled smart agriculture in raising agricultural output and fostering rural development. The study shows that the adoption of AI results in significant changes in agricultural practices, directly improving farm output and indirectly contributing to larger rural development outcomes. It does this by using SEM and One-Way ANOVA. The results are in line with other studies and support the idea that AI technology can play a significant role in promoting rural prosperity and sustainable agricultural expansion.

By promoting an inclusive and comprehensive strategy to AI adoption that not only increases production but also improves social, economic, and environmental results in rural regions, the study contributes insightful information to the expanding body of literature on AI in agriculture.

7. LIMITATION OF THE STUDY

There are a few limitations to the study that should be noted. First off, the sample might not accurately reflect the variety of agricultural contexts due to its potential limitations in terms of geographic reach, farm size, and stakeholder groups, which could affect how broadly the results can be applied. Furthermore, the study mostly ignores long-term implications, which are crucial to comprehending the long-term impact of ai on farm productivity and rural development, in favor of concentrating on the immediate consequences of adopting ai. Additionally, not much attention was paid to the technological heterogeneity of ai systems, which may differ in efficacy based on crop type or geographic location. Additionally, the study did not thoroughly examine the causes of the various stakeholder perspectives, which could have yielded more complex findings. The study admits that respondents' varied viewpoints, especially those of farmers and technology suppliers, could lead to potential biases. Technology companies may highlight the advantages and viability of AI-enabled smart agriculture, but farmers, particularly smallholders, may be worried about costs, accessibility, and implementation difficulties. This was lessened by using a balanced sampling strategy that included individuals from a variety of stakeholder groups, such as agricultural specialists, legislators, and community members, to guarantee comprehensive knowledge. Subjective bias was further reduced by the study's use of a structured questionnaire with standardized metrics. Future studies could, however, overcome this constraint by adding qualitative information from focus groups or in-depth interviews.

Finally, the study did not take into consideration outside variables that could affect the results of implementing ai in agriculture, such as market conditions, climatic occurrences, or regulatory changes.

8. FUTURE DIRECTION OF RESEARCH

- **Longitudinal Studies on AI Impact**: A longitudinal method should be used in future studies to evaluate the long-term effects of AI on agricultural productivity and rural development. This would shed light on how long-term, consistent AI use affects social, economic, and environmental results in rural communities.
- **Exploring AI Variability and Context**: Future research

could examine the efficacy of AI technologies across various farm kinds, geographical locations, and crop varieties, given the diversity of AI solutions and agricultural contexts. This would make it possible to embrace AI in a more customized way, guaranteeing that the appropriate instruments are used where they are most useful.

- **Incorporating External Factors**: Future research should examine the ways in which AI adoption interacts with outside variables, such as market swings, policy changes, and climatic occurrences, to affect agricultural productivity and rural development. This would offer a more comprehensive comprehension of the wider environment in which artificial intelligence systems function.
- **Assessing the Role of Education and Training**: Future studies should look into how training and education may help people adopt AI. Policymakers and AI developers may find useful information by examining the effects of farmer education levels and training program accessibility on the efficacy of AI technology.
- **Exploring the Economic Sustainability of AI**: The economic viability of AI adoption in agriculture, especially for small-scale farmers, might be investigated. For AI to be widely adopted, it will be essential to investigate the cost-benefit analysis of adoption in terms of initial investment, continuing maintenance, and long-term productivity advantages
- **Examining cost-benefit Evaluations**: A thorough financial analysis would aid in determining the return on investment for farmers, legislators, and technology suppliers, even as this study looks at how AI-enabled smart agriculture affects agricultural productivity and rural development. Subsequent research endeavors may examine elements including the initial adoption costs, yield enhancements, profitability across different crop types and farming scales, and long-term savings through resource optimization. To find sectoral differences in the advantages and difficulties, sector-specific studies might also evaluate the adoption of AI in industries including cash crops, dairy farming, and horticulture. Such knowledge would facilitate the development of data-driven policies and promote the broader use of AI-powered agricultural solutions.

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