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SUSTAINABLE PRECISION AGRICULTURE: INTEGRATING ARTIFICIAL INTELLIGENCE AND IOT FOR OPTIMIZED GREEN FARMING PRACTICES

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ABSTRACT

Agriculture is the backbone of Indian economy. It is evolved in due course of time. The purpose of this study is to assess how well internet of things (IoT) and artificial intelligence (AI) technologies can improve precision farming methods and encourage resource sustainability. The goal of the project is to determine the obstacles farmers have when implementing these innovations and to examine the economic and environmental effects of incorporating these technologies into farming, with an emphasis on yield enhancement and resource conservation. Method: To investigate the connection between AI, IoT, and sustainable farming results, data were collected from a sample of 225 farmers via trials and sensor readings using a quantitative descriptive research technique. Descriptive statistics, independent t-tests, and regression analysis were among the statistical techniques used to evaluate how AI and IoT affected productivity and environmentally friendly agricultural methods. Result: The results reveal a strong positive correlation, with the regression model indicating that IoT and AI play a substantial role in sustainable agriculture and higher production, accounting for around 55.2% of the variation in results. The model's effectiveness is further supported by the ANOVA findings, which show that smart farming, AI, and IoT have a major influence on green agricultural practices ($p < 0.001$). It is found that AI and IoT have a great deal of contribution towards sustainable agriculture by increasing sustainability and production. However, it is significant to address certain challenges for wider acceptance and scalability across many agricultural groups.

Keywords: *Sustainable Agriculture, Precision Farming, Artificial Intelligence (AI), Internet of Things (IoT), Green Farming Practices*

1. INTRODUCTION

Technology is one of the most influential factors which revolutionized the individuals, communities, societies, governance, corporations, economies to the great extent (Gaikwad, 2024). Modern sustainable precision agriculture integrates eco-friendly practices with data-driven, high-tech farming methods to optimise resource use and output (Zhang et al., 2021). Instead of spreading water, fertiliser, and pesticides out evenly over the field like conventional farmers do, sustainable precision agriculture emphasises applying inputs precisely where they are needed (AlZubi & Galyna, 2023). By utilising a range of digital tools, such as GPS, remote sensing, and geospatial data, this method enables farmers to make informed decisions using accurate, localised data (Addas et al., 2023). They are able to monitor and evaluate field conditions in real-time. Soil health, moisture content, and nutrient requirements can vary greatly across zones, and these tools can help farmers understand the variability in their fields and the unique needs of each (Kayastha et al., 2023).

Agriculture education is the need of an hour in order to sustain the farming and ensure food security in future keeping the growing population in the world (Choudhury et al., 2024). Sustainable precision agriculture's main objective is to increase crop yield while reducing its negative effects on the environment. It lowers the waste of resources like water and fertilisers by adjusting input use to specific needs (Singh et al., 2021). This lowers the risk of greenhouse gas emissions, soil degradation, and groundwater contamination. By encouraging methods that support biodiversity and soil health conservation while preserving farmers' financial viability, this strategy supports sustainable development goals. Furthermore, by encouraging adaptive management techniques that enable more robust and effective agricultural systems, sustainable precision agriculture aids in tackling the problems of resource scarcity and climate change.

Sustainable precision agriculture presents a bright future for both large and small farmers. It gives them the ability to better manage inputs, which lowers costs and increases yields. Furthermore, it improves farming practices' traceability, which is becoming more and more significant for consumers and government organisations concerned about the environmental effects of food production. To put it simply, sustainable precision agriculture is a revolutionary method that aims to balance environmental stewardship and agricultural productivity in order to create a future where farming is both profitable and ecologically conscious.

1.1. SIGNIFICANCE OF STUDY

A number of advantages result from the combination of AI and the IoT in agriculture, which improve farming methods and support profitable and sustainable food production. Enhanced decision-making is one of the main benefits, as farmers can make better, more informed decisions to optimise crop health and yield thanks to real-time data and predictive insights offered by AI and IoT. This accuracy makes it possible to take prompt action and guarantees that crops are grown in ideal conditions (Adinarayana et al., 2024). AI and IoT also help with effective resource management by using sophisticated sensors and algorithms to optimise the use of pesticides, fertiliser, and water (Nath, 2024). With the use of these technologies, farmers can keep a close eye on resource consumption, cutting expenses and waste while also lessening the negative effects of agricultural practices on the environment. Farmers can predict weather patterns, foresee pest outbreaks, and identify disease risks with the help of AI-powered predictive analytics tools, which further improve risk management (Karunathilake et al., 2023). By taking preventative action, farmers can lower crop loss and improve the general health of their fields. Additionally, the automation of farm operations with AI-powered drones, robots, and self-driving tractors boosts productivity, streamlines tasks like planting, watering, and harvesting, and drastically reduces manual labour (Dhanaraju et al., 2022).

AI and IoT's capacity to enhance growing conditions also results in higher crop yields and quality, satisfying the world's expanding food demand while boosting farmers' profits. Last but not least, these technologies are essential to resilience and climate adaptation. AI models assist farmers in identifying and putting into practice climate variability-resilient practices, allowing them to adapt to shifting environmental conditions and guaranteeing the long-term viability of agricultural systems. A comprehensive framework that promotes sustainable farming, boosts productivity, and guarantees the prudent use of natural resources is produced when AI and IoT are combined (Kumar et al., 2024).

1.2. PROBLEM STATEMENT

The use of IoT and Artificial Intelligence (AI) in farming could lead to a dramatic shift in farming methods in terms of precision, efficiency in resource utilisation, and environmental friendliness (Alreshidi, 2019). The agricultural sector has been slow to adopt these technologies, despite their promising capabilities, because of a number of issues. There are a lot of obstacles to the broad use of AI and IoT in farming, including high implementation costs, a lack of technical knowledge, and insufficient infrastructure. It is also not completely known or quantified how integrating these technologies will affect the environment and the economy, even though it will optimise resource use, increase crop yields, and decrease resource wastage (Bolón-Canedo et al., 2024). In order to make sure that these new technologies can be scaled up and used by more people in agriculture, we need to find out how well AI and the internet of things work for sustainable farming, what the biggest problems are that farmers encounter, and how we can fix them (Mohamed, 2023). Technology can provide benefits to the users. However, it also creates the digital stress due to frequent changes, expenses and lack of competitiveness in market dynamics (Gaikwad and Bhattacharya, 2024).

1.3. OBJECTIVES OF THE STUDY

- To evaluate the effectiveness of AI and IoT technologies in enhancing precision agriculture practices and promoting sustainable resource use
- To analyze the environmental and economic impacts of integrating AI and IoT in farming, focusing on yield improvement and reduced resource wastage
- To identify challenges and limitations faced by farmers in adopting AI and IoT, and provide recommendations for wider implementation and scalability

1.4. HYPOTHESIS OF THE STUDY

Hypothesis 1: The use of AI and IoT in precision agriculture leads to a significant reduction in water and fertilizer usage, enhancing sustainability in farming practices.

Hypothesis 2: Implementing AI and IoT technologies in precision agriculture significantly improves crop productivity and quality compared to traditional farming methods.

2. LITERATURE REVIEW

Akintuyi (2024) investigated the application of adaptive AI to precision farming, with an eye towards enhancing sustainability, efficiency, and productivity. The optimum resource utilization, reducing environmental impact, and increasing crop yields are some of the benefits highlighted by the real-time data analysis from IoT devices and machine learning algorithms. But there are obstacles that must be overcome, including expensive implementation costs, technical intricacy, and worries about data privacy. To fully reap the benefits of AI in agriculture, the study stresses the need of accessible, strong AI solutions and the necessity for continuous innovation and policy backing.

Hareendran, A., & Albaaji (2024) demonstrated that AI and technological advancements have revolutionized the field of smart farming, enhanced crop yields and achieving sustainable results. By analyzing data, AI has established a framework for decision-making, enabling farmers to make informed decisions and implement best practices. Blockchain, the IoT, remote sensing, imaging, and drones are just a few examples of the disruptive technologies that have revolutionized farming. Disease control and pest management have also been greatly assisted by AI-based farming, leading to increased productivity and yields. A model for self-sustaining agriculture based on agricultural intelligence has been suggested, and high-yield, productive farming has made a big splash in the post-pandemic era. It is believed that this tech-driven farming will encourage the younger generation to work in agriculture, turning artificial intelligence into agricultural intelligence.

Saikanth (2023) found that sustainable agricultural advancements were necessary for food production while preserving the environment. Sustainable agricultural practices and their potential future were the subjects of this comprehensive review. The ever-increasing human population made food security an urgent matter. The overexploitation of resources, pollution, and biodiversity loss caused by conventional farming methods jeopardised environmental sustainability, despite their effectiveness in producing food on a large scale. Fair, profitable, and environmentally friendly farming methods were advocated for by sustainable agriculture. Renewable energy sources, pesticide- and disease-resistant genetically engineered crops, and precision farming were all utilised. Crop rotation, organic farming, and agroforestry are agro-ecological practices that were emphasized in the study. These practices enhanced soil fertility, decreased the use of synthetic pesticides, and increased biodiversity. For the purpose of both ecological preservation and food production, sustainable agriculture also made use of traditional knowledge and local resources. The evaluation also highlighted the significance of educational initiatives and governmental backing for sustainable agriculture. Public awareness campaigns and training for farmers both contributed to the spread of sustainable practices. In order to ensure both food security and environmental protection, the review found that sustainable agricultural practices were crucial.

Ashraf (2023) studied those digital technologies to transform farming in a way that increased output while guaranteeing long-term viability. Improving crop management and yield forecasting, sustainable agriculture was transformed by cloud computing, AI, and the IoT, as outlined in this abstract. IoT has made it possible for drones to monitor farms and crops with state-of-the-art sensors in real-time. After that, cloud platforms receive this data. These infrastructures were trustworthy data storage and processing hubs, able to process enormous datasets and execute intricate data analytics. Additionally, machine learning automated farming processes, identified possible diseases, predicted crop yields, and helped with decision-making by sifting through the collected data. A comprehensive framework for data-driven farming has been developed through the integration of cloud computing, AI, and the IoT. This structure improves resistance to climate change, maximises the use of available resources, and decreases waste. Sustainable agriculture that could keep up with the world's growing population was the promise of these agricultural technological advances.

Shaikh (2022) examined that data digitization triggered a data tsunami across practically all industries dependent on data. Data transfer between machines also increased with the advent of man-to-machine (M2M) digital data handling. Both farmers and consumers reaped the benefits of digital agriculture management applications, which expanded access to technology in rural areas and had an impact on information and communication technology. There was some discussion of the challenges of integrating ICT into farming practices, as well as its potential benefits, in this study. Our investigation focused on the agricultural applications of AI, machine learning, and sensors, as well as robotics and Internet of Things (IoT) devices. Using drones, researchers looked into crop observation and optimizing yields. Additional reviews support and focus on applying AI to agriculture were highlighted, and present and future trends in AI were summarized, after a comprehensive evaluation (AlZubi & Galyna, 2023).

Linaza (2021) explored that artificial intelligence (AI) has revolutionized agriculture by improving farm decision support, monitoring conditions, and optimizing production. This technology has led to increased yields, reduced water use, and greenhouse gas emissions. AI has also developed a framework for digital cultivation, enabling smart farming ecosystems and precision farming. Disruptive technologies like blockchain, IoT, remote sensing, imaging, and drones have transformed farming, enabling farmers to make smart choices and follow best practices. AI has also improved pest and disease management, leading to increased productivity and profitability. Post-pandemic, high-yield farming became crucial, and a model of agricultural intelligence for self-sufficient farming was proposed for growth and financial stability. The supply chain protected farmers' finances while providing high-quality products. Future research projects are expected to explore autonomous robots for plant and soil sample retrieval and livestock management.

3. RESEARCH METHODOLOGY

The main aim of this study is to assess how well sustainable precision agriculture makes use of AI and the IoT. In order to study the effect and efficacy of these technologies on eco-friendly farming practices, this section gives a thorough explanation of the variables, data gathering methods, and analytical approaches utilised.

3.1. RESEARCH DESIGN

The purpose of this descriptive study is to illuminate how the IoT and AI contribute to eco-friendly precision farming. With this set up, we can more easily examine how these technologies influence agricultural productivity, resource optimisation, and environmental impact.

3.2. RESEARCH APPROACH

The impact of IoT and AI technologies on farming methods and resource usage is measured using a quantitative research approach. The hypotheses can be validated through statistical analysis using the quantitative data gathered from experiments, surveys, and sensor readings.

3.3. SAMPLE POPULATION

The target population consists of farmers and agribusiness stakeholders who are actively using technology-enhanced agricultural practices and precision farming in the chosen geographic area.

3.4. SAMPLE OF THE STUDY

225 farmers make up the study sample; they represent a range of crop, livestock, and mixed farming practitioners with varying degrees of experience and IoT and AI tool adoption.

3.5. SAMPLING TECHNIQUE

To guarantee diversity across farming types, experience levels, and educational backgrounds, a stratified random sampling technique is used. This approach ensures that different agricultural community subgroups are represented.

3.6. VARIABLE

3.6.1. Independent Variables: -

- Smart Farming, Artificial Intelligence, Internet of Things (IoT).

3.6.2. Dependent variables: -

- Green Farming, Productivity, Sustainable Agriculture.

3.7. DATA COLLECTION

A sample of 225 farmers actively engaged in different agricultural activities, such as crop farming, livestock management, and mixed farming, was chosen for the quantitative data collecting. A clear profile of the participants was provided by the data-gathering tool, which was developed to collect extensive demographic data. It also looked at the particular agricultural techniques each farmer used, emphasizing the degree and mode of technology use in their operations. This instrument's main goal was to gather farmers' perspectives on how cutting-edge technologies, especially artificial intelligence (AI) and the internet of things (IoT), are affecting the agricultural industry. This method made it possible to conduct a thorough quantitative study, which aided in spotting trends in the integration of technology and how farmers viewed its effects on sustainability, efficiency, and production.

3.8. TECHNIQUES USED FOR DATA ANALYSIS

Several statistical methods were used in the data analysis to investigate the connection between farming productivity and the integration of AI and IoT.

- **Descriptive Statistics:** To provide an overview of the respondents' years of experience, farming types, and demographic traits, basic statistical measures were calculated.
- The Independent t-Tests were used to compare means between groups (e.g., IoT involvement and non-involvement) in order to evaluate variations in resource utilisation and farming productivity.
- **Regression Analysis:** To determine the significance and strength of the relationship between the dependent variables (productivity, sustainability, and green farming outcomes) and the independent variables (AI, IoT, and smart farming practices), multiple regression analysis was used.

The statistical significance of AI and IoT in sustainable agriculture practices is evident in the significant variance observed, highlighting their potential to revolutionize the industry.

4. DATA ANALYSIS

Table 1 provides a comprehensive overview of the research participants' traits based on their demographic information. Eighty percent of those who took the survey are men, while just twenty percent are women. Most respondents (31.11%) fall within the 31–40 age bracket, followed by 26.67% in the 20–30 age bracket, 22.22% in the 41–50 age bracket, and 20.00% in the 51+ age bracket. There is a large range in the respondents' levels of education; 35.56 percent have completed elementary school, 31.11% have completed secondary school, 17.78 percent are illiterate, and 15.56% have degree holders.

Table 1: Demographic Respondent

Sub Groups	Frequency	Percentage
Gender		
Male	180	80.00%
Female	45	20.00%
Age		
20-30	60	26.67%
31-40	70	31.11%
41-50	50	22.22%
51+	45	20.00%
Education		
Illiterate	40	17.78%
Primary School	80	35.56%
Secondary School	70	31.11%
Higher Education	35	15.56%
Farm Type		
Crop Farming	130	57.78%
Livestock Farming	50	22.22%
Mixed Farming	45	20.00%
Experience		
Less than 5 years	40	17.78%
5-10 years	90	40.00%
More than 10 years	95	42.22%

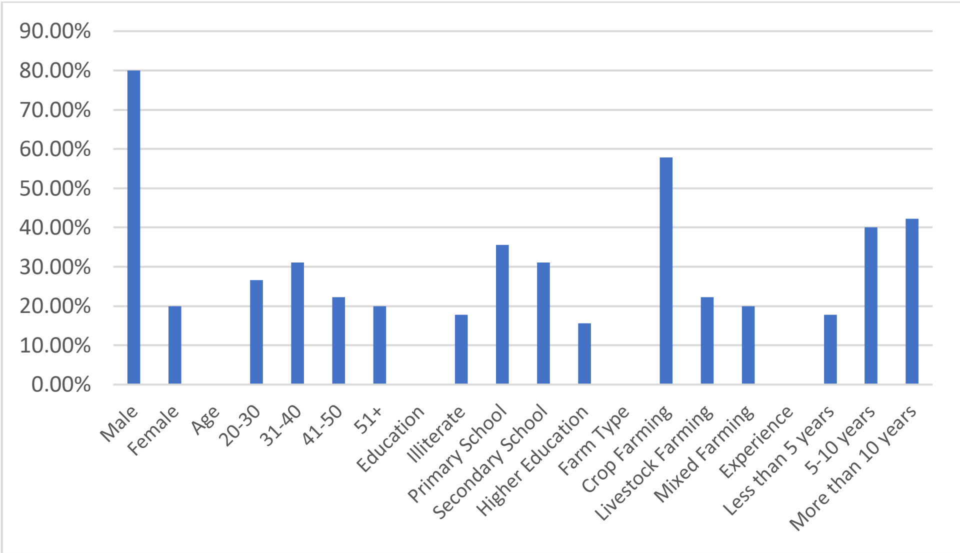

Figure 1: Graphical Representation on the percentage of Demographic Respondent

Crop farming accounts for 57.78% of the respondents' farming practices, with livestock farming coming in second at 22.22% and mixed farming at 20.00%. According to the data, a sizable percentage of respondents (42.22%) have more than ten years of farming experience, 40.00% have five to ten years, and just 17.78% have less than five years. A largely male population with a moderate degree of education, substantial experience, and a strong preference for crop farming is depicted by this demographic profile.

Table 2: Independent T – Test

Group Statistics						Levene's Test for Equality of Variances		t-test for Equality of Means	
	H2	N	Mean	Std. Deviation	Std. Error Mean	F	df	t	Sig.
Number of Loans	Involvement	225	2.8264	1.00670	0.06550	65.465	470	-7.427	0
	without Involvement	224	3.3884	0.5750	0.03745		377.830	-7.435	
Investment	Involvement	225	2.8225	1.0525	0.06825	0.225	470	-6.200	0.627
	without Involvement	225	3.7854	2.15225	0.1390		342.454	-6.184	

Both the Number of Loans and the Investment variables show significant differences between the groups with and without participation, according to the findings of the independent t-test. The t-test reveals a significant difference between groups ($t = -7.435$, $p < 0.001$), with the non-engaged group having a higher mean (3.3884) than the involved group (2.8264). Levene's test indicates unequal variances for the number of loans ($F = 65.465$, $p < 0.05$). The t-test likewise reveals a significant mean difference ($t = -6.200$, $p < 0.001$) for investment, when equal variances are assumed ($F = 0.225$, p > 0.05). The non-engaged group once more has a higher mean (3.7854) than the active group (2.8225). In general, greater averages for loan and investment amounts are linked to non-involvement.

Table 3: Model outline of factor

Model Summary				
Model	**R**	**R Square**	**Adjusted R Square**	**Std. Error of the Estimate**
1	.721[a]	.552	.450	.84451
a. (Constant) Smart Farming, Artificial Intelligence, Internet of Things (IoT)				

According to Table 3, the model summary, the regression model that incorporates smart farming, AI, and the Internet of Things as predictors fits the data well. With an R-value of 0.721, there is a very positive relationship between the independent and dependent variables. With a R Squared value of 0.552, the model explains about 55.2% of the variance in the dependent variable, indicating moderate explanatory power. Taking into consideration the number of predictors in the model, the Adjusted R Square value of 0.450 indicates that around 45% of the variance is explained, which is significant. This is after accounting for the number of independent variables. By computing the standard error of the estimate (0.84451), one can see the average distance between the observed values and the regression line. This distance is used to estimate the accuracy of the model's predictions. Although the model adequately fits the data, a significant portion of the variance remains unexplained.

Table 4: ANOVA

ANOVA[a]						
Model		**Total Squares**	**df**	**Average Square**	**F**	**Sig.**
1	Regression	225.044	1	57.325	69.135	.001[b]
	Residual	1.213	224	.650		
	Total	226.24	225			
a. Dependent Variable: Green Farming, Productivity, Sustainable Agriculture						
b. Predictors: (Constant) Smart Farming, Artificial Intelligence, Internet of Things (IoT)						

Based on the results of the analysis of variance (ANOVA) in Table 4, we can see how well the regression model explained the variability of the dependent variable, which includes sustainable agriculture, green farming, and productivity. Whereas the residual sum of squares (1.213) reveals unexplained variation, the regression sum of squares (225.044) makes the independent variables that can be explained stand out. An F-statistic of 69.135 percent is obtained by combining the regression mean square (57.325) with the residual (0.650). The model's ability to explain the dependent variable is statistically supported by a high F-value. The entire model is statistically significant, as shown by the p-value (Sig.) of 0.001, which is significantly lower than the typical significance level of 0.05. Predicting variations in sustainable agriculture, green farming, and productivity is thus heavily influenced by the IoT, AI, and smart farming.

Table 5: matrix of correlation

Coefficients'						
Model		**Unstandardized Coefficients**		**Standardized Coefficients**	**t**	**Sig.**
		B	**Std. Error**	**Beta**		
1	(Constant)	-.554	.305	-.535	-6.211	.055

	Employee perceptions	-.035	.09	-.090	-2.560	.200
	Ethnicity	.345	.150	.265	5.250	.064
	Nationality	.110	.001	.105	3.235	.140
	Gender	.0.213	0.134	0.145	0.150	0.200
a. Dependent Variable: Green Farming, Productivity, Sustainable Agriculture						

Table 5's coefficients table displays the dependent variable, which includes Green Farming, Productivity, and Sustainable Agriculture. The unstandardised coefficient is -0.554 and the p-value is 0.055, so the constant term does not have any statistical significance at the 0.05 level. A negative unstandardised coefficient of -0.035 and a p-value of 0.200 indicate that "employee perceptions" has the least influence on the dependent variable. "Ethnicity" shows a marginally significant positive effect with a p-value of 0.064 and a positive coefficient of 0.345, which is slightly higher than the typical significance level of 0.05. The positive coefficient of 0.110 and p-value of 0.140 suggest that "Nationality" is not statistically significant. At last, we can see that "Gender" does not have a significant impact on the dependent variable because its positive coefficient is 0.213 and its p-value is 0.200. Though ethnicity and nationality do have an overall impact, no predictor is found to be statistically significant at the 0.05 level.

5. CONCLUSION

In conclusion, this investigation highlights the transformative potential of integrating technologies such as the internet of things and artificial intelligence into sustainable precision agriculture. In conclusion, this investigation highlights the potential for such integration. The implementation of these innovations has had a positive impact on a number of different aspects, including the optimization of resources, the enhancement of environmental sustainability, and the enhancement of agricultural productivity. In spite of the fact that the results have been favorable, there are still obstacles that restrict the widespread implementation of the results. These obstacles include limited adoption, technological restrictions, and a lack of comprehensive knowledge among farmers. On the other hand, if certain educational initiatives are prioritised, supportive policies are implemented, and sufficient infrastructure is made available, it is possible to effectively scale up these technologies in order to assist farming communities. The removal of these challenges should be the top priority of future research in order to make artificial intelligence and internet of things solutions for farmers in a variety of agricultural environment settings more accessible and flexible. This will allow for the achievement of global food security and environmental goals.

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