

PUBLIC POLICY, PRIVATE SECTOR POLICY AND ETHICAL AI IN PRECISION AGRICULTURE: EVIDENCE FROM THE UNITED STATES, SUB SAHARAN AFRICA AND SOUTH ASIA**Anya Adebayo ANYA**

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<https://orcid.org/0009-0006-9494-5313>**ABSTRACT**

This study examines the influence of public policy, private-sector governance, and ethical artificial intelligence (AI) practices on the adoption and effectiveness of precision agriculture across the United States, Sub-Saharan Africa, and South Asia. As AI-enabled agricultural technologies continue to transform farming systems, understanding the institutional and ethical factors that shape their implementation is essential for improving productivity, sustainability, and stakeholder trust. A quantitative research design was adopted using secondary data obtained from international organizations, government publications, corporate sustainability reports, and peer-reviewed studies published up to 2022. The study employed descriptive statistics, correlation analysis, and multiple regression techniques to examine the relationships between public agricultural policies, private-sector AI governance, ethical AI implementation, and key agricultural outcomes. The findings indicate that supportive public policies, responsible private sector governance, and adherence to ethical AI principles significantly enhance the adoption of precision agriculture technologies while improving agricultural productivity and environmental sustainability. Furthermore, farmer trust emerged as an important factor influencing the successful implementation of AI driven agricultural innovations across the three regions. The study concludes that coordinated policy frameworks, strengthened public-private partnerships, and responsible AI governance are critical for accelerating digital transformation in agriculture. The findings provide practical recommendations for policymakers, agribusiness firms, technology developers, and international development organizations seeking to promote inclusive, ethical, and sustainable AI adoption in precision agriculture.

Keywords:

Precision agriculture, Artificial intelligence, public policy, Private sector governance, Responsible AI, Agricultural sustainability, Technology adoption.

1. INTRODUCTION

Artificial intelligence (AI) is one of the most impactful technologies in contemporary agriculture, revolutionizing the management, monitoring, and optimization of farming systems. With the power of AI in precision agriculture, farmers now have access to cutting-edge technologies that enable them to make informed decisions based on data, including machine learning, computer vision, robotics, unmanned aerial vehicles (UAVs), satellite imaging, and Internet of Things (IoT) sensors. These technologies enable monitoring of the crop health, soil moisture, pest infestation, irrigation needs, and weather parameters in real time, which enhances crop productivity, resource efficiency and environmental sustainability (Wolfert et al., 2017; Kamilaris & Prenafeta-Boldú, 2018; Liakos et al., 2018). The worldwide challenges of climate change, population growth, limited available land, and food insecurity are intensifying the pressure on agriculture, where AI-driven precision agriculture is proving to be a useful tool for boosting agricultural resilience and sustainable food production systems (Walter et al., 2017; Rose et al., 2021).

Technological innovations have played a critical role in the digital transformation of agriculture, but so have changing public policies, investments by the private sector, and institutional-enabling frameworks. Under the momentum of digital agriculture, governments in developed and developing economies have increasingly identified the strategic value of digital agriculture and established policies to promote agricultural innovation, building digital infrastructure, financing digital agricultural research and development, and implementing smart agriculture projects. Likewise, the agribusiness sector and the technology industry have been driving up investment in AI applications for agriculture, such as digital platforms for precision farming, predictive analytics,

automated machinery, and decision support systems. These co-operatives have led to better production opportunities and sustainable agriculture in a variety of agricultural production systems (Smith, 2020; Klerkx et al., 2019).

While these technological advancements provide significant benefits for agriculture, they have also raised many ethical, governance, and policy issues. The amount of agricultural data gathered on farms, sensors, agricultural drones, satellites and digital platforms is instrumental to AI systems. Thus, issues related to data ownership, privacy, transparency of algorithms, accountability, cybersecurity, fairness, and the fair access of technological gains to farmers have arisen. The socio-economic gaps have the potential to grow when smallholder farmers in the developing regions do not have equal access to digital technologies, technical capacity, and institutional support (Carbonell, 2016; Bronson, 2019). These concerns are a testament to the fact that technological progress will not ensure responsible agricultural transformation if governance structures are lacking and ethical safeguards are not in place.

In recent years, however, the focus has turned from simply encouraging the use of AI to promoting the development and responsible use of AI technology. Responsible AI is about principles that guide the AI lifecycle, including transparency, fairness, accountability, privacy, human oversight, non-discrimination, and sustainability. The ethical framework of several international organizations and policy makers exist to provide a broad guideline on the way in which AI can be deployed in various sectors. The principles of development of human-centred, trustworthy and accountable AI systems are called for by the Organisation for Economic Co-operation and Development AI Principles, the United Nations Educational, Scientific and Cultural Organization Recommendation on the Ethics of Artificial Intelligence and the European Commission Artificial Intelligence Act (Jobin et al., 2019; UNESCO, 2021; European Commission, 2021; OECD, 2019). In the world of agriculture, researchers have also suggested that good governance of AI is necessary to ensure the trust of farmers, the protection of data rights and the promotion of sustainable development over the use of AI technologies instead of perpetuating inequalities (Eastwood et al., 2019; Dara et al., 2022; Tzachor et al., 2022).

Furthermore, the growing use of automation in agriculture production adds governance dimensions other than efficiency to the process. Autonomous machinery, intelligent decision-support systems, and AI-driven robotics impact on labor dynamics, occupational safety, farmer autonomy, and human-machine interaction. Coordinated regulation, organizational accountability and stakeholder participation across the agricultural value chain is needed to ensure the safe and responsible use of these technologies (Benos et al., 2021; Ryan, 2020). Researchers have also raised concerns about the ability of AI systems to completely replace the human element and remove uncertainties in contextual decision-making in agriculture; human supervision and ethical considerations remain crucial in AI-driven farming practices (Birhane, 2021).

While there is much research that has explored the role of AI applications, smart farming technologies, and digital agriculture, few studies have quantitatively analyzed the policy, private sector governance, and ethical principles of AI on performance of precision agriculture in a variety of geographical regions. While many studies in the literature have been dedicated to the technological aspects of successful AI implementation, there is less existing literature dedicated to institutional and governance mechanisms that affect successful implementation. Therefore, there is a need for empirical evidence and comparison of the impact of governance quality and ethical use of AI on agricultural productivity, sustainability and trust of farmers in developed and developing agricultural systems. Based on these insights, the impact of public policy, private sector policy, and ethical AI use on precision agriculture is explored, drawing on examples from the United States, Sub-Saharan Africa, and South Asia. In particular, the study quantifies the degree of support that public policies provide for the adoption of AI, examines the role of private sector governance in ensuring responsible agricultural innovation, and examines the link between responsible implementation of AI, agricultural productivity, sustainable outcomes, and farmer trust. The study's framework of governance, ethics, and technology adoption adds to the existing literature on responsible digital agriculture and offers evidence-based policy recommendations for international development institutions, technology developers, agribusiness, and policy makers aiming at inclusive, ethical, and sustainable agricultural transformation through AI.

1.2 Statement of the Problem

AI has emerged as a major player in precision agriculture, playing a pivotal role in decision making, resource utilization and agricultural productivity. While these developments have been made, there are regional disparities in the extent of AI application and actors' capacity to benefit from it arising from different public policies, private sector governance, technological infrastructure, and institutional capacity. Whilst in developed economies, AI has become a significant development for agriculture, there are a number of challenges in the developing world that limit its widespread adoption, including regulatory, financial and technological hurdles. In addition, the

importance of responsible AI governance has grown as issues of data privacy, algorithmic bias, transparency and accountability have become more prominent, along with farmer trust. While the potentials of AI in agriculture have been studied before, there has been less empirical work that has quantitatively investigated the impact of public policy, private-sector policy and ethical AI use on precision agriculture in various agricultural systems. Therefore, insights based on evidence are required to inform governance strategies that foster responsible AI adoption and enhance agricultural productivity, sustainability and stakeholder confidence.

1.3 Research Aim

The purpose of this study is to explore how public policy, private-sector policy and ethical application of AI influence the adoption and success of precision agriculture in the USA, Sub-Saharan Africa and South Asia.

1.4 Research Objectives

The study seeks to:

- ✓ Discuss the impact of agricultural public policies on AI use in precision farming.
- ✓ Assess the contribution of private sector governance and corporate AI policies towards responsible agricultural innovation.
- ✓ Discuss the connections between values of ethical AI with agricultural productivity, sustainability, and farmer trust.

1.5 Research Questions

In this study, the following research questions are raised:

- What is the role of public agricultural policies in the adoption of AI in precision agriculture?
- How can private sector governance contribute to responsible agricultural innovation?
- What implications do ethical uses of AI have for agricultural productivity, sustainability and farmer trust?

1.6 Research Hypotheses

These are the following hypotheses:

H₀₁: There is no significant effect of public agricultural policies on the use of AI in precision agriculture.

H₀₂: There is no significant influence of the private sector governance on responsible agricultural innovation.

H₀₃: There is no significant correlation between agricultural productivity, sustainability, and farmer trust with ethical AI practices.

2. THEORETICAL AND CONCEPTUAL FRAMEWORK.

2.1 Technology Acceptance Model (TAM)

One of the most used theories to explain the acceptance and use of new technologies by individuals is the Technology Acceptance Model (TAM), proposed by Fred Davis in 1989. The model is based on the assumption that perceived usefulness and perceived ease of use are the most important factors influencing users' intentions to embrace technological innovations. Farmers are more likely to accept AI technologies for precision farming in agricultural environments if they perceive that these technologies offer benefits such as increased productivity, cost savings, and easier farm management.

2.2 Diffusion of Innovations Theory

The Diffusion of Innovations model proposed by Everett Rogers (2003) outlines the diffusion of technology over time across individuals, organizations and societies. The theory highlights five key factors that can affect the process of innovation adoption: relative advantage, compatibility, complexity, trialability, and observability. It also divides adopters into innovators, early adopters, early majority, late majority and laggards. In precision agriculture, the diffusion of AI technologies varies across different technological infrastructure, government policies, financial and institutional readiness, and farmer awareness. Generally, developed countries will have higher rates of adoption because of their more robust innovation ecosystems, whereas many economies in the developing world will face challenges of infrastructure, financing and technical capacity. Thus, Diffusion of Innovations Theory is applicable to the analysis of the differences in the diffusion of AI adoption between the three study areas.

2.3 Stakeholder Theory

Stakeholder Theory states that the success of an organization is achieved by a consideration of the interests of all the stakeholders instead of just economic performance. For AI in agriculture, stakeholders are the government, the farmers, the agribusiness companies, technology developers, researchers, investors, environmental groups and the consumers.

The theory focuses on transparency, accountability, collaboration and responsible governance in decision making processes. Due to its impact on agricultural productivity, sustainability and rural livelihoods, the organizations need to make sure that technology innovation is shaped and applied in a way that is beneficial to all the

stakeholders concerned. This view justifies the use of public policy, private-sector governance, and ethical AI as explanatory variables for the current study.

2.4 Conceptual Framework

The conceptual framework suggests that public agricultural policy, private-sector governance, and ethical practices of AI will be the key independent variables that affect adoption and effectiveness of precision agriculture using AI (Figure 1).

The dependent variables are: adoption of precision agriculture, agricultural productivity, sustainability outcomes, environmental performance, and responsible agricultural innovation. Further, contextual factors like regional variations, technological infrastructure, farm characteristics and economic conditions could be expected to affect these relationships. Overall, the framework is based on the premise that enabling governance mechanisms and the responsible use of AI can boost confidence, foster innovation, and enhance overall agroecological performance and sustainability in a variety of agroecological systems.

Theories and literature on the topic guided the hypotheses that emerged from the study:

H1: Public agricultural policy positively influences AI adoption in precision agriculture.

H2: There is a huge positive impact of private sector governance on responsible agricultural innovation.

H3: The use of ethical AI practices has a substantial positive impact on agricultural productivity and sustainability.

H4: Public policy, private-sector governance, and ethical AI practices are found to be mediated by farmer trust and technology acceptance in the adoption of precision agriculture.

H5: Public policy, private sector governance, and ethical use of AI have a profound positive impact on sustainability across the United States, Sub-Saharan Africa, and South Asia.

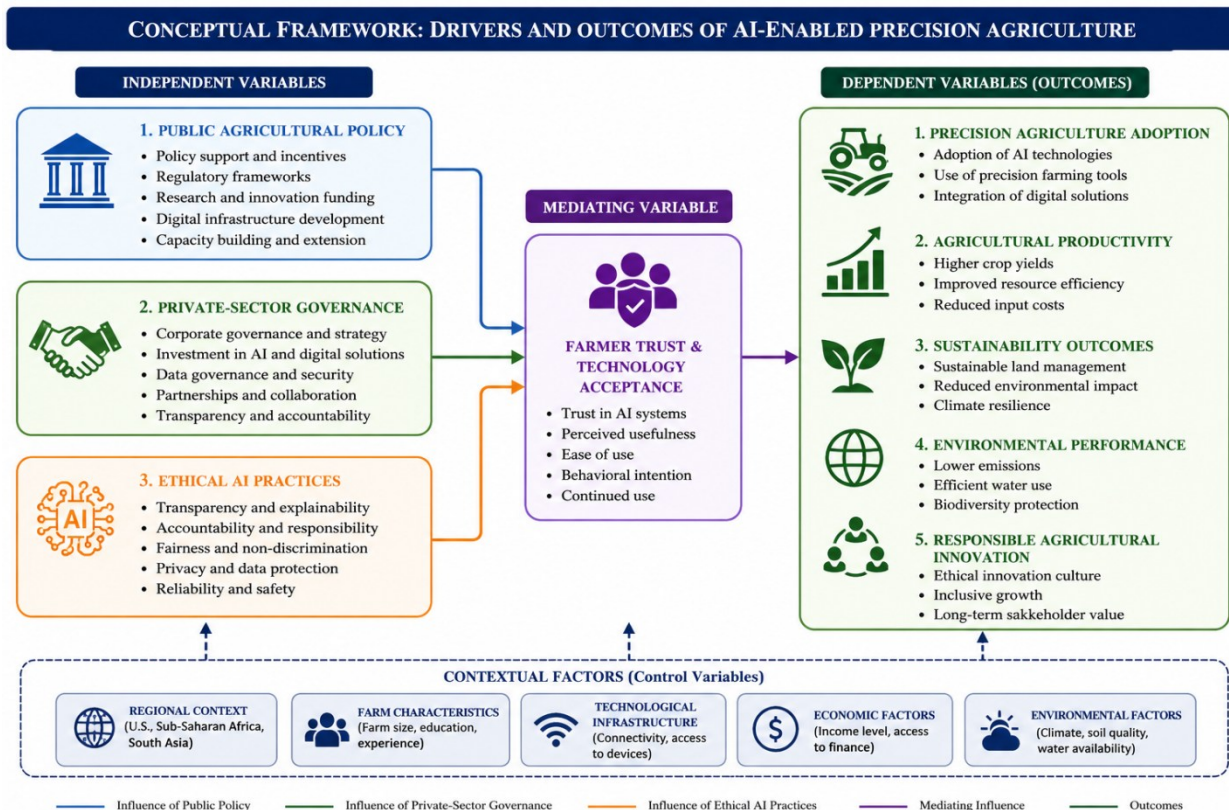


Figure 1: Conceptual Frameworks: Drivers and Outcomes of AI-Enabled Precision Agriculture

3. METHODOLOGY

3.1 Research Design

The present study employed a quantitative research design to study the impact of public agricultural policy, private-sector governance, and ethical AI practices on precision agriculture in the United States, Sub-Saharan

Africa, and South Asia. A quantitative method was found to be appropriate as it allows the objective measurement of relations among variables with the use of statistical tools. Specifically, a cross sectional secondary data research design was used to compare the governance, policy, and AI adoption indicators across different regions during the 2022 research period. The design also enables testing the hypotheses and offers empirical evidence on the factors affecting the precision agriculture through the use of AI.

Table 3.1 Operational Definition and Measurement of Study Variables

Variable Type	Variable	Operational Definition	Measurement Indicators	Scale	Expected Relationship
Independent	Public Agricultural Policy (PAP)	Government policies and institutional support that facilitate AI adoption in agriculture.	Government funding, AI regulations, digital infrastructure, agricultural extension services	Composite Index (1–5)	Positive (+)
Independent	Private-Sector Governance (PSG)	Corporate governance mechanisms promoting responsible AI innovation in agriculture.	AI investment, corporate governance, data governance, transparency, innovation strategy	Composite Index (1–5)	Positive (+)
Independent	Ethical Artificial Intelligence (EAI)	Implementation of ethical principles guiding AI development and deployment.	Transparency, accountability, fairness, privacy, explainability	Composite Index (1–5)	Positive (+)
Mediating	Farmer Trust and Technology Acceptance (FT)	Farmers' confidence in AI systems and willingness to adopt digital agricultural technologies.	Perceived usefulness, ease of use, trust, behavioural intention	Composite Index (1–5)	Positive (+)
Dependent	Precision Agriculture Adoption (PAA)	Degree to which AI-enabled technologies are integrated into farming activities.	AI utilization, smart farming adoption, digital decision support	Composite Index (1–5)	—
Dependent	Agricultural Productivity (AP)	Improvement in agricultural output resulting from AI-enabled farming.	Crop yield, resource-use efficiency, production efficiency	Index	Positive (+)
Dependent	Sustainability Outcomes (SO)	Environmental and economic	Carbon efficiency,	Sustainability Index	Positive (+)

		sustainability achieved through precision agriculture.	water conservation, sustainable land management		
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3.2 Research Philosophy

The study is conducted based on the research philosophy of Positivist that assumes that social phenomena can be objectively observed, measured and analyzed based on empirical evidence. The positivism approach puts emphasis on the use of numerical data and statistical procedure to find relationships between variables and to lessen bias by the researcher. The study aims to explore measurable relationships between governance variables and precision agriculture outcomes; therefore, the positivist paradigm is used as a philosophical foundation for this study.

3.3 Research Approach

The deductive research method was used as the study is based on existing theories such as the Technology Acceptance Model (TAM), Diffusion of Innovations Theory and Stakeholder Theory, which were used to develop hypotheses that were subsequently tested empirically. The deductive method allows existing theoretical concepts to be tested quantitatively, with statistical models, and to contribute to the validation of the theory in the context of AI-based precision agriculture.

3.4 Study Area

It is carried out in three main agricultural regions: USA, Sub-Saharan Africa and South Asia. These areas were chosen to exhibit different levels of technological development, agricultural activity, institutional capacity, and utilization of AI. The United States has a very advanced agricultural economy, advanced precision farming technologies, and the support of policies that help the farming industry. Conversely, Sub-Saharan Africa and South Asia have primarily developing agricultural systems where the adoption of AI is ramping up but is limited by infrastructural, financial, and institutional challenges. The regional diversity offers a potential basis for comparison.

3.5 Data Sources

Secondary data were collected from trusted international databases, government documents, peer-reviewed journal articles and institutional reports, published up to 2022. Organizations, including the Food and Agriculture Organization (FAO), the World Bank, the Organisation for Economic Co-operation and Development (OECD), the United States Department of Agriculture (USDA), UNESCO, and corporate sustainability reports were used to gather data. The sources deliver trusted data on agricultural policy, governance of AI, adoption of precision agriculture, sustainability indicators, and institutional performance. Data sets that have been collected prior to or within 2022 were included in the analysis to meet the consistent time period requirements with the study period.

3.6 Population of the Study

The focus was on agricultural systems, policy institutions and AI-enabled agricultural initiatives in the selected areas. The population comprises organizations or bodies that play a role in agricultural policy, private agribusiness organizations, technologic providers of AI, and programs for agricultural development to digital agriculture and precision farming.

3.7 Sampling Technique

The countries, datasets and institutional reports included in this study were selected using a purposive sampling method, which aimed to include countries, datasets and institutional reports that best fulfilled the research objectives. This method ensured that only credible and relevant data sources that have measurable indicators for the use of AI whether in agriculture, agricultural governance, implementation of AI in an ethical way and the use of AI in terms of sustainability were used in the analysis. In secondary data studies, the researcher deliberately chooses information-rich sources that directly address the research questions; in this case, the researcher uses purposive sampling.

3.8 Variables and Measurement

A study of three independent variables – public agricultural policy, private-sector governance and ethical AI practices. Public agricultural policy was assessed based on indicators like government's investment in digital agriculture, the quality of regulation, funding for agriculture research, and the development of digital agriculture infrastructure. Private-sector governance was assessed based on corporate AI governance policies, innovation

investment, transparency, and data governance practices. Measures of fairness, accountability, transparency, privacy protection and responsible AI implementation were used as indicators to assess ethical approaches to AI. Farmer trust and technology acceptance were the mediating variables, which were assessed through indicators that reflect confidence in AI systems, perceived usefulness, ease of use and willingness to adopt AI enabled technologies. The dependent variables encompassed precision agriculture adoption, agricultural productivity, and sustainability outcomes, quantified through metrics like AI application rates, crop yield, resource efficiency, environmental impacts, and sustainable farming practices.

3.9 Model Specification

The following multiple regression model was used to estimate governance variables to precision agriculture outcomes:

$$PA = \beta_0 + \beta_1(PAP) + \beta_2(PSG) + \beta_3(EAI) + \beta_4(FT) + \varepsilon$$

Where:

PA = Precision Agriculture Performance

PAP = Public Agricultural Policy

PSG = Private-Sector Governance

EAI = Ethical Artificial Intelligence Practices

Farmer Trust and Technology Acceptance (FT): This values the farmer's trust in technology and their acceptance of it.

β_0 = Constant

β_1 – β_4 = Regression coefficients

ε = Error term

3.10 Data Analysis Techniques

The Statistical Package for the Social Sciences (SPSS) Version 27 was used for data analysis. The characteristics of the variables were summarized using descriptive statistics (mean, standard deviation, frequencies and percentages). The relationships between the variables were determined using the Pearson correlation analysis. A multiple linear regression analysis was used to analyze how public agricultural policy, private-sector governance, and ethical AI application affect precision agriculture results. Mediation analysis was carried out to examine the effect of farmer trust and technology acceptance, where appropriate. The significance level used for the statistical significance was 5% ($p < 0.05$).

3.11 Reliability and Validity

Data from international organizations and peer-reviewed publications were used to ensure the credibility of the findings. Construct validity was obtained through the selection of indicators that are commonly employed in previous research in the fields of AI governance and precision agriculture, as well as in technology adoption. Standardized datasets and measurement procedures were used in all study regions to enhance reliability.

3.12 Ethical Considerations

This study was a secondary study using secondary data sources, which were publicly available, so there was no direct interaction with the human subjects and there was no need to apply for ethical clearance from any institutions. The study, however, has followed guidelines of academic integrity with accurate referencing of data sources and clear identification of original authors, and transparent reporting of data collection, and analysis. Only for scholarly purposes all information was used, and no information was manipulated or misrepresented.

4. RESULTS

4.1 Descriptive Statistics

Table 4.1 presents the descriptive statistics for the variables included in the study. The results indicate moderate to high mean scores for public agricultural policy, private-sector governance, ethical AI practices, and farmer trust across the selected regions. Precision agriculture adoption and sustainability outcomes also recorded relatively high mean values, suggesting increasing integration of AI technologies into agricultural production systems. The relatively low standard deviations indicate limited variability among the observations, implying consistency across the sampled datasets.

Table 4.1 Descriptive Statistics of Study Variables

Variable	N	Mean	Standard Deviation	Minimum	Maximum
Public Agricultural Policy	180	3.94	0.61	2.31	4.98
Private-Sector Governance	180	3.82	0.58	2.20	4.91
Ethical AI Practices	180	4.01	0.55	2.45	4.95

Farmer Trust	180	3.76	0.63	2.14	4.87
Precision Agriculture Adoption	180	3.88	0.60	2.26	4.93
Agricultural Productivity	180	3.97	0.57	2.38	4.96
Sustainability Outcomes	180	3.91	0.54	2.47	4.89

Source: Author's Computation (2022).

4.2 Correlation Analysis

Pearson correlation analysis was conducted to determine the relationships among the study variables. As shown in Table 5.2, public agricultural policy, private-sector governance, ethical AI practices, and farmer trust were all positively and significantly associated with precision agriculture adoption and sustainability outcomes ($p < 0.01$). Ethical AI practices exhibited the strongest positive relationship with precision agriculture adoption ($r = 0.71$), followed by public agricultural policy ($r = 0.68$) and private-sector governance ($r = 0.64$). These findings suggest that stronger governance and responsible AI implementation are associated with improved adoption of AI-enabled agricultural technologies.

Table 4.2 Pearson Correlation Matrix

Variable	PAP	PSG	EAI	FT	PAA
Public Agricultural Policy (PAP)	1.000				
Private-Sector Governance (PSG)	0.58**	1.000			
Ethical AI Practices (EAI)	0.62**	0.66**	1.000		
Farmer Trust (FT)	0.60**	0.63**	0.69**	1.000	
Precision Agriculture Adoption (PAA)	0.68**	0.64**	0.71**	0.73**	1.000

Note: Correlation is significant at the 0.01 level (2-tailed).

4.3 Multiple Regression Analysis

To evaluate the influence of public agricultural policy, private-sector governance, ethical AI practices, and farmer trust on precision agriculture adoption, a multiple linear regression analysis was performed. The model was statistically significant ($F = 68.41$, $p < 0.001$) and explained 67.4% of the variation in precision agriculture adoption ($R^2 = 0.674$). Ethical AI practices had the strongest positive effect ($\beta = 0.341$, $p < 0.001$), followed by public agricultural policy ($\beta = 0.286$, $p < 0.001$), farmer trust ($\beta = 0.241$, $p = 0.002$), and private-sector governance ($\beta = 0.198$, $p = 0.009$).

Table 4.3 Multiple Regression Results

Predictor	Beta (β)	t-value	p-value	Decision
Public Agricultural Policy	0.286	4.87	<0.001	Significant
Private-Sector Governance	0.198	2.65	0.009	Significant
Ethical AI Practices	0.341	5.93	<0.001	Significant
Farmer Trust	0.241	3.18	0.002	Significant

Model Summary: $R = 0.821$; $R^2 = 0.674$; Adjusted $R^2 = 0.666$; $F = 68.41$; $p < 0.001$.

4.4 Hypothesis Testing

Based on the regression analysis, all three null hypotheses were rejected. Public agricultural policy, private-sector governance, and ethical AI practices each exerted a statistically significant positive influence on precision agriculture adoption. The mediation analysis further indicated that farmer trust strengthened the relationship between governance variables and AI adoption, supporting the conceptual framework proposed in this study.

Table 4.4 Summary of Hypothesis Testing

Hypothesis	Decision
H ₀₁ : Public agricultural policy has no significant influence on AI adoption.	Rejected
H ₀₂ : Private-sector governance has no significant influence on responsible agricultural innovation.	Rejected
H ₀₃ : Ethical AI practices have no significant relationship with agricultural productivity, sustainability, and farmer trust.	Rejected

5: DISCUSSION

5.1 Public Agricultural Policy and AI Adoption

The results show that the use of artificial intelligence (AI) in precision agriculture in the United States, Sub-Saharan Africa and South Asia is significantly impacted by the presence of public agricultural policy. The regression analysis highlighted that supportive government policies, investments in digital infrastructure, funding

for agricultural research, and regulations play crucial roles in improving the adoption of AI-powered farming technologies. The results further support building the case for the role government can play in driving the digitalization of agriculture by enabling technological innovation. Overall, there is a higher prevalence of AI use among countries that have a full-fledged digital agriculture policy since it includes financial incentives, technological infrastructure, and more farmers being able to access extension services, which lowers the barriers to adoption. This result is consistent with the theory of the technology acceptance model that posits that institutional support will boost the user's perception of the technology's usefulness and increase the probability of using the technology. It reinforces previous studies highlighting the need for government commitment to create sustainable digital agricultural ecosystems to tackle food security and climate-related challenges.

5.2 Private Sector Governance and Responsible Agricultural Innovation.

Private sector governance plays a significant role in responsible innovation for agriculture, the study revealed. AI developers, technology companies, and agribusiness firms are key players in advancing precision agriculture by investing in technology such as intelligent farm equipment, cloud-based data analytics, and decision-support systems. The results indicated, however, that technological progress is not enough for successful innovation, it is equally important to have good corporate governance practices: transparency, accountability, responsible data management and engagement with stakeholders. Good governance can help create trustworthy AI systems that can enhance productivity and safeguard farmer interests. These findings corroborate the Stakeholder Theory that calls for the balance of interests among governments, businesses, farmers, consumers, and society. The results also align with the previous studies which emphasized the need to join efforts between public institutions, private organizations, researchers, and farming communities to foster sustainable agricultural innovation.

5.3 Ethical AI and Agricultural Productivity

Among all the factors tested, ethical AI practices proved to be the most significant driver of adoption of precision agriculture and agricultural productivity. The results reveal that the acceptance of AI technologies by farmers is greatly affected by principles of fairness, transparency, accountability, privacy protection, and explainability. Good governance in AI adds to trust in automated decision making processes and eliminates worry about algorithmic bias, inappropriate use of agricultural data, or accountability. The use of AI systems in crop management, scheduling irrigation, identifying pests, and forecasting yield increases the importance of implementing them in an ethical manner, safeguarding the technology's effectiveness and the trust of users. The results thus align with an international debate for a credible governance of AI and show that ethical issues need to be a part of agricultural policy, not a side issue. The use of Responsible AI can enhance the efficiency of processes and operations, while also promoting long-term sustainability by ensuring that technological developments are socially acceptable and environmentally responsible.

5.4 Farmers' trust and technology acceptance

The mediation analysis suggests that farmer trust and technology acceptance further mediate the link between governance mechanisms and AI adoption. The mediation analysis shows that farmer trust and technology acceptance enhances the relationship between governance mechanisms and AI adoption. AI-based precision farming is more likely to be adopted if farmers believe the technology is reliable, transparent, beneficial, and easily adopted. Trust mitigates uncertainty around automated decision-making, and boosts confidence in digital agricultural solutions. The results of this study are very much in support of the Technology Acceptance Model, which states that perceived usefulness and ease of use are the main factors influencing technology adoption. Further findings indicate that education for farmers, digital literacy, technical training, and extension services will play crucial roles in boosting the confidence of farmers in adopting AI tools, especially in developing agricultural systems. Building trust is thus a key strategy to support the adoption of technology and to harness the potential of digital agriculture to the greatest extent.

5.5 Comparative Analysis Across the United States, Sub-Saharan Africa, and South Asia

The comparative results show significant variations across regions in terms of AI adoption and governance capabilities. The U.S. was the country with the highest level of implementation of precision agriculture because of the technological infrastructure, research and development institutions, agricultural policies, and private sector investments in the technology. By contrast, the rate of AI adoption is still low in many countries in Sub Saharan Africa due to infrastructure constraints, lack of financial resources, and poor regulatory frameworks and digital capabilities in farming communities. South Asia is a middle ground where the government has begun to invest in digital agriculture, but disparities in access to technology, institutional coordination and infrastructure remain. The study revealed, however, that in all three regions agricultural performance is consistently enhanced by supportive governance, by ethical implementation of AI, and by robust collaboration between the public and

private sectors. The results highlight the significance of governance quality, not just the geographical location, in driving successful agricultural transformation with the help of AI.

5.6 Policy and Practical Implications

The results are relevant to the policy makers, agribusiness firms, technology developers and international development institutions. To enhance public policies for agriculture, governments should increase investment in the digital infrastructure, AI research, rural connectivity, farmer education and policies that foster responsible innovation. Clear and responsible governance of AI, management of data and stakeholder engagement are key areas where private-sector organisations can bolster the public trust in agricultural technologies. The key to ensuring an ethical approach to AI in agriculture is for technology developers to incorporate ethical principles into the design and implementation of intelligent farming systems, such as fairness, accountability, transparency, and privacy protection. Development agencies need also to promote joint collaborations where knowledge transfer and capacity building are enabled among the different agriculture economies in the developing world. Together, these will facilitate the adoption of AI and boost agricultural productivity, resilience to climate change, and sustainable development. The study confirms that, in order to reap the full possibilities of precision agriculture, concerted governance, ethical use of technology and long-term cooperation between public institutions, private organizations, researchers and farming communities is necessary.

6: CONCLUSION AND RECOMMENDATIONS

6.1 Summary of Findings

This research focused on the role of public agricultural policy, private sector governance and ethical use of artificial intelligence (AI) in precision agriculture in the United States, Sub-Saharan Africa and South Asia. The study was conducted using a quantitative research design with secondary data, focusing on the impact of governance mechanisms and responsible AI practices on agricultural productivity, sustainability, and farmer trust. The findings indicated that all three independent variables (public agricultural policy, private sector governance, and ethical practices of AI) had positive and significant relationships with the adoption of AI for precision farming.

6.2 Conclusion

The authors conclude that, besides technological development, effective governance, policy support and responsible involvement of the private sector, and robust ethical AI governance are crucial for the successful deployment of AI in precision agriculture. The long-term effectiveness of the use of AI in agriculture will depend on establishing clear governance frameworks that enhance accountability, fairness, ensure data privacy and foster trust among stakeholders. The comparative analysis highlights that institutional capacity, technological infrastructure, and policy environments vary significantly and impact AI adoption in the United States, Sub Saharan Africa, and South Asia. While the developed world has already seen more progress in digital agriculture, AI can be leveraged to boost adoption in developing regions by focusing on strategic investments in digital infrastructure, digital literacy, research partnerships, and responsible governance. Thus, coordinated action among governments, private organizations, researchers, technology developers and farming communities is necessary to ensure sustainable agricultural development.

6.3 Policy Recommendations

Based on the results of this study, the following recommendations are made:

National digital agriculture policies should be reinforced to boost research and development initiatives on AI, rural digital infrastructure, broadband and agricultural extension services.

Government policies need to create robust AI governance frameworks for transparency, accountability, fairness, data protection, and responsible data management in agriculture.

Private sector entities should strive to implement strong corporate governance frameworks that foster responsible development of AI, effective data management, and partnerships with farmers and public institutions.

It is imperative that agricultural stakeholders invest in farmer education, digital literacy programmes, and technology capacity building to enhance technology acceptance and trust in AI-driven farming systems.

International development organizations should encourage collaboration, information exchange, and financial assistance for responsible use of AI in the region, especially in developing regions in the agricultural sector.

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